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Robots on Sale: The effect of tax policy on robot adoption and employment*

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Abstract

We study the effect of a tax policy on adopting industrial robots and firm performance, notably in terms of employment. Combining the policy variation in the Tax Credit for Promoting Productivity-Enhancing Equipment Investment (TC-PPEI) in Japan and newly collected Japanese firm-level longitudinal data on robot adoption, we find that the firms eligible for the TC-PPEI increased the adoption of robots. Our event-study analysis reveals that when firms adopt robots, they do not decrease the total number of workers but significantly increase employment after 1-3 years of adoption events and sales. Our results suggest that adopting robots can create employment instead of destroying it at the firm level.

Keywords: Automation, Industrial Robots, Accelerated Depreciation, Tax Credit for Promoting Productivity-Enhancing Equipment Investment, Survey on Industrial Robot Ownership

JEL classification: J23, O33, O38

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1 Introduction

As the number of industrial robots worldwide tripled in the last decade, concern is rising that they might deprive workers of their jobs. Given this recent trend, there is an increasing demand for understanding the economic impact of the increased use of robots, particularly on employment. Emerging literature has used microdata on robot adoption and analyzed how it affects firm-level employment. However, these studies have examined the impact of robots by comparing firms with and without robots or using variations in the timing of robot introduction, and none have identified and examined the exogenous incentives for firms to introduce robots. This paper combines a novel survey of Japanese firms with variations brought by tax policies promoting the introduction of robots in Japan to ask about the causal effects of adopting robots on employment.

We use variations on the introduction, modification, and termination of the Tax Credit for Promoting Productivity-Enhancing Equipment Investment (TC-PPEI). The TC-PPEI is intended to promote investment by providing accelerated depreciation for investments to improve productivity, and it has undergone a series of policy reforms. To use them to identify the causal effect of robot adoption, we designed the first firm-level survey on the adoption of industrial robots in Japan, joint with the Research Institute of Economy, Trade and Industry (RIETI) and Tokyo Shoko Research (TSR), which is one of the largest credit rating companies in Japan. As a result, we obtain data on the robot introduction of about 1,600 companies annually from 2009 to 2021. We link the survey information to TSR credit file information, including sales and employment.

Accelerated depreciation in the TC-PPEI policy aims to promote investment in advanced technologies, such as robots, by compressing the present discounted value of the corporate tax burden. After its introduction in 1998, the TC-PPEI has changed the eligibility requirement in various dimensions, including target industries, firm size, and accelerated depreciation rates. While the policy had been targeting SMEs since its inception, the 2014 revision temporarily expanded the coverage to larger firms until 2017; for example, the special depreciation expanded from 0% to 100% for larger firms in January 2014. We leverage the substantial decrease in the capital cost of robots induced by this policy change to examine the impact of robot adoption on firm-level outcomes such as sales and employment.

We conduct a firm survey to capture the robot purchases of individual firms that are unavailable in conventional data sets, such as the International Federation of Robotics (IFR) and firm-level productivity surveys in other countries. Our robot survey is unique in the following two points. First, we ask about the value of the robot purchase and the quantity, which helps us quantitatively understand the implication of robot adoption on firm performance and employment. Second, we randomize the follow-up notices (letter and telephone) to slow respondents. The heterogeneity in the response rate across the treatment and control groups helps to test the existence of survey-nonresponse bias, which is one of the primary concerns of survey data (DiNardo et al., 2021).

Our main empirical results are summarized as follows. When firms are TC-PPEI eligible, they significantly increase their investment in robots and the depreciation rate.Furthermore, we find that partial evidence that this policy-induced robot adoption increases sales and employment with some time lag. In contrast, we do not find evidence that the number of production workers decreased following robot adoption, contrary to past studies such as Acemoglu et al. (2020) and Koch et al. (2021).[1] Further qualitative analysis using the interview with robot adopters reveals that when firms consider adopting robots, they plan worker reallocation from the task for robots to the one for workers. Our results suggest that a careful organizational design could allow us to enjoy efficiency gains brought by technological advancement without disruptions in labor markets.

[1] Among others, in French context, Aghion et al. (2020) and Bonfiglioli et al. (2020) find evidence supporting the positive employment effect of automation, including robotization. However, their identifying variation has nothing to do with the policy variation.

2 Background

We describe a tax system of our focus, the Tax Credit for Promoting Productivity-Enhancing Equipment Investment (TC-PPEI). The description includes the period, qualifying firms, qualifying equipment, and types of benefits.[2] We also review a few more tax systems relevant in periods without the TC-PPEI. We define our sample period from 2010 to 2021 based on our survey data described in the Data section.

2.1 The TC-PPEI

The TC-PPEI was established to encourage the introduction of advanced equipment and equipment that contributes to the improvement of production lines and operations in order to improve the productivity of businesses by promoting high-quality capital investment and thereby developing Japan's economy. It applies to the case where a corporation acquires specified productivity-improving equipment (SPIE) and uses it for the corporation's business in Japan during the period from the date of enforcement of the Industrial Competitiveness Enhancement Act (ICEA) of January 20, 2014, to March 31, 2017.[3] The stated purpose of the ICEA is to ensure the implementation of the third "arrow" measure of so-called Abenomics included in the Revitalization Strategy for Japan. The TC-PPEI was abolished and reorganized to the Tax Credit for Enhancing Management of Small and Medium Enterprises (TC-EMSME) after the expiration date of March 31, 2017, which we will review in the following.

The SPIE includes specific items of fixed assets such as machinery, equipment, and software that fall under the category of productivity-improving facilities defined in the ICEA and meet the following requirements of acquisition costs. The definition of productivity-improving facilities includes that (i) the item is the latest model and (ii) the item enhances productivity by 1% or more on average. The acquisition cost requirement for machinery

[2] The detail can be found in `https://www.meti.go.jp/policy/jigyou_saisei/kyousouryoku_kyouka/seisanseikojo.html` (in Japanese, accessed on June 30, 2022).

[3] The ICEA did not specify the details of the exact policy measures when it was established in December 2013. Therefore, it was an unexpected change for individual firms.

and equipment is 1.6 million Japanese yen (JPY) or more per unit. Since our focus is on industrial robots under the machinery and equipment category, we will describe the policy for adopting machinery and equipment in detail. Firms are eligible for the tax credit regardless of how many times they have bought targeted robots in the past. Note that these latest machines are in the process of being installed, and there is little concern about over-investment due to tax incentives.

The tax benefits are either special depreciation or tax credit. On the one hand, the special depreciation limit is 50% of the acquisition cost of the SPIE. However, the entire acquisition cost may be depreciated immediately if the item is acquired and placed in service from January 20, 2014, to March 31, 2016, which we call the "boost period." On the other hand, the maximum tax credit amount is 4% of the acquisition cost of the SPIE. However, for the item acquired and used during the boost period, the maximum tax credit amount is 5% of the acquisition cost. In addition, the above tax credit limit is bounded by 20% of the amount of corporate tax for the fiscal year for which the credit is claimed.

2.2 Other Tax Systems for Fixed Asset Purchases

We briefly review the Tax Credits for Promoting Investment for Small and Medium Enterprises (TC-PISME) that existed before the TC-PPEI and the TC-EMSME after the TC-PPEI was abolished.

The TC-PISME The TC-PISME preceded the TC-PPEI before the enforcement of the ICEA. It began on June 1, 1998, and allows special depreciation up to 30% or tax credits up to 7% for qualified corporations that purchase qualified assets. In addition to the difference in the limit on the special depreciation and tax credit, the policy is characterized by a selection of firm size. Namely, a qualified firm must be a small and medium enterprise (SME) that satisfies (i) the stated capital amount is 100 million JPY or less and (ii) the number of regular employees must be 1000 or fewer. Furthermore, suppose SMEs acquire equipment subject to the TC-PPEI between April 1, 2016, and March 31, 2017. In that case, they can receive further preferential treatment of 100% special depreciation or 7% tax credit under the TC-PISME.

The TC-EMSME As mentioned above, the TC-PISME took over the TC-PPEI after the termination of the ICEA and began on April 1, 2017. It allows special depreciation up to 100% or tax credit up to 7% (10% for specified SMEs) for qualified corporations that purchase qualified assets. In addition to the difference in the limit on the special depreciation and tax credit, the policy sets the same selection on firm size as the TC-PISME.

2.3 Summary of the Policy Changes

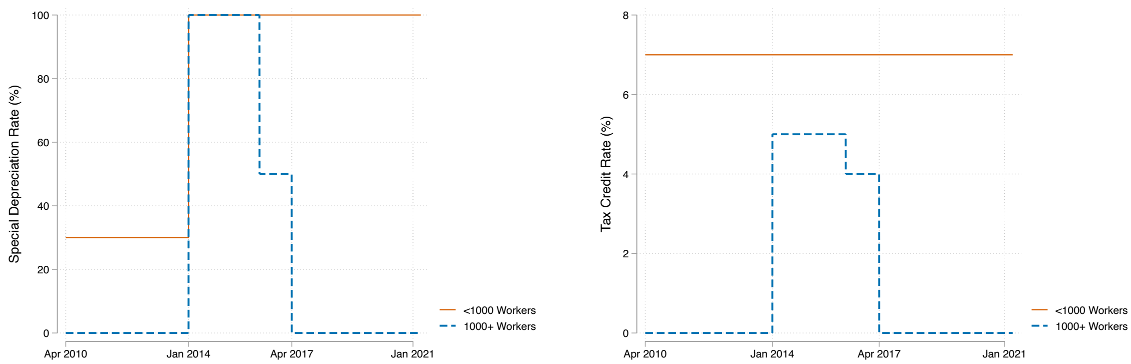
To summarize the policy changes described above, it is worthwhile to consider two cases, whether a firm is regarded as an SME in the TC-PISME and eligible for the TC-PISME. On the one hand, if it does, the firm is eligible for special depreciation and tax credit throughout our sample period since it can use either the TC-PISME, the TC-PPEI, or the TC-EMSME, depending on the calendar date. On the other hand, if a firm is not an SME in the TC-PISME, the firm is eligible for the policy benefits if and only if the TC-PPEI is in effect. Figure 1 summarizes these policy variations across firm size and time. It also depicts the policy rates of special depreciation and tax credits, varying over the sample period.

While tax credits clearly incentivize the adoption of qualified assets for qualified firms, it is worth mentioning the role of special depreciation. As summarized in Curtis et al. (2021), accelerated depreciation (special depreciation in the case of the TC-PPEI) provides an investment incentive for qualified assets by compressing the present discounted value of the corporate tax burden. Specifically, it allows firms to increase the fraction of depreciation that they can record as a current-year expense, compressing the accounting profit in the current year and, therefore, backloading the amount of corporate tax payment. Given that firms discount the future, this policy provides a stronger incentive to invest among those eligible for the TC-PPEI than among those not. Therefore, we expect

Figure 1: Policy Trends

(a) Special Depreciation

(b) Tax Credit



Notes: The trends of policy changes due to the introduction, modification, and termination of the Tax Credit for Promoting Productivity-Enhancing Equipment Investment (TC-PPEI) are shown. The left panel plots special depreciation rates, while the right panel plots tax credit rates. SME indicates firms that satisfy the small and medium enterprise requirement in the Tax Credits for Promoting Investment for Small and Medium Enterprise (TC-PISME) discussed in the main text.

that a firm adopt more robots when it is eligible for the special depreciation scheme due to policy changes exogenous to each firm. In the following, we exploit the variation of policy rates across firm size and time to examine the effect on robot adoption and other outcome variables such as employment.

3 Data

We explain data from the Survey of Industrial Robot Ownership (SIRO), a designed survey for this study, as well as other standard firm-level data sources.

3.1 SIRO Data

We designed a novel survey on adopting industrial robots in conjunction with the Research Institute of Economy, Trade and Industry (RIETI). Tokyo Shoko Research (TSR), a primary credit rating agency in Japan and the Japanese counterpart of Dun and Bradstreet's worldwide network, is entrusted to conduct the survey. TSR invited 13,000 firms on the TSR list that hire 50 employees or more and hold 30 million Yen or more in paid capital operating in the manufacturing sector between January 25th and February 25th, 2022.

This paper focuses on robots among advanced equipment since the definition of industrial robots is fixed in the ISO standards and since we can relate our findings to the ones in the literature with ease. Therefore, the questionnaire asks model, quantity, and values of robots based on the information in fixed asset registry during 2010-2021 retrospectively. To mitigate the concern of memory bias, we design the survey in the following way. First, we restrict the set of questions to be the ones that are answerable only by referring to the fixed asset registry. This reduces the respondent's burden for referring to field experts who actually uses the robots. Therefore, we primarily send the questionnaire to an accounting department of each firm. Second, we split the target years into three groups, 2010-2013, 2014-2017, and 2018-2021, to make sure a respondent also answers robot adoption in the past. Note that the split coincides with the period of the TC-PPEI, so it is suitable to study the policy effect. The questionnaire is shown in Appendix A.1.

Another unique feature of this survey is a randomized reminder to non-respondents. To the non-response firms whose TSR id ends with even numbers, TSR sent out a reminder post card on February 4th and called from February 7th. TSR did not harass non-responding firms with TSR ids that end with odd number. Figure 5a shows that daily number of survey collection is almost in parallel until February 7th between the firm that received the calls and not received the calls, although the series are somewhat volatile due to the small sample size. This finding reassure the validity of the random assignment. On the other hand, the number of collections substantially increased among the called firms but not among the non-called firms after February 7th, reassuring the relevance of the randomly assigned reminders. In the end of the survey period, 1,681 firms responded to the survey, thus the response rate was 12.9%. The response rate was 14.9% among the firms that received reminder and was 10.8% among firms that did not receive the reminder. This substantial difference of the response rates between randomly assigned groups allows us to assess the degree of non-response bias proposed by DiNardo et al. (2021). As reported in Appendix A.3 the non-response bias seems minimal.

3.2 TSR Data

The primary dataset used in this study is the firm-level credit report compiled by Tokyo Shoko Research (TSR), which is a major credit rating agency in Japan and is the Japanese counterpart of Dun and Bradstreet's worldwide network. The dataset aims to cover all firms in Japan regardless of their size, industry, and region. It includes information on the year of establishment, the head quarter location, the industry defined by the major product or service, the amount of sales, the number of employees, profit, and information regarding the CEO.

The TSR data reveals the characteristics of the firms included in the SIRO survey. Namely, we compare the characteristics based on the firms' information as of December 2010, extracted from the TSR database. We find that firms with higher credit scores, higher profits per employee, more employees, and that are not SMEs are more likely to be included in the survey, as reported in Appendix Table A.3. This is to better capture the mass of firms around the threshold of policy changes, one of which is 1,000 workers and is higher than the average number of workers in the whole Japanese firms. In terms of industry, the manufacturing and wholesale and retail sectors are over-represented, whereas construction, real estate and lease, hotel and restaurant, and health and welfare sectors are underrepresented. Therefore, we have to keep in mind that our dataset is not designed to represent the whole economy but to study the policy change with great statistical power. For example, the industries that are considered to have suffered especially during the pandemic, such as hotel and restaurant, are underrepresented in our sample.

4 Empirical Strategy

We describe our empirical strategies to estimate the effect of robot adoption on firm outcomes using event study and policy analysis.

Event Study First, following the recent empirical literature on the effect of robot adoption, we analyze the dynamic treatment effect of adopting robots. Given the rapidly growing nature of robotics technologies, we expect that the treatment effects are heterogeneous across cohorts of robot adoption year. Therefore, we formulate our event-study design based on Sun and Abraham (2021), who develop an estimation method robust to treatment effects heterogeneity across cohorts. Specifically, write the robot adoption status as $D_{it} = 1$ if firm i adopts robots in year t, and the year of initial robot adoption observed in the SIRO data by $E_i \equiv \min\{t : D_{it} = 1\}$. For firm i that never adopts robots during the sample period, we write $E_i = \infty$. Based on when they adopt robots for the first time, we can uniquely categorize firms into disjoint cohorts e for $e = 2010, \ldots, 2021, \infty$. Define Y_{it}^e to be the potential outcome in year t when firm i adopts robots for the first time in the SIRO data in period e and baseline outcome Y_{it}^∞ to be the potential outcome if firm i never adopts robots during the sample period. Then we can represent the observed outcome Y_{it} for firm i in year t as

$$Y_{it} = Y_{it}^{E_i} = Y_{it}^\infty + \sum_{2010 \leq e \leq 2021} \left(Y_{it}^e - Y_{it}^\infty\right) \cdot \mathbf{1}\left\{E_i = e\right\}.$$

In this framework, an average treatment effect in period l are cohort e-specific in general and can be defined as $CATT_{e,l} \equiv E\left[Y_{i,e+l} - Y_{i,e+l}^\infty | E_i = e\right]$. Our target parameter is the weighted average of $CATT_{e,l}$ for each relative year $l \in \{-5, \ldots 5\}$, where the weights are shares of cohorts that experience at least l periods relative to treatment

$$v_l \equiv \sum_e \Pr\left\{E_i = e | E_i \in [-l, T-l]\right\} CATT_{e,l}. \tag{1}$$

We implement the interaction-weighted estimator using `eventstudyinteract` package, which runs an algorithm proven to compute an unbiased and consistent estimator under standard parallel trends and non-anticipation assumptions.

Policy Analysis To estimate the causal effect of robot adoption on firm-level outcomes, we estimate the following two-stage least squares equation.

$$Y_{it} = \alpha_i + \gamma_t + \beta R_{it} + \epsilon_{it}, \tag{2}$$

where Y_{it} is the firm-level outcome variable, employment and sales, R_{it} is the robot adoption measure, the indicator of robot adoption and the log value of adoption plus one, and α_i and γ_t are firm- and year-fixed effects.

Since firm-level employment and sales are simultaneously determined with robot adoption, firm-level shocks such as productivity or demand shocks cause the error term and the robot adoption measure to be positively correlated. To mitigate this concern, we use the instrumental variable (IV) that are plausibly orthogonal to such firm-level shocks. In particular, we construct the statutory depreciation rate to adopt robots, Z_{it} and use it as the IV for R_{it}. As we have discussed in Section 2, there are firm-size, temporal, and industry-level variation in the eligibility status and the relevant depreciation rate, and its determination is politically determined independent from each firm.

5 Results

After reviewing descriptive statistics, we show our main empirical results.

5.1 Descriptive Statistics

SIRO Table 1 shows the summary statistics of the SIRO data. The unit of observation is a robot adoption event. The table reveals several novel facts. First, adoption by lease is rare with the share of 0.6%. Therefore, for many robot adoption events, applied depreciation

Table 1: Summary Statistics of the SIRO Data

	N	mean	sd	p10	p50	p90
Acquisition year		2016	3.3	2011	2017	2021
Lease indicator		.0059	.077	0	0	0
Quantity		1.4	1.7	1	1	2
Total Value (Million JPY)		21	46	2.2	8.8	44.1
Declining balance indicator		.69	.46	0	1	1
Service life		9	2.3	7	9	12
Depreciation amount (Million JPY)		11	35	.318	3.74	24.3
Online reply indicator		.8	.4	0	1	1
Observations	2695					

Notes: Summary statistics of the Survey of Industrial Robot Ownership (SIRO) data is shown. The unit of observation is a robot adoption event. Declining balance indicator is 1 if the declining balance method is taken for depreciation of the item, and 0 otherwise. Depreciation amount is yearly. Online reply indicator is 1 if the answer is recorded by online response, and 0 otherwise (handwritten response).

rates matters. Second, the total value of robot adoption is skewed toward right, with the mean (20.5 million JPY) is largely greater than the median (8.8 million JPY). Third, service life has a mean and median of 9 years, which is slightly shorter than the standard practice of 12 years used in the literature. As another unique feature of the SIRO data, Table A.1 in the appendix shows the tabulation of robot makers for each adoption event.

TSR Table 2 shows the summary statistics of the TSR data among the subject firms of the survey. We categorize firms into two groups, those who answered survey and those not, and examine the firm-level characteristics available in the TSR data. The table reveals a balanced pattern between the two groups in terms of employment, the number of establishment, sales, profit margin, year of establishment and CEO birth, CEO gender, and the credit score rated by the TSR.

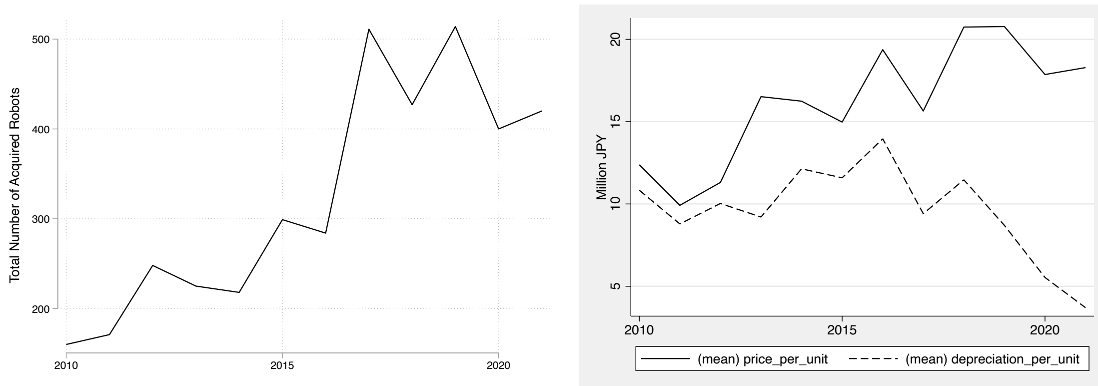
Table 2: TSR Summary Statistics

variable	answered	N	mean	sd	p10	p50	p90
Log employment	0	10585	4.84	1.01	3.85	4.65	6.12
	1	1532	4.64	0.93	3.81	4.48	5.69
Log number of establishment	0	10585	0.99	1.00	0.00	0.69	2.40
	1	1532	0.89	0.93	0.00	0.69	2.08
Log sales	0	10585	15.14	1.35	13.65	14.93	16.87
	1	1532	14.85	1.23	13.54	14.70	16.33
Profit margin	0	10585	-0.00	0.13	-0.06	0.01	0.05
	1	1532	-0.05	1.87	-0.07	0.01	0.04
Year of establishment	0	10585	1964.87	18.90	1944.00	1963.00	1991.00
	1	1532	1965.39	17.90	1946.00	1964.00	1990.00
Year of CEO birth	0	10585	1950.23	9.31	1940.00	1949.00	1963.00
	1	1532	1950.07	9.18	1939.00	1949.00	1963.00
Male CEO dummy	0	10585	0.99	0.12	1.00	1.00	1.00
	1	1532	0.99	0.12	1.00	1.00	1.00
Credit Score	0	10585	56.04	6.62	48.00	55.00	65.00
	1	1532	55.09	6.28	48.00	54.00	64.00

Notes: Summary statistics of the Tokyo Shoko Research (TSR) data for firms included in the Survey of Industrial Robot Ownership (SIRO) is shown. The unit of observation is a firm and the statistics are taken in 2010, the initial year of the SIRO survey. The "Answered" column indicates the status of firm's response to the SIRO survey (1 if responded, and 0 otherwise). The profit margin is defined by profit divided by sales. The credit score is the credit rating researched and published by the TSR.

Figure 2: Trends of Average Robot Adoption

(a) Total Number of Acquired Robots (b) Price and Depreciation of Robots per Unit



Notes: The trend of firm-level average robot adoption is shown. The left panel is that for the total number of acquired robots, while the right panel is that for the average price and depreciation value per unit in 10 thousand JPY.

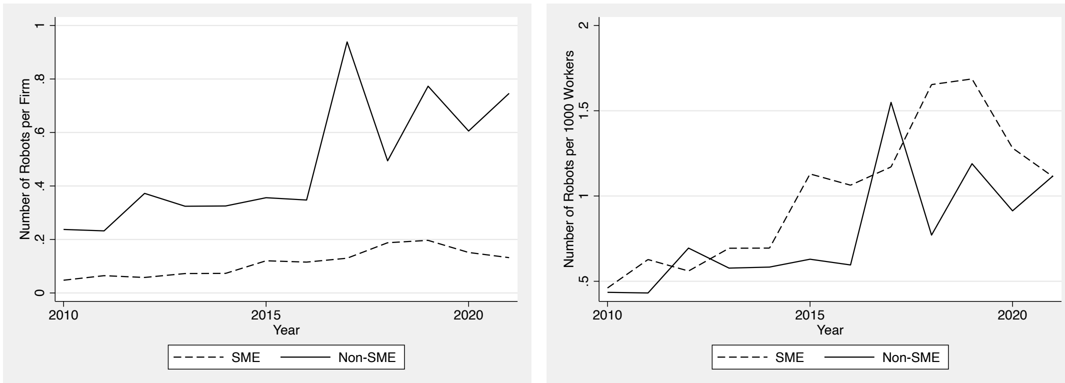
Figure 2 shows the firm-average trend of industrial robots. Panel 2a plots the firm-level average number of robot adoptions. It shows that the average number of robot adoption increased significantly during the period in which the TC-PPEI is active. Panel 2b reveals the trend of average robot prices and depreciation values per unit. The average price per unit gradually increases over time, while the average depreciation value per unit reaches its peak during the period in which the TC-PPEI is active and decreases afterward. This decrease may reflect the fact that large fraction of the depreciation is over during the period of TC-PPEI.

Figure 3 shows the robot adoption trends by SME status. Panel 3a plots that of the number of robots per firm, while Panel 3b of the number of robots per thousand workers. Consistent with the expansion of the target firms from only SMEs to all-sized firms during the period of TC-PPEI, we find a significant increase in the number of robots per firm for non-SME firms. Since non-SME firms employ more workers by definition, the pattern for the number of robots per thousand workers show a less dramatic pattern, but one still can find a sharp increase in the measure during the TC-PPEI period.

Figure 4 shows the robot price trends by SME status. In contrast to the results found in Figure 3, we do not find a clear pattern for price per unit between SMEs and non-SMEs

Figure 3: Robot Adoption by SMEs and Non-SMEs

(a) Robots per Firm (b) Robots per Thousand Workers

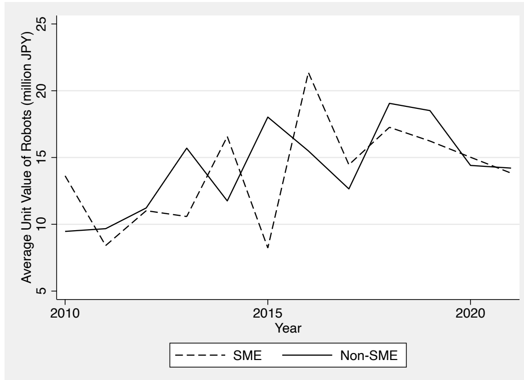


Notes: The trends of robot adoption by the status of small and medium enterprise (SME) is shown. A firm is SME if (i) the stated capital amount is 100 million JPY or less and (ii) the number of regular employees must be 1000 or fewer, which is an eligibility requirement by the TC-PISME and TC-EMSME described in Section 2. The left panel shows the trends of the average number of robots per firm, while the right panel shows those of the average number of robots per thousand workers.

during our sample period, including the TC-PPEI period. This mitigates a concern that the type of purchased robots may differ depending on the SME and non-SME status or the policy in the period, and thus that the effect may not be generalizable to the other scenarios.

Figure 5 shows the patterns of reply by follow-up calls. On the one hand, Panel 5a plots the number of survey collections at the firm level for each response date the random call status. As expected, the number of collections does not differ between group, but it increases significantly from firms randomly assigned to the call group after the call. This reveals the effectiveness of the follow-up calls to increase the survey response. On the other hand, Panel 5b plots the average number of robots at the firm level for each response date and the random call status. Although firms in the call group increased the response significantly after the call date, the answer contents in terms of the average number of robots do not change significantly. This also address the concern that the type of firms that were induced to answer the survey due to the call but would not have answered without the call (compliers) may be different from those who would answer independent of the follow-up call (always answerers) are different.

Figure 4: Robot Prices by SMEs and non-SMEs



Notes: The trends of robot unit prices by the status of small and medium enterprise (SME) is shown. A firm is SME if (i) the stated capital amount is 100 million JPY or less and (ii) the number of regular employees must be 1000 or fewer, which is an eligibility requirement by the TC-PISME and TC-EMSME described in Section 2.

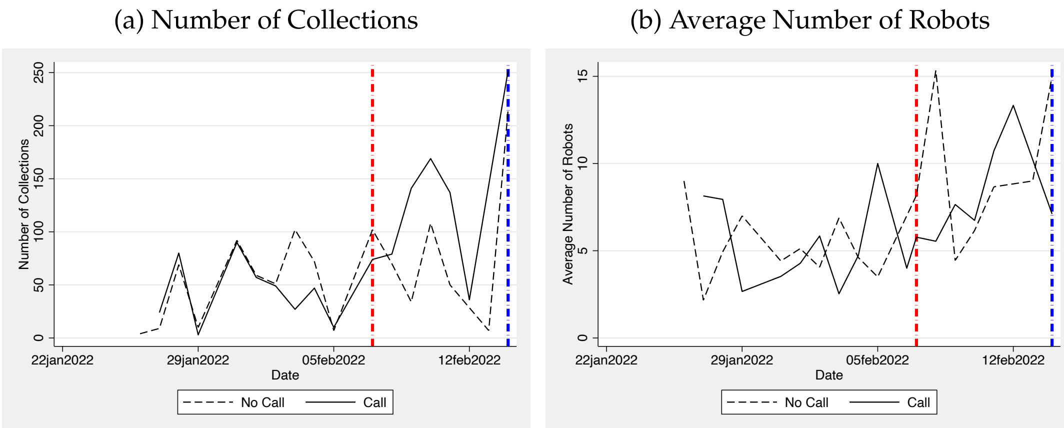
5.2 Main Results

Event Study Figure 6 shows the event-study results and plots the point estimates and the two-sided 95% confidence intervals of the weighted CATT in equation (1). Panel 6a reveals the result with the outcome variable of log employment, while Panel 6b of log sales. It reveals that when firms adopt robots, they do not decrease the total number of workers but significantly increase it after 1-3 years of adoption event as well as sales. Furthermore, the joint F-test for all the coefficients on pre-treatment dummies does not reject the null hypothesis of $v_l = 0$ for all $l \leq 2$ at conventional critical values.[4]

Policy Analysis Table 3 shows the result of the policy analysis. In panel A, we take the log robot adoption value as the main explanatory variable (intensive margin), and panel B takes the robot adoption indicator (extensive margin). Column 1 shows the result of the first-stage regression where robot adoption measures are regressed on the statutory depreciation rate. We find positive significant reactions to the depreciation rate variation at both intensive and extensive margin, indicating the intended effect of the tax policy on

[4]The power analysis suggested by Roth (forthcoming) yields power, or "the probability that no significant pre-period coefficient would be detected under the hypothesized trend," of 0.50 for log employment and 0.50 for log sales.

Figure 5: Reply Patterns By Follow-up Call



Notes: The patterns of reply are shown by the random call status. A random call status is on if and only if the firm's respondent ID is even. Red line indicates the date of call (February 7, 2022). Blue line indicates the deadline (February 14, 2022). The left panel plots the number of collected survey response, and the right panel plots the average total number of robots per firm.

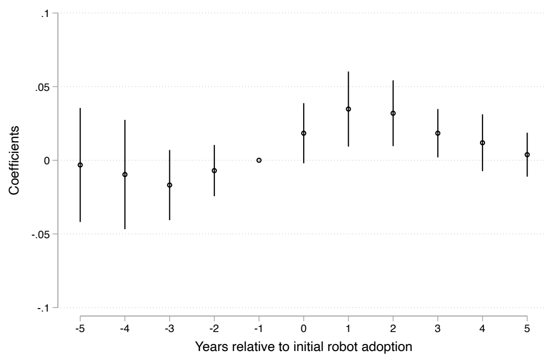
robot adoption.

In columns 2 and 3, we estimate the effect on log employment using the reduced form regression and the two-stage least square (2SLS) regression, respectively. We find that the policy-induced depreciation rates covary positively with the employment. Combined with the first-stage regression, this implies that the robot adoption caused by the policy rate variation *increases* the employment, after controlling for the individual firm- and year-fixed effects. Therefore, we conclude that robot adoption increases employment at the firm-level.

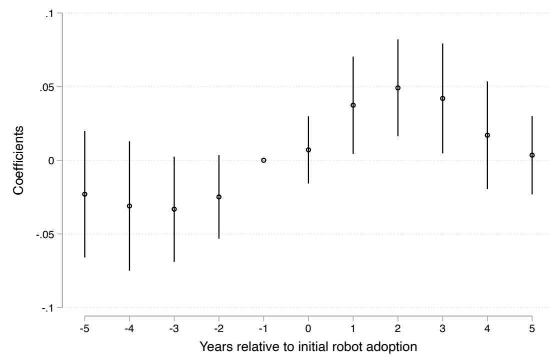
Columns 4 and 5 show the results of similar regressions where the outcome variable is log sales. We find even stronger positive significant results, consistent with the literature's finding (e.g., Aghion et al., 2020). This indicates the role of scale effects to explain the positive employment effect shown above. Indeed, the 2SLS estimate in panel A, column 5 reveals that 10% increase in the robot adoption value implies 2.7% increase in the total sales at the firm-level, while column 3 shows that the same robot value increase is accompanied by 1.0% increase in employment. This relatively muted employment effect is in line with the substitution of employment. Still, the positive effect of the increased

Figure 6: Event Study Results

(a) Log Employment



(b) Log Sales



Notes: The point estimates and standard error of weighted cohort average treatment effect (CATT) is shown. As an outcome variable, the left panel takes log of the total number of workers, while the right panel takes log sales. Both outcome variables are 95% winsorized to minimize the effect of outliers. Standard errors are clustered at the industry and year level. The *p*-values of the joint F-test for all the coefficients on pre-treatment dummies are 0.448 for log employment and 0.469 for log sales.

productivity and thus the firm scale dominates such a substitution effect, implying a net positive impact on employment.

6 Conclusion

Using unique firm-level survey on robot adoption and tax policy changes in Japan, we apply dynamic difference-in-difference and two-stage least square estimation methods to show that the firm-level robot adoption is positively associated with the employment in Japan between 2010 and 2021. The future research should associate this firm-level data with other firm measures, such as productivity, markups, labor shares, composition of worker skills, tasks, and wages, to examine the mechanism of this positive finding unique in the literature.

Table 3: Policy Analysis

VARIABLES	(1) Robot (10M JPY)	(2) ln(emp)	(3) ln(emp)	(4) ln(sales)	(5) ln(sales)
			Panel A: Robot value		
Depreciation Rate	0.195***	0.0196**		0.0530***	
	(0.0177)	(0.00645)		(0.0123)	
Robot value (10M JPY)			0.101**		0.271***
			(0.0443)		(0.0683)
			Panel B: Robot adoption (Extensive margin)		
Depreciation Rate	0.0252**	0.0196**		0.0530***	
	(0.00813)	(0.00645)		(0.0123)	
Robot adoption			0.779**		2.103**
			(0.351)		(0.811)
Firm FE	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓
Specification	First Stage	Reduced Form	2SLS	Reduced Form	2SLS
Observations	18,317	18,317	18,317	18,317	18,317

Notes: The two-stage least square (2SLS) regression results about special depreciation rates are shown. Panel A takes the value of robots as the endogenous variable, while Panel B the dummy for robot adoption. Column 1 shows the first-stage result where the endogenous variable is regressed on the special depreciation rate under each policy regime. Column 2 (4) shows the reduced form result of log employment (sales), while column 3 (5) combines the first stage and reduced form to produce the 2SLS estimates. All columns control for the firm and year fixed effects. Standard errors are clustered at the industry and year level and shown in the parenthesis. *** p<0.01, ** p<0.05, * p<0.1.

References

Acemoglu, Daron, Claire Lelarge, and Pascual Restrepo, "Competing with robots: Firm-level evidence from france," in "AEA Papers and Proceedings," Vol. 110 2020, pp. 383–88.

Aghion, Philippe, Céline Antonin, Simon Bunel, and Xavier Jaravel, "What are the labor and product market effects of automation? new evidence from france," 2020.

Bonfiglioli, Alessandra, Rosario Crinò, Harald Fadinger, and Gino Gancia, "Robot imports and firm-level outcomes," 2020.

Curtis, E. Mark, Daniel G. Garrett, Eric Ohrn, Kevin A. Roberts, and Juan Carlos Suárez Serrato, "Capital Investment and Labor Demand: Evidence from 21st Century Tax Policy," November 2021.

DiNardo, John, Jordan Matsudaira, Justin McCrary, and Lisa Sanbonmatsu, "A Practical Proactive Proposal for Dealing with Attrition: Alternative Approaches and an Empirical Example," *Journal of Labor Economics*, 2021, *39* (S2), S507–S541.

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

Roth, Jonathan, "Pre-test with Caution: Event-Study Estimates after Testing for Parallel Trends," *American Economic Review: Insights*, forthcoming.

Sun, Liyang and Sarah Abraham, "Estimating dynamic treatment effects in event studies with heterogeneous treatment effects," *Journal of Econometrics*, 2021, *225* (2), 175–199.

Appendix

A Data Appendix

A.1 The SIRO Questionnaire

Figure A.1: Survey Questionnaire

2021 "Survey of Industrial Robot Ownership"

◆ Please answer the following questions while looking at the fixed asset ledger.

◆ The industrial robot in this study refers to "a machine that is automatically controlled, reprogrammable, and has a versatile arm with three or more axes and is used for industrial automation applications."

Question 1 . Please answer the new industrial robots purchased from 2018 (Heisei 30) to 2021 (Reiwa 3) in **descending order of total acquisition price .** Please also answer about industrial robots that have already been depreciated. [Note] It is not necessary to describe waste assets.

*** If you do not know the asset name, please enter the corresponding number from the "Application classification" below.**

1. Resin molding 2. Welding 3. Painting 4. Machining 5. Electronic component mounting
6. Assembly 7. Receipt and shipment 8. Material handling 9. Clean room
10. Other uses 11. Unknown use

	Acquisition Year month [AD]	Asset name	Application Classification	Account item	Number of units [Table]	Acquisition cost (the amount) 【Ten thousand yen】	Depreciation method 【Selection】	service life 【Year】	Depreciation amount (total amount) 【Ten thousand yen】
Entry example	2020 April	Kawasaki Heavy Industries · Medium-sized general-purpose robot RS003N	1	Mechanical equipment	3	1, 000	1. Declining balance method 2. Straight - line method	12	83
1							1. Declining balance method 2. Straight - line method		
2							1. Declining balance method 2. Straight - line method		
3							1. Declining balance method 2. Straight - line method		
4							1. Declining balance		

1

Notes: The first page of the Survey of Industrial Robot Ownership is shown. The original document is written in Japanese and the figure shows the version translated into English using the Google Translate. Although the first page shows question 1 up to 4 answer fields, there are three questions (including question 1) that ask similar questions but with regard to different adoption years (2014-2017 for question 2, and 2010-2013 for question 3), and each question has 10 answer fields as well as a field that the respondent can use to report remaining robot quantity and value that do not fit into the 10 answer fields.

A.2 Robot Makers

Table A.1: Tabulation of Robot Makers

	Freq.	Percent
ABB	16	0.594
DMG-Mori	29	1.076
Daihen	84	3.117
Denso	76	2.820
EPSON	4	0.148
FANUC	285	10.58
Fuji	10	0.371
Fujikoshi	75	2.783
Fujiyusoki	53	1.967
KHI	86	3.191
Mitsubishi	61	2.263
Others	1575	58.44
Panasonic	79	2.931
Yamaha	42	1.558
Yaskawa	179	6.642
Yushin	41	1.521
Total	2695	100

Notes: Tabulation of reported robot makers is shown. An observation is robot adoption event. "KHI" abbreviates Kawasaki Heavy Industry. "Others" include adoption of minor companies not listed in the table as well as no report of a specific maker.

A.3 Assessment of Non-response Bias

To assess the non-response bias, we compare the responses among the firms that received calls and not. Those firms that respond to the survey due to the reminder call are presumably closer to non-responding firms, thus the difference of the response between two groups suggests the presence of unit non-response bias.

Formally, we consider the mean estimation of a random variable X_i when X_i is observed only when the unit i is included in the sample. The inclusion in the sample is expressed as the binary indicator S_i, which takes 1 if the unit i is included in the sample and 0 otherwise. The sample mean $\bar{x} = \frac{1}{n}\sum_{i=1}^{n} x_i$ is an unbiased estimator of $E(X_i)$ if x_i is randomly sampled from the population because $E(\frac{1}{n}\sum_{i=1}^{n} x_i) = E(X_i)$. If x_i is not randomly sampled from the population, $E(\bar{x}) = E(X_i|S_i = 1) \neq E(X_i)$. The selection is ignorable if $E(X_i|S_i = 1) = E(X_i|S_i = 0) = E(X_i)$. Thus, we want to know if the sample selection is ignorable.

We test of ignorability using an instrumental variable that satisfies the following two conditions:

- Relevance: $\Pr(S_i = 1|Z_i = 1) > \Pr(S_i = 1|Z_i = 0)$.
  The IV affects the sample selection.
- Exclusion restriction (Redundancy): $E(X_i|S_i, Z_i) = E(X_i|S_i)$.
  The IV does not affect the mean of the target variable conditional on S_i.

We generate such an IV by randomly hassling non-respondents after a certain response period as proposed byDiNardo et al. (2021). Given the relevance of IV and the exclusion restriction, $E(X_i|Z_i) = E(X_i)$ implies $E(X_i|S_i) = E(X_i)$ because of the following discussion.

The conditional expectations of X_i on the hassle status Z_i are

$$
\begin{aligned}
&E(X_i|Z_i = 1) \\
&= E(X_i|S_i = 1, Z_i = 1)\Pr(S_i = 1|Z_i = 1) \\
&+ E(X_i|S_i = 1, Z_i = 1)\Pr(S_i = 1|Z_i = 1) \\
&= E(X_i|S_i = 1)\Pr(S_i = 1|Z_i = 1) + E(X_i|S_i = 0)\Pr(S_i = 0|Z_i = 1)
\end{aligned}
$$

and

$$
\begin{aligned}
&E(X_i|Z_i = 0) \\
&= E(X_i|S_i = 1, Z_i = 0)\Pr(S_i = 1|Z_i = 0) \\
&+ E(X_i|S_i = 0, Z_i = 0)\Pr(S_i = 0|Z_i = 0) \\
&= E(X_i|S_i = 1)\Pr(S_i = 1|Z_i = 0) + E(X_i|S_i = 0)\Pr(S_i = 0|Z_i = 0).
\end{aligned}
$$

Therefore, the difference of the conditional expectations is

$$
\begin{aligned}
& E(X_i|Z_i = 1) - E(X_i|Z_i = 0) \\
& = E(X_i|S_i = 1)[\Pr(S_i = 1|Z_i = 1) - \Pr(S_i = 1|Z_i = 0)] \\
& + E(X_i|S_i = 0)[\Pr(S_i = 1|Z_i = 1) - \Pr(S_i = 1|Z_i = 0)].
\end{aligned}
$$

Given $\Pr(S_i = 1|Z_i = 1) - \Pr(S_i = 1|Z_i = 0) > 0$, $E(X_i|Z_i = 0) = E(X_i|Z_i = 1)$ implies $E(X_i|S_i = 0) = E(X_i|S_i = 1)$.

As an example of the response item, we pick up the total number of robots purchased. Figure 5b draws the daily average of the total number of robots purchased. Contrary to the figure for the daily number of responses in Figure 5a, two series do not deviate in a systematic way even after the random follow up class starts on February 7th.

As a way to quantitatively assess the degree of non-response bias, we implement the difference-in-differences analysis regarding the reminder calls as the treatment. We first regress the number of responses per date on the dummy variable indicating if the firm receives the reminder call, the dummy variable indicating if the date is after the reminder call starts, the interaction of these two dummy variables, and a constant. The unit of observations of this analysis is the treatment status times dates. The DiD estimates reported in Column 1 of Table A.2 indicate that the response behavior of the treatment group and the control group are identical before the reminder call started. On the other hand, the reminder call increases the number of responses by 7 whereas the average number of responses is 10 among the control group. The reminder call promotes responses quantitatively and statistically significant way.

We next examine the responses to questionnaire items are different between the control and treatment units. In terms of the quantity of purchase, Column 2 of Table A.2 indicates that the treatment effect on the natural logarithm of the robot purchase quantity is negligible both in quantitative and statistical ways. In contrast, Column 3 indicates that the firms belonging to the treatment group happens to purchase more expensive robots by 0.23 log points, although the difference is not statistically significant. Reflecting this

Table A.2: The Effect of Follow-up Calls

VARIABLES	(1) Reply Count	(2) Log Quantity	(3) Log Price
Follow-up group	-0.667	-0.0554	0.236
	(1.910)	(0.133)	(0.156)
Follow-up $\times$ Dates after call	7.359***	-0.0187	-0.298
	(2.485)	(0.204)	(0.218)
Constant	10.32***	1.228***	2.376***
	(0.864)	(0.0830)	(0.0846)
Observations	44	538	538
R-squared	0.936	0.064	0.035
Date FE	✓	✓	✓

Notes: The difference-in-difference results with respect to random follow-up call and after call indicator are shown. The unit of observation is a group-date pair in column (1) and a firm in columns (2) and (3). For outcome variables, Column (1) takes the number of replies by the group and date count, column (2) takes log robot quantity, and column (3) takes log robot unit price. Standard errors are in parenthesis. * $p<0.1$, ** $p<0.05$, *** $p<0.01$.

randomness, the firms in the treatment group purchase 0.30 log points cheaper robots in the treatment period, again not statistically significant. This bumpy feature is due to the substantial heterogeneity of the per unit robot prices.

We assess our random harassment design worked as we planned. The analysis results indicate that the non-response bias is at least not serious in terms of the number of robot purchases. In terms of the non-response bias in the unit value of robot purchased, the survey sample size does not allow us to conclude anything definitive due to the substantial heterogeneity in unit price. However, at least, we do not detect the sign of serious non-response bias.

Table A.3: TSR Summary Statistics between Firms Included in the Survey and Not

variable	surveyed	N	mean	sd	p10	p50	p90
Log employment	0	1288522	1.74	1.24	0.00	1.61	3.40
	1	12117	4.82	1.00	3.83	4.62	6.08
Log number of establishment	0	1288522	0.40	0.65	0.00	0.00	1.10
	1	12117	0.98	0.99	0.00	0.69	2.30
Log sales	0	1288522	11.39	1.73	9.37	11.33	13.51
	1	12117	15.10	1.34	13.64	14.90	16.81
Profit margin	0	1288522	-0.22	59.62	-0.09	0.01	0.09
	1	12117	-0.01	0.68	-0.06	0.01	0.05
Year of establishment	0	1288522	1983.20	16.13	1960.00	1986.00	2003.00
	1	12117	1964.94	18.78	1944.00	1963.00	1991.00
Year of CEO birth	0	1288522	1950.06	11.15	1936.00	1949.00	1966.00
	1	12117	1950.21	9.29	1940.00	1949.00	1963.00
Male CEO dummy	0	1288522	0.93	0.25	1.00	1.00	1.00
	1	12117	0.99	0.12	1.00	1.00	1.00
Credit Score	0	1288522	46.47	5.76	40.00	46.00	53.00
	1	12117	55.92	6.59	48.00	55.00	65.00

Notes: Summary statistics of the Tokyo Shoko Research (TSR) data is shown. The "surveyed" column indicates if the firm is included in the survey (1 if included, and 0 otherwise). The profit margin is defined by profit divided by sales. The credit score is the credit rating researched and published by the TSR.