Automation, Concentration, and Labor Share*

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Abstract

Search for determinants of declines in labor share is one of the core agendas in macroeconomics. This paper shows that the labor share in Japan declined steadily and that automation was a contributing factor to the decline in labor share from 1980 to 1995. The analysis reveals that the decline was particularly prominent in larger firms that were more likely to adopt automation. However, from 1995 to 2010, market concentration in large firms, rather than automation, was the primary factor in reducing the aggregate labor share, albeit not necessarily large in size.

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JEL Classification: E22, E24, E25, O33

Preliminary.

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Introduction

A growing body of studies reports that the labor share has been declining (*e.g.* Elsby et al. (2013); Karabarbounis and Neiman (2014)). The decline in the labor share has always been at the center of policy debates because of its very large implications for the economic composition of the labor force. In particular, in recent years, wage growth has remained small under rising inflation, an environment that has led to pleas from the government to the private sector for higher wages from the perspective of maintaining workers' standard of living. Thus, the search for determinants of declines in labor share is one of the core agendas in macroeconomics (Grossman and Oberfield, 2022).[1]

This paper studies the role of automation and concentration in the declining labor share in the Japanese manufacturing sector since 1980. We first provide three stylized facts about the Japanese economy since 1980. The first fact is that the labor share in the Japanese manufacturing sector decreased by 5% points. This pattern is robust if we use either net value added or gross value added. The second fact is that, at the same time period, robot stocks have increased in Japan. The third fact is that concentration within each narrow manufacturing industry increased after 1995.

Second, we theoretically argue that both automation and concentration can decrease labor share. Automation decreases labor share because of displacing labor with capital or robots as in the task framework as in Acemoglu and Restrepo (2018, 2022b). Concentration also decreases labor share via composition effects because larger firms typically have a lower labor share as in Autor et al. (2020).

Finally, we empirically test these predictions by combining establishment-level data (Census of Manufactures) and industry-level data (JARA and JIP data). We use both the shift-share design in the cross-commuting-zone analysis as in Autor et al. (2013) and establishment-level analysis. We show that, between 1980 and 1995, automation contributed to decreases in labor share. We also show that larger establishments have a lower labor share and have decreased their labor shares in the same period (1980-1995), which is consistent with the fact in other countries that larger establishments disproportionally adopt automation technology. After 1995, however, we do not find evidence that automation decreased labor share. We find that concentration rose after 1995 and contributed to decreases in labor share, but the contribution can be quantitatively not large.

Related Literature

This paper relates to the literature that empirically investigates the causes of the decline in labor share. Some papers study the role of technology, including automation (Acemoglu and Restrepo, 2022b), ICT capital (Dinlersoz et al., 2018; Autor et al., 2020). Other papers examine increased product market concentration (De Loecker et al., 2020; Autor et al., 2020; Barkai, 2020), globalization (Elsby et al., 2013; vom Lehn, 2018), the declining market power of workers (Stansbury and Summers, 2020; Berger et al., 2022).

Our paper focuses on automation and concentration as well, but the context—the Japanese economy since 1980—is different. This has two key advantages. First, our paper can analyze longer time periods for the role of automation because of our data. We combine unique data on robot adoption data before 1980 and the Japanese establishment-level administrative data also available since 1980. As discussed in the next section in detail, robot data from the International

[1] We will summarize the related papers in the literature review section.

Federation of Robots (IFR), which are typically used in the literature (Graetz and Michaels, 2018; Acemoglu and Restrepo, 2018; Dauth et al., 2021; Acemoglu and Restrepo, 2022a,b), only starts in 1989 and becomes comprehensive in the mid-1990s. Longer sample periods allow us to isolate one potential channel from another and to draw more robust results. Second, labor share decreases in Japan regardless of whether using gross or net value-added while some papers have cast doubt on the decrease in labor share in the US depending on the measurement (Koh et al., 2020; Grossman and Oberfield, 2022). By analyzing the decreasing Japanese labor share, on which there is less doubt, we contribute to the literature by providing the role of potential factors unrelated to these measurement issues. Notice also that most of the empirical studies on the decline in the labor share are for the U.S.[2]

This paper is also related to the growing literature on the effects of automation on the local labor market (Acemoglu and Restrepo, 2020; Adachi et al., 2022; Dauth et al., 2021). Unlike these and previous studies, our paper studies the impact on labor share.

Layout Section 1 provides stylized facts about the Japanese economy since 1980. Section 2 lays out a simple theoretical framework to study the role of automation and concentration in the declining labor share. Section 3 provides empirical analysis using establishment-level data. Section 4 concludes and discusses the next steps.

1 Stylized Facts about the Japanese Economy

In this section, we first present the various data sets we use and provide details on sample construction. We then provide several stylized facts about the Japanese economy since 1980.

1.1 Data

Census of Manufactures Data Our primary data source is the Japanese Census of Manufactures (kogyo-tokei-chosa) for the manufacturing sector. The Ministry of Economy, Trade, and Industry conduct the Japanese Census of Manufactures annually to gather information on the current status of establishments in the manufacturing sector. Specifically, this census covers all manufacturing establishments with at least 4 employees in Japan.[3] The number of establishments surveyed is 192,047 (as of 2020). The survey response rate is high at 95.1 percent. We restrict samples to establishments with a minimum of 30 employees.[4]

JARA Data Our second data source is the Production and Shipments of Manipulators and Robots from the Japan Robot Association (JARA) from Adachi et al. (2022). JARA data is the primary source of Japan's robot data from the International Federation of Robots (IFR), which is well known and widely used in previous studies (*e.g.* Graetz and Michaels (2018), Acemoglu and

[2] In fact, all of the papers cited in the previous paragraph are for the U.S.

[3] In years when the first decimal place of the survey year is 0, 3, 5, or 8, entire manufacturing establishments are surveyed.

[4] While all manufacturing establishments with at least 4 employees are included in the census, only those with a minimum of 30 employees are required to provide additional in-depth information regarding their properties and characteristics, including inventory and depreciation, which are essential to calculate value-added or labor share.

Restrepo (2020)). JARA data consists of robot shipments (both in units and sales value) by destination industry and robot application from 1978 to 2017.[5]

Compared to the IFR data, which is available only after 1989, JARA data has an advantage in its extended time series and its granularity. In the 2018 table, 44 industries are covered with 28 major categories and their sub-categories in columns. Rows present 36 applications for 17 major categories with attending sub-categories. To ensure diachronic continuity, we consolidate the data into 12 industries and 6 applications.

Our 12 aggregated industries consist of "iron and steel," "nonferrous metals," "metal products," "general machinery and equipment," "electrical machinery and equipment," "transport machinery and equipment," "food, beverage, tobacco, and feedstuff," "pulp, paper, paper products, and printing," "chemical," "ceramic and stone products," "other manufacturing," and "non-manufacturing."[6]

Our 6 applications consist of "assembling," "dispensing," "handling," "processing," "welding," and "others". Table 1 presents the detailed mapping of sub-categories of applications.

Table 1: Mapping of application classifications in the JARA data

Application classification	Sub-categories
Assembling	General assembling
	Inserting and mounting
	Pointing
	Sealing and gluing
	Screwing
	Other assembling
Dispensing	Dispensing
	Plating
Handling	Material handling
	Picking and packaging
	Shipments
Processing	Load and unload
	Grinding and cutting
	Deburring
	Other processing
Welding	Welding (Arc, spot, laser, other)
	Soldering
Others	Others, education, research and development, clean room

JIP Data We also use the Japan Industrial Productivity Database 2015 (JIP), which is compliant with the EU-KLEMS dataset.[7] JIP data contains labor inputs, capital stocks, exports, imports, and outputs by industry.[8]

[5]The JARA booklet "Production and Shipments of Manipulators and Robots" consist of Table A, B, and C. Table A presents sales and the number of robots by industry and robots' structure. Table C presents exports of robots by country and applications.

[6]Our classification is the same as that in Adachi et al. (2022), which use 13 categories of industries. The only difference is the treatment of "general machinery and equipment" and "precision machinery and equipment." Although **?** treat these industries differently, we consider these two a single industry due to the data availability. The precision machinery industry becomes discontinued in the latest Basic Survey on Wage Structure because of the 12th revision of the Japan Standard Industrial Classification.

[7]For details, see Fukao et al. (2007) and Fukao et al. (2021).

[8]ICT stocks are calculated in the following manner. First, for the period 1995-2018, we add stocks of information equipment, telecommunications equipment, and computer software in the investment-asset table of JIP2018, which is

1.2 Stylized Facts

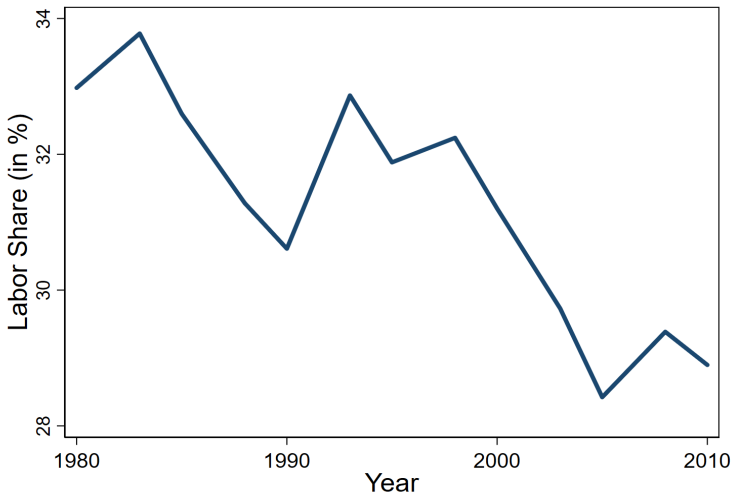
In this subsection, we document various facts regarding macroeconomic aggregate variables in the Japanese manufacturing sectors from 1980 to 2010.

Fact 1. *Labor share of net value added in manufacturing sectors has decreased by 5% point since 1980.*

Figure 1 shows the labor share of net value added in the manufacturing sector in Japan since 1980. In 1980, the labor share of net value added was high at around 33%, but it decreased by 5% points to reach 28% in 2010.

The overall picture is similar to that of the labor share calculated using National Accounts. According to the trend of the labor share, as reported by the Cabinet Office[9], the decline has been about the same, down 4 percentage points from its peak in the early 1980s. The developments of continuing to decline in the 1980s, rising once in the mid-1990s, and then declining again are also similar. The higher labor share in the national accounts can be attributed to the fact that the national accounts include services and that we compute establishment-level data while the national accounts use firm-level data. This pattern is also true when we use the labor share of gross value added as shown in Figure A.1 in Appendix.[10]

Figure 1: Labor Share of Net Value Added in the Japanese Manufacturing Sectors



Note: This figure shows the labor share of net value added in the Japanese manufacturing sector from 1980 to 2010. Labor share is computed as the share of total payroll to net value added (from the Japanese Census of Manufactures). The samples are establishments with more than or equal to 30 employees, in manufacturing sectors.

Fact 2. *Robot stocks have increased since 1980*

compiled under the 2008SNA standard. For earlier periods, we use the ITC stocks of the JIP2015, which are compiled under the 1993SNA standard. In connecting these two data, we use the industry correspondence table of JIP2018.

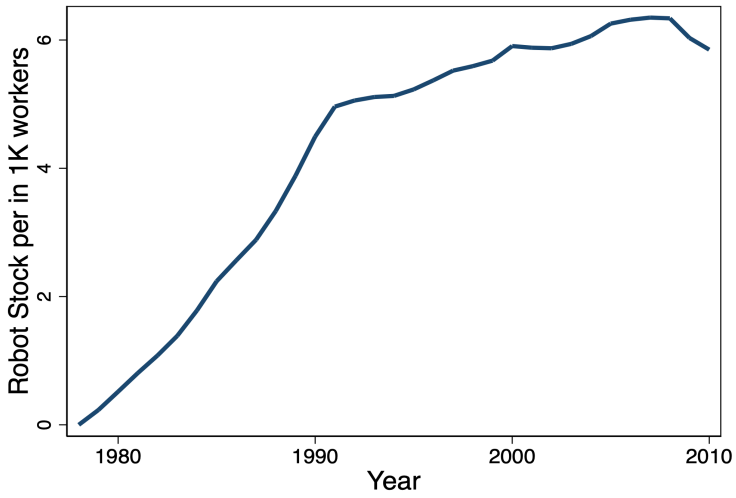
[9] Link: https://www5.cao.go.jp/keizai2/keizai-syakai/k-s-kouzou/shiryou/1th/shiryo4-3.pdf

[10] Grossman and Oberfield (2022) argues that the labor share in the US did not decrease if using net value added instead of gross value added.

Figure 2 illustrates that the adoption of robots progressed rapidly in the 1980s. In fact, JARA defines 1980 as the first year of robot dissemination. For a long time, Japan was once the top producer of robots globally. However, China has now overtaken Japan, producing three times the amount of robots, according to the "World Robotics 2020" report by the International Federation of Robotics. In terms of robot density, Singapore and South Korea also have the highest robot density and have more robots per worker than Japan. In spite of this, Japan still holds the title of being the second-largest producer of robots and ranks third in terms of robot density.

Despite continuing to be one of the world's top robot manufacturing countries, it is surprising that the growth rate of robot stock has slowed significantly since about 1990. This trend in robot stock looks very different from that of other countries, where robot stocks have continued to rise.

Figure 2: Robot Stock



Note: The figure shows the robot stock per 1,000 workers in Japan. For the robot stock, we take the robot shipment data from the JARA data from Adachi et al. (2022) and use a 10% annual discounted rate to construct stock in quantity. For the number of workers, we use the JIP data.

Fact 3. *Concentration ratios within narrow manufacturing industries have increased since the mid-1990s.*

Figure 3 shows the average concentration ratio (CR4), the average of the share of revenue of the largest four establishments within each 4-digit manufacturing industry. We weigh industries by their revenue each year. From 1980 to 1993, the CR4 modestly declined from 28% to 27%. Since 1993, the CR4 increased by around 3.5% to reach 30.5% in 2010.

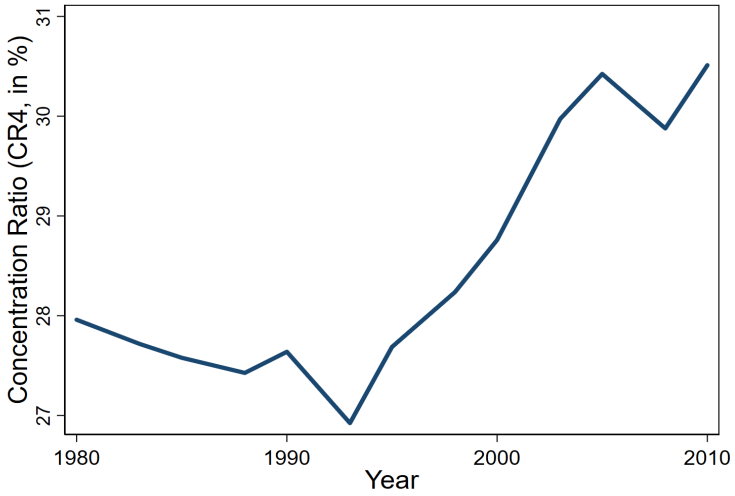
As analyzed in Covarrubias et al. (2019), De Loecker et al. (2020) and Autor et al. (2020), market concentration is progressing in the U.S. In Japan, on the other hand, industrial concentration has not progressed to the same degree. In fact, international comparisons show that the level of market concentration in Japan remains low compared to other developed countries[11]. Companies produce similar products, resulting in excessive competition, low profitability, and a low level of competition.

[11]See, for example, the report by the Cabinet Office; https://www5.cao.go.jp/j-j/wp/wp-je13/pdf/p02011.pdf

However, Figure 3 suggests the progress in market concentration in Japanese manufacturing firms, although the increase is not large. It is worth noting that product market concentration made no progress in the late 1980s, despite the unprecedented economic boom, and has continued to rise since the mid-1990s when the severity of the structural problems in the Japanese economy was becoming apparent.

This pattern is also true when we use the 3-digit industries or CR5 (top 5 firms) as shown in Figures A.2 and A.3 in Appendix

Figure 3: Concentration Ratio in the Japanese Manufacturing Sectors



Note: This figure shows the average concentration ratio (CR4) of revenue across the 4-digit Japanese manufacturing industries from 1980 to 2010. The concentration ratio (CR4) is the share of the revenue of the largest four establishments within each 4-digit manufacturing industry, and industry-level CR4 is aggregated into aggregate level using the industry's total revenue in each year as the weight. The data is from the Japanese Census of Manufactures, and the samples are establishments with more than or equal to 30 employees, in manufacturing sectors.

Summary In sum, between 1980 and 1995, the labor share declined, robot adoption rapidly increased, and concentration was unchanged. Between 1995 and 2010, the labor share kept declining, robot adoption increased but stagnated, and concentration rose. These altogether suggest that the continuing decline in the labor share seen in Figure 1 was not necessarily caused by the same reasons throughout the period and calls for investigation into the causes behind it.

2 Simple Theoretical Framework

To fix the idea of how automation and concentration affect labor share, we provide a simple theoretical framework before going to the empirical assessment. To do so, we consider a simple two-sector model with the task framework.

2.1 Final good producer

The final good producer minimizes the total cost:

$$P_1 Y_1 + P_2 Y_2,$$

subject to the aggregating technology:

$$Y = \left[\gamma_1^{\frac{1}{\sigma}} Y_1^{\frac{\sigma-1}{\sigma}} + \gamma_2^{\frac{1}{\sigma}} Y_2^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}}.$$

Y and P denote output and price. Y_j and P_j denote sectoral output and sectoral good price in sector $j = 1, 2$. γ_j is the share parameter in aggregating technology ($\sum_j \gamma_j = 1$), and σ the elasticity of substitution between two sectors.

2.2 Sectoral Production

A representative firm in sector $j = 1, 2$ maximizes the profit Π_j:

$$\Pi_j = P_j Y_j - W L_j - P^R R_j,$$

where W and P^R denote the wage rate and the price of robots, respectively, and L_j and R_j denote labor and robots used in sector j.

The sectoral goods Y_j are produced by combining tasks following the task framework used in the literate such as Acemoglu and Restrepo (2018, 2020). Task are combined as the Cobb-Douglas structure as follows:

$$\ln Y_j = \int_0^1 \ln Y_j(z) dz$$

where task $Y_j(z)$ task can be produced either by labor or robots if the task is not too complex ($z \in [0, \theta_j]$) and can only be produced by labor otherwise.

$$Y_j(z) = \begin{cases} L_j(z) + R_j(z) & \text{if } z \leq \theta_j \\ L_j(z) & \text{if } z > \theta_j \end{cases}$$

We assume that machines, $R_j(z)$ are supplied at an exogenously fixed rental price P^R. We also assume $P^R < w$ so that robots are always cheaper than labor, and task producers always want to replace labor with robots for tasks $z \leq \theta_j$.[12]

[12] This assumption is a typical assumption in the literature just for saving spaces and notations, and qualitative results will not change.

2.3 Market Clearing and Resource Constraint

The labor market clears as

$$\bar{L} = L_1 + L_2.$$

The resource constraint is given by

$$C = Y.$$

2.4 Equilibrium

We take the price of final goods as a numeraire ($P = 1$). An equilibrium is a set of prices $\{P_j\}_j$, wage w, factor demand $\{L_j, R_j\}$, sectoral output $\{Y_j\}$, and total output Y such that the final good producer maximizes its profit, the sectoral good producers maximize their profits, and the labor market clears.

2.5 Characterization

Demand for Sectoral Goods The CES structure leads to

$$Y_j = \gamma_j P_j^{-\sigma} Y \tag{1}$$

and the ideal price index condition is

$$\left(\sum_j \gamma_j^{\sigma} P_j^{1-\sigma} \right)^{\frac{1}{1-\sigma}} = 1 \tag{2}$$

Sectoral Output The Cobb-Douglas aggregation of the tasks leads to

$$Y_j(z) = \frac{Y_j}{P_j(z)}$$

Using the assumption that robots are always cheaper than labor ($p^R < w$), we have

$$Y_j(z) = \begin{cases} R_j(z) & \text{if } z \leq \theta_j \\ L_j(z) & \text{if } z > \theta_j \end{cases}$$

Using symmetry,

$$R_j(z) = \frac{P_j Y_j}{P^R} = \frac{K_j}{\theta_j}$$

$$L_j(z) = \frac{P_j Y_j}{W} = \frac{L_j}{1 - \theta_j}$$

Aggregating these tasks, we have

$$\begin{aligned} \ln Y_j &= \int_0^1 \ln Y_j(z) dz \\ &= \int_0^{\theta_j} \ln R_j(z) dz + \int_{\theta_j}^1 \ln L_j(z) dz \end{aligned}$$

$$= \int_0^{\theta_j} \ln\left(\frac{K_j}{\theta_j}\right) dz + \int_{\theta_j}^1 \ln\left(\frac{L_j}{1-\theta_j}\right) dz$$

Thus, we have a reduced-form production function at the sectoral level as follows:

$$Y_j = \left(\frac{K_j}{\theta_j}\right)^{\theta_j} \left(\frac{L_j}{1-\theta_j}\right)^{1-\theta_j}$$

The unit cost is given by

$$P_j = \left(P^R\right)^{\theta_j} (W)^{1-\theta_j} \tag{3}$$

Factor Demand Factor demand in each sector j is given by

$$P^R = \theta_j \frac{P_j Y_j}{R_j} \tag{4}$$

$$W = (1-\theta_j) \frac{P_j Y_j}{L_j} \tag{5}$$

Labor Market Clearing Condition

$$\sum_j L_j = \bar{L} \tag{6}$$

Solution Equations (2) and (3) pin down wage W and sectoral price P_j. We can then use Equations (1), (5), and (6) to determine sectoral outputs Y_j, sectoral labor L_j, and aggregate output Y. We finally get sectoral robots R_j using Equation (4).

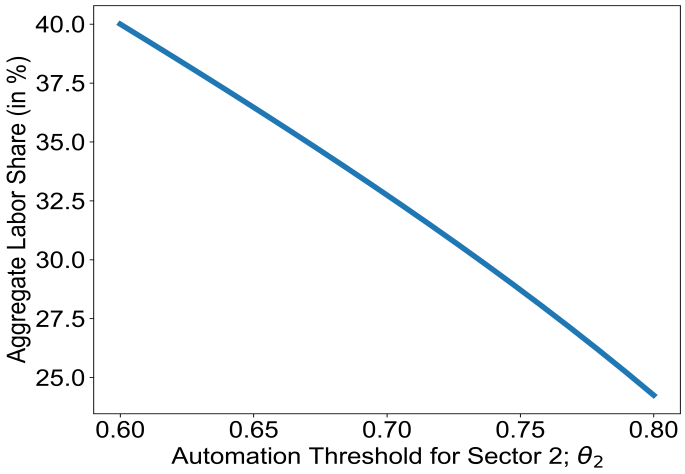
2.6 Numerical Illustration

Here, we provide a numerical illustration to show how automation and concentration affect labor share based on our toy model. While still parsimonious, we plan to extend this model fully in the next draft to quantify the role of automation and concentration in the pattern of labor share at the aggregate level.

Effects of Automation Technology on Labor Share We first study the effects of automation technology on labor share. Our experiment is to change θ_2 fixing other parameters constant and to see how the aggregate labor share changes. In particular, we set $\sigma = 2$, $(\gamma_1, \gamma_2) = (0.4, 0.6)$, $P^R = 0.2$, and $\theta_1 = 0.6$. Then, we change $\theta_2 \in [0.6, 0.8]$ and see how the aggregate labor share wL/Y changes.

Figure 4 shows the result. As expected, when θ_2 increases, firms in Sector 2 can enjoy cost savings by using more robots. Thus, the labor share declines while wages may increase. In this calibration exercise, increases in θ_2 from 0.6 to 0.8 decrease labor share from 24% to 20.5%.

Figure 4: Illustration: Automation and Labor Share

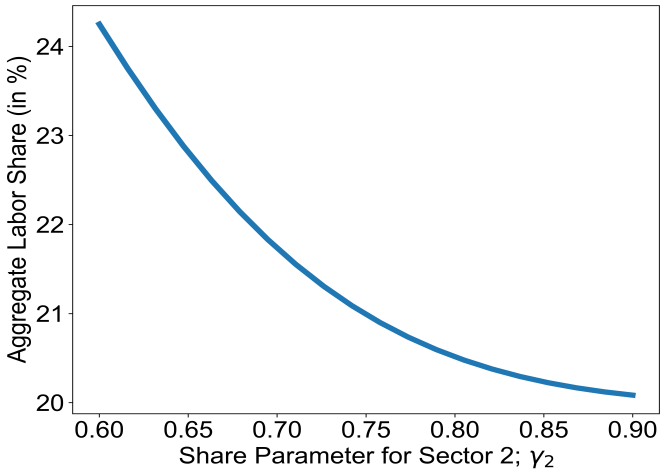


Note: The figure shows the relationship between the automation threshold for sector 2, θ_2 and aggregate labor share in the toy model.

Effects of Concentration on Labor Share The next exercise is to study the effects of concentration on labor share. While simple, we can consider this two-sector model as a two-firm model within a single sector. Then the increase in γ_2 from 0.6, which is initially larger than $\gamma_1 = 1 - \gamma_2 = 0.4$, corresponds to an increase in market concentration—firm 2 was initially larger and now gets even larger. For this exercise, we set $\sigma = 2$, $P^R = 0.2$, and $\theta_1 = 0.6, \theta_2 = 0.8$. Then, we change $\gamma_2 \in [0.6, 0.9]$ and see how the aggregate labor share wL/Y changes.

Figure 5 shows the result. As sector 2 gets larger, aggregate labor share declines. This is because the labor share is larger in sector 2, initially, and aggregate labor share increases from the composition effect.

Figure 5: Illustration: Automation and Labor Share



Note: The figure shows the relationship between the share parameter for sector 2, γ_2 and aggregate labor share in the toy model..

3 Evidence from Establishment-level Data

3.1 Automation and Labor Share

First, we study how automation affects labor share. At the aggregate level, the Japanese economy has experienced a rapid increase in robot stock and a decrease surge in We leverage variation across commuting zones. This design allows us to isolate the effect of our interest from industry-level unobserved characteristics.

Robot Exposure Our main variable of interest is robot exposure across commuting zones. Following Acemoglu and Restrepo (2020), we define adjusted penetration of robots, $\text{APR}_{c,t,t+5}$ as follows.

First, we compute the adjusted penetration of robots at the industry level as follows:

$$\text{APR}_{i,t,t+5} \equiv \frac{R_{i,t+5} - R_{i,t}}{L_{i,t}} - \frac{Y_{i,t+5} - Y_{i,t}}{Y_{i,t}} \frac{R_{i,t}}{L_{i,t}}$$

where $R_{i,t+5} - R_{i,t}$ is the changes in discounted robot stock in industry i from year t to $t+5$ from the JARA data, $L_{i,t}$ is the total employment in industry i at year t from JIP data, and $\frac{Y_{i,t+5} - Y_{i,t}}{Y_{i,t}}$ is the GDP growth rate in industry i from year t to $t+5$ from the JIP data. By having the second term, we subtract the changes in labor demand in sector i so that we can only extract changes in a robot supply shock at industry i.[13]

Second, we use the shift-share design as in Acemoglu and Restrepo (2020) to translate industry-level robot exposure into commuting zone level robot exposure by interacting $\text{APR}_{i,t,t+5}$ with the initial share of industrial employment in industry i in commuting zone c. We use 1980 as the initial

[13] See Acemoglu and Restrepo (2020) for details.

period to construct this share.

$$\text{APR}_{c,t,t+5} \equiv \sum_{i \in I} \left(\frac{L_{c,i,1980}}{L_{c,1980}} \right) \times \text{APR}_{i,t,t+5}$$

Stacked-Difference Specification Our specification is a 5-year stacked difference specification.

$$\Delta \ln(\text{Labor Share})_{c,t,t+5} = \beta \text{APR}_{c,t,t+5} + \Delta X'_{c,t,t+5} \Gamma + \mu_c + \mu_t + \varepsilon_{c,t} \tag{7}$$

where $\Delta \ln(\text{Labor Share})_{c,t,t+5}$ is the change in labor share at commuting zone c from year t to year $t+5$, $\text{APR}_{c,t,t+5}$ is the adjusted penetration of robot exposure at commuting zone c from year t to year $t+5$, $\Delta X_{c,t,t+5}$ is the vector of change in the variables at commuting zone c from year t to year $t+5$, μ_c is commuting zone fixed effect, and μ_t is year fixed effect. These fixed effects isolate the effect of robot exposure on labor share from unobserved characteristics at industry or commuting zone levels.

Table 2: Summary Statistics

Variables	Unit	Mean	Std. Dev.	Median	p10	p90	N
	Panel A: 1980-2010 (1980-85,...,2005-2010)						
APR	APR	0.33	0.24	0.39	-0.04	0.91	1,366
Changes in Labor Share	% pt	-0.84	8.80	-0.79	-9.39	7.04	1,366
	Panel B: 1980-1995 (1980-85, 1985-90, 1990-95)						
APR	APR	0.54	0.38	0.48	0.06	1.05	688
Changes in Labor Share	% pt	-0.43	8.56	-0.29	-9.32	7.07	688
	Panel C: 1995-2010 (1995-2000, 2000-05, 2005-10)						
APR	APR	0.13	0.29	0.07	-0.18	0.49	678
Changes in Labor Share	% pt	-1.24	9.02	-1.21	-9.54	7.04	678

Notes: This table shows the summary statistics for the dependent and treatment variables. The table shows the unit, mean, standard deviation, median, 10% tile, 90% tile, and the number of observations. All the statistics are unweighted. Panel A shows the statistics for all the 5-year windows between 1980 and 2010 (1980-85,...,2005-2010). Panel B is for 1980-1995 (1980-85, 1985-90, 1990-95), and Panel C is for 1995-2010 (1995-2000, 2000-05, 2005-10). The data is from the Japanese Census of Manufactures.

Results Table 3 shows the results. The unit of observation is a pair of 5-year periods (1980-1985, 1985-1990, ..., 2005-2010) and commuting zones. All columns include period fixed effects and commuting zone fixed effects. Columns (2), (3), and (4) add covariates, including changes in export exposures, import exposures, and ICT capital exposures. Column (4) includes the initial labor share. All columns use the total employment in the commuting zone as weights.

In all the columns, increases in exposure to robots decrease labor share, which is consistent with the macro trends. The mean of the APR reported in Table 2 is 0.33, and this translates into 0.57 (0.33×-1.74) % pt decrease in labor share, which is more than half of the average across commuting zones (0.84 % pt decreases). This is large given that period fixed effects (macro trends) and commuting zone fixed effects (CZ-specific trends) are already residualized.

We also study the effect of automation by sub-sample, motivated by the macro trends in robot stock: before and after 1995. Table 4 shows the results of the sub-sample analysis. Panel A shows

Table 3: Automation and Changes in Labor Share

Dependent Variable: Changes in Labor Share				
	(1)	(2)	(3)	(4)
Adjusted Penetration of Robots	-1.73	-1.76	-1.76	-1.74
	(0.65)	(0.67)	(0.67)	(0.52)
Initial Labor Share				-0.82
				(0.03)
Observation	1,361	1,361	1,361	1,361
Period fixed effects	Yes	Yes	Yes	Yes
Commuting Zone fixed effects	Yes	Yes	Yes	Yes
Covariates		Yes	Yes	Yes

Notes: This table shows the relationship between changes in labor share and robot adoption. The unit of observation is a pair of 5-year periods (1980-1985, 1985-1990, ..., 2005-2010) and commuting zones. All columns include period fixed effects and commuting zone fixed effects. Columns (2), (3), and (4) add covariates, including changes in export exposures, import exposures, and ICT capital exposures. Column (4) includes the initial labor share. All columns use the total employment in the commuting zone as weights. The data is from the Japanese Census of Manufactures.

the results for the periods between 1980 and 1995. The estimates are now larger in absolute terms (-6.07 without controlling the initial labor share and -3.54 with controlling the initial labor share). Panel B shows the results for the periods between 1995 and 2010.

Other Labor Market Outcomes Table 5 shows the results for the effect of robots on other labor market outcomes. The dependent variable is employment in Column (1), manufacturing employment in Column (2), net value added in Column (3), and total payrolls in Column (4). Column (3) shows that value-added increased substantially while Column (4) shows that total payrolls did not increase. This shows that the decrease in labor share comes from disproportional increases in value-added compared to total payrolls and not from decreases in total payrolls.

3.2 Establishment Size and Labor Share

This section studies the relationship between the establishment size and labor share.

3.2.1 Cross-sectional Relationships between Establishment Size and Labor Share

We first study the static relationship between these variables by running the following regression:

$$\text{Labor Share}_{e,c,i,t} = \gamma \ln(L_{e,c,i,t}) + \mu_c + \mu_i + \mu_t + \varepsilon_{e,c,i,t}$$

where $\text{Labor Share}_{e,c,i,t}$ is the labor share of establishment e in municipality c in industry i at year t, $L_{e,c,i,t}$ is the employment, μ_c is the municipality (narrower than commuting zones) fixed effects, μ_i is the four-digit industry fixed effects, μ_t is the year fixed effect.

Table 6 shows the results. Column (1) has no covariate, Column (2) adds year fixed effects, Column (3) adds 4-digit industry fixed effects, and Column (4) adds municipality fixed effects.All columns are weighted by the establishment's value-added.

In all the specifications, larger establishments have a lower labor share, and the magnitude is sizable—establishments larger by 1 log point have about 2 to 2.5% lower labor share on average.

Table 4: Automation and Changes in Labor Share

Dependent Variable: Changes in Labor Share				
	(1)	(2)	(3)	(4)
	Panel A: 1980-1995			
Adjusted Penetration of Robots	-4.38	-6.07	-6.07	-3.54
	(1.12)	(1.32)	(1.32)	(0.93)
Initial Labor Share				-0.94
				(0.04)
Observation	911	911	911	911
	Panel B: 1995-2010			
Adjusted Penetration of Robots	0.91	0.54	0.54	0.26
	(1.55)	(1.53)	(1.53)	(1.24)
Initial Labor Share				-0.89
				(0.06)
Observation	675	675	675	675
Period fixed effects	Yes	Yes	Yes	Yes
Commuting Zone fixed effects	Yes	Yes	Yes	Yes
Covariates		Yes	Yes	Yes

Notes: This table shows the relationship between changes in labor share and robot adoption. The unit of observation is a pair of 5-year periods and commuting zones. Panel A shows the results for the periods between 1980 and 1995. Panel B shows the results for the periods between 1995 and 2010. All columns include period fixed effects and commuting zone fixed effects. Columns (2), (3), and (4) add covariates, including changes in export exposures, import exposures, and ICT capital exposures. Column (4) includes the initial labor share. All columns use the total employment in the commuting zone as weights. The data is from the Japanese Census of Manufactures.

Table 5: Automation and Changes in Other Labor Market Outcomes

	Dependent Variable (in log change)			
	Emp.	Mfg Emp.	Value Added	Payrolls
	(1)	(2)	(3)	(4)
Adjusted Penetration of Robots	2.75	-0.51	6.50	0.84
	(0.46)	(1.57)	(2.64)	(1.90)
Observations	1,382	1,361	1,361	1,361
Period fixed effects	Yes	Yes	Yes	Yes
Commuting Zone fixed effects	Yes	Yes	Yes	Yes
Covariates	Yes	Yes	Yes	Yes

Notes: This table shows the relationship between changes in several labor market outcomes and robot adoption. The unit of observation is a pair of 5-year periods (1980-1985, 1985-1990, ..., 2005-2010) and commuting zones. The dependent variable is employment in Column (1), manufacturing employment in Column (2), net value added in Column (3), and total payrolls in Column (4). All columns include period fixed effects, commuting zone fixed effects, and covariates, including changes in export exposures, import exposures, ICT capital exposures, and the initial labor share. All columns use the total employment in the commuting zone as weights. All the data is from the Japanese Census of Manufactures, except for total employment, which is from the Cabinet Office.

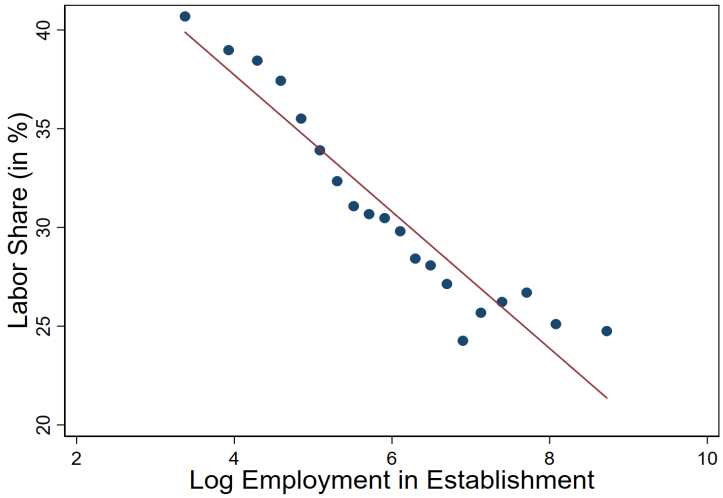
This explains cross-sectional variations well. To see it, we provide binned scatter plots version of Column (4) as Figure 6. The figure shows the relationship between log employment in establishments and labor share, and year fixed effects, 4-digit industry fixed effects, and municipality fixed effects are residualized. The figure clearly shows that establishment sizes are important for labor share in cross-sections within narrow industrial categories (4-digits).

Table 6: Establishment Size and Labor Share

Dependent Variable: Labor Share (in % pt)				
	(1)	(2)	(3)	(4)
Log Employment	-2.43	-2.44	-2.63	-1.98
	(0.01)	(0.01)	(0.01)	(0.01)
Observation	1,774,376	1,774,376	1,774,373	1,774,345
Year fixed effects		Yes	Yes	Yes
Industry fixed effects			Yes	Yes
Municipality fixed effects				Yes

Notes: This table shows the relationship between establishment size and labor share. The unit of observation is an establishment. Column (1) has no covariate, Column (2) adds year fixed effects, Column (3) adds 4-digit industry fixed effects, and Column (4) adds municipality fixed effects. All columns are weighted by the establishment's value-added. The data is from the Japanese Census of Manufactures.

Figure 6: Labor Share across Establishment Size



Note: The figure shows the binned scatter plots for Column (4) in Table 6. The figure shows the relationship between log employment in establishments and labor share, and year fixed effects, 4-digit industry fixed effects, and municipality fixed effects are residualized. The model is weighted by the establishment's value-added. The data is from the Japanese Census of Manufactures.

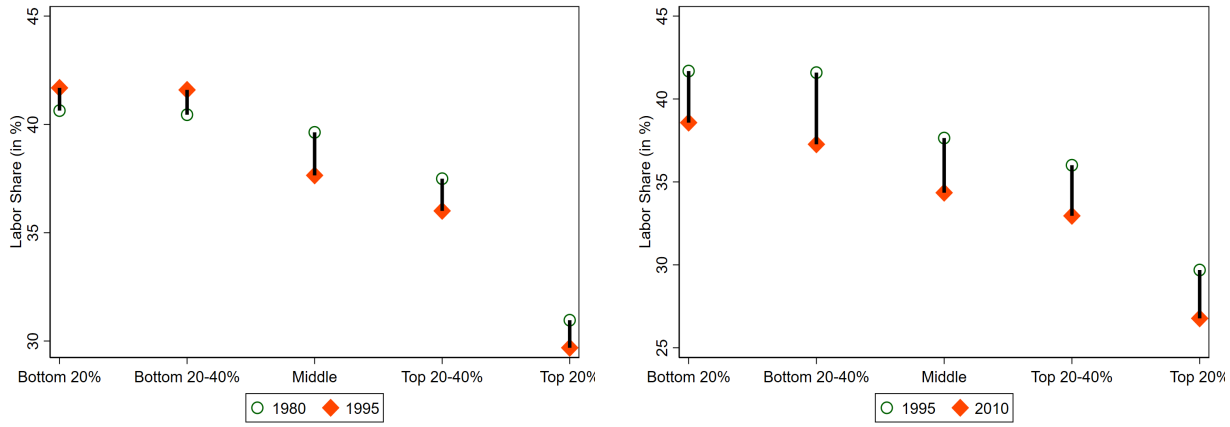
3.2.2 Dynamic Relationships between Establishment Size and Labor Share

Finally, we examine whether establishments with different sizes change labor share differently. To do so, we divide establishments into five groups based on employment in 1980, 1995, and 2010.

We then compute changes in labor share for each group for 1980-1995 and 1995-2010.

Figure 7 shows the results. Between 1980 and 1995, only the large establishments decrease their labor share. This timing is consistent with our previous finding that automation decreased labor share between 1980 and 1995 and in line with the finding of Humlum (2019); Acemoglu et al. (2022) that large establishments disproportionally adopt automation technology more. Between 1995-2010, there are no substantial differences in the decline in labor share across establishment sizes, which automation cannot explain the *cross-sectional* heterogeneity in the decline in labor share.

Figure 7: Changes in Labor Share by Employment Size Bins



(a) 1980-1995

(b) 1995-2010

Note: The figures show the changes in the labor share of net value added in 1980-1995 and 1995-2010 for each group of establishments. We define these groups based on the employment sizes in the initial year in each time window (1980 for 1980-1995 and 1995 for 1995-2010). We aggregate value-added and total payrolls for each group in 1980, 1995, and 2010. The data is from the Japanese Census of Manufactures.

4 Conclusion

This paper first showed that, for Japan, the labor share continued to decline robustly. Next, a commuting-zone-based analysis combining industry- and establishment-level data revealed that automation contributed to the decline in the labor share from 1980 to 1995. This paper also showed that the labor share declined in large firms that reportedly were more likely to embark on automation. On the other hand, from 1995 to 2010, this paper did not find any evidence that automation decreased labor share. Rather, product market concentration, i.e., concentration in large firms with lower levels of labor share, reduced the aggregate labor share, albeit not necessarily large in size.

Possible issues to be addressed in the future include the following. First, the root cause of the decline in labor share since 1995 is still unclear. The decline since 1995 is common across establishments of different sizes, and we did not find evidence that automation explains the decrease in labor share since 1995. One potential factor is the financial crisis, one of the major characteristics of the Japanese economy since 1995, and subsequent worsened financial conditions.[14] We

[14] In a different project, we also study the role of labor market power in the declining labor share.

are currently working on an empirical analysis of the role of firms' financial constraints on labor share. We believe that financial constraints may have had a direct impact on both the slowdown in robotic investment and market concentration, and may have contributed to the resulting decline in the labor share. Second, we can discipline a quantitative model by cross-sectional estimates in Section 3 to quantify the aggregate effects of automation, product market concentration, and financial constraints. We are currently working on this as well.

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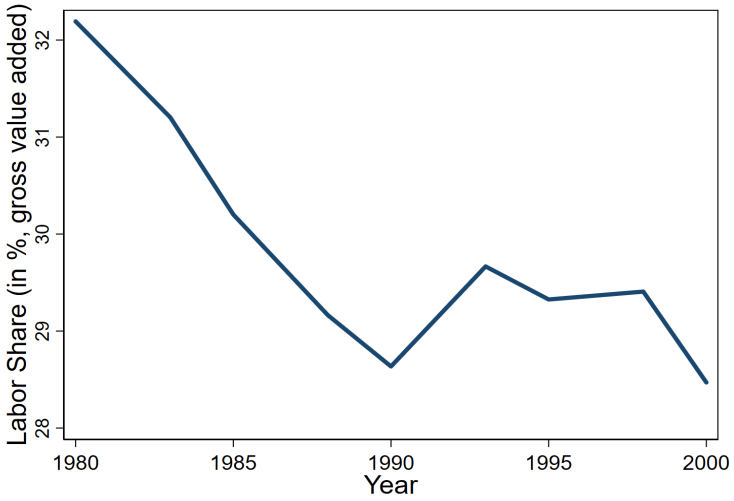
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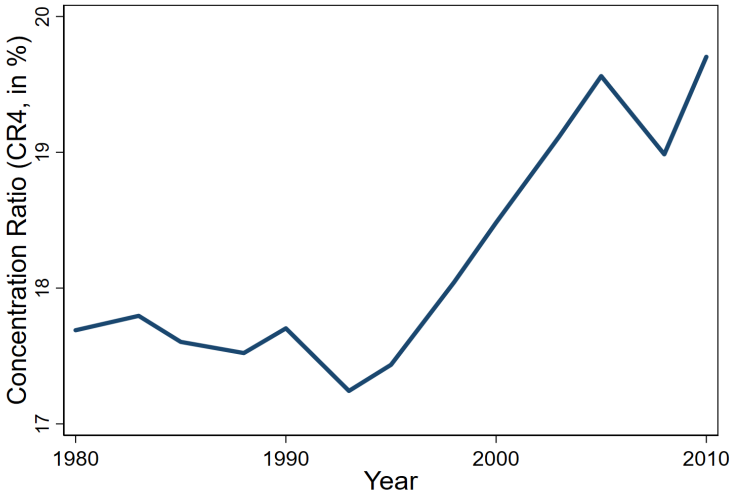
A More Figures

Figure A.1: Labor Share of Gross Value Added in the Japanese Manufacturing Sectors



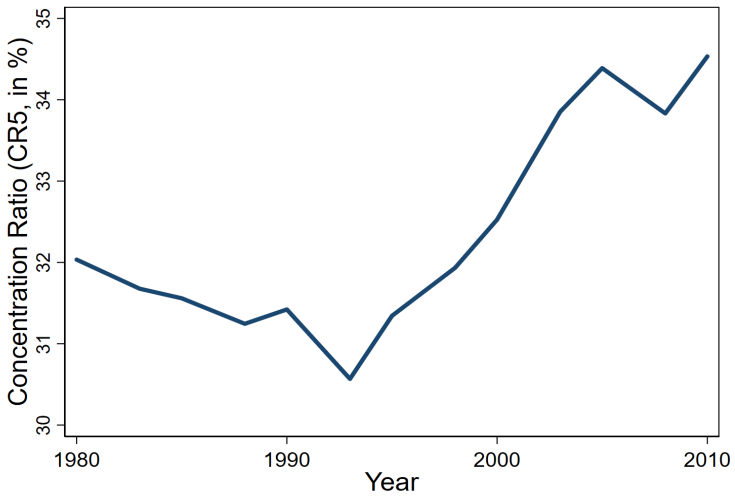
Note: This figure shows the labor share of gross value added in the Japanese manufacturing sector from 1980 to 2010. Labor share is computed as the share of total payroll to net value added (from the Japanese Census of Manufactures). The samples are establishments with more than or equal to 30 employees, in manufacturing sectors.

Figure A.2: Concentration Ratio in the Japanese Manufacturing Sectors, 3-digit



Note: This figure shows the average concentration ratio (CR4) of revenue across the 3-digit Japanese manufacturing industries from 1980 to 2010. The concentration ratio (CR4) is the share of the revenue of the largest four establishments within each 3-digit manufacturing industry, and industry-level CR4 is aggregated into aggregate level using the industry's total revenue in each year as the weight. The data is from the Japanese Census of Manufactures, and the samples are establishments with more than or equal to 30 employees, in manufacturing sectors.

Figure A.3: Concentration Ratio in the Japanese Manufacturing Sectors, CR5



Note: This figure shows the average concentration ratio (CR5) of revenue across the 4-digit Japanese manufacturing industries from 1980 to 2010. The concentration ratio (CR5) is the share of the revenue of the largest five establishments within each 4-digit manufacturing industry, and industry-level CR5 is aggregated into aggregate level using the industry's total revenue in each year as the weight. The data is from the Japanese Census of Manufactures, and the samples are establishments with more than or equal to 30 employees, in manufacturing sectors.