Labor Market Concentration, Automation, and Labor Share *

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Abstract

I study how labor market concentration affects labor share with endogenous technology. First, I provide a set of covariates on the relationship between local labor market power, labor share, and automation, using longitudinal establishment-level data in the Japanese manufacturing sector. I show that higher labor market concentration correlates with higher labor share and lower automation both across and within local labor markets. Second, I develop a model with oligopsonistic competition in labor markets with endogenous automation, which rationalizes the empirical patterns. The intuition is that higher labor market concentration keeps wages low and discourages automation, which leads to increases in labor share. Finally, I quantify the mechanism and show that *increasing* local labor market concentration added 1.7 percentage points to the median labor's share of income between 1990 and 2019.

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1 Introduction

This paper studies how labor market concentration affects labor share with endogenous technology. A starting point of this paper is to argue that the implication of labor market concentration can be different if one takes into account how firms' technology choices react. Consider two similar establishments located in different local labor markets with different degrees of labor market competition—one labor market with many competitors and another with few competitors. Establishments need to raise wages to attract workers in the labor market with many competitors. In the other labor market, however, establishments can keep wages low. This environment discourages establishments to pay costs for machines or equipment, which can save labor costs. If labor market concentration discourages automation to replace labor, labor share can be kept higher in more concentrated labor markets.

I begin in Section 2 by presenting stylized facts on the labor market concentration in the Japanese manufacturing sector. The number of establishments has halved since 1990, and the speed of this decline is faster than the decrease in the number of workers. As a result, the average number of workers per establishment increases by about 60% (25 to 40 per establishment) since 1990. This trend echoes the rise in standard labor market concentration measures, such as average payroll HHI or average CR4 at the local labor market level. I also estimate markdown, the ratio of wage to marginal revenue product of labor, following Yeh et al. (2022) and show the trend aligns with those of concentration measures—labor market concentration has been increasing and the markdown has been decreasing since 1990.

I then provide a set of new empirical evidence that local labor market concentration positively correlates with labor share and negatively with capital-labor ratio, using the establishment-level panel data. Comparing the same-sized establishments or using longitudinal within-establishment variations, I show that labor share in establishments is higher in more concentrated labor markets. This contradicts the naive extrapolation of low wages from higher labor market concentration to lower labor share, where technology is counter-factually fixed. I also show that the machine-labor ratio is negatively associated with higher labor market concentration.

In Section 3, I present a simple model of oligopsonistic competition in labor market as in Berger et al. (2022) with endogenous automation as in task model developed by Acemoglu and Restrepo (2018). There are many local labor markets in an economy, and each local labor market contains a fixed number of firms. They compete for labor within and across local labor markets, but behave strategically within a local labor market, knowing that their employment choices affect wages in the local labor market. This leads to markdown below one, meaning that the wage becomes lower than the marginal revenue product of labor. The markdown depends on the number of competitors within the local labor market and affects technology choices. If markdown and wage are low, there is less incentive to automate. Thus, lower markdown (higher labor market concentration) leads to lower automation and higher labor share.

Section 4 quantifies the implication of the rising labor market concentration in the Japan manufacturing sector since 1990 on labor share. If the labor markets in 2019 were as competitive as those in 1990, the median labor share would have been 1.7 percentage points *lower*.

I finish with some concluding thoughts in Section 5.

Related Literature

There is a growing attention in the implication of labor market concentration (Azar et al., 2022; Azkarate-Askasua and Zerecero, 2023; Berger et al., 2022; Brooks et al., 2021; Engbom, 2022; Jarosch et al., 2019; Lamadon et al., 2022; Rubens, 2023a; Yeh et al., 2022). Relative to this growing literature, this paper makes two main contributions.

First, this paper incorporates endogenous technical change. While many papers have studied the implication of product market power on technology, there is almost no paper on the implication of labor market power on technology.[1] One exception is Rubens (2023b), which theoretically studies the effect of oligopsony on factor-augmented technology and estimates the model in the coal mining industry in Illinois, from 1884 to 1902. My paper is complementary and has three main differences. First, theoretically, my paper endogenizes price-setting behaviors of establishments, which are affected by local labor market concentration. The comparative statics in Rubens (2023b) assumes exogenous markdown, which firms do not choose. Second, also theoretically, I focus on automation technology which is factor replacing, not factor augmenting. As I focus on labor share, this is a more relevant way of modeling technology, as emphasized in Acemoglu and Restrepo (2019), Acemoglu and Restrepo (2022), and their related work. Finally, my focus is on the macroeconomy.

Second, I believe that this is the first paper to run the regression of outcomes on *local* labor market concentration measures, not *national* market concentration measures, when studying the implication of labor market power, except Berger et al. (2023).[2] The focus is different than Berger et al. (2023) because its primary goal is to decompose the effect on wage into various sources of labor market power while I study the implication for labor share and capital-labor ratio.

2 Empirical Analysis

2.1 Data

Data Source My primary data source in this paper is the Japanese Census of Manufactures (CoM) for the manufacturing sector. The Ministry of Economy, Trade, and Industry (METI) conducts 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 in years when the last digit of the survey year is 0, 3, 5, or 8, and for other years, the census covers all establishments with at least 4 employees in Japan. The CoM survey was not conducted in 2011 and 2015, and instead, another government survey, the Economic Census of Business Activity (ECBA) was conducted.[3] I use the ECBA survey to substitute the CoM survey in 2011 and 2015.

The advantage of this data is that it has panels of all the establishments with a minimum of 4 employees and contains standard establishment-level variables such as payroll, shipments, and employment. It further contains shipments by detailed 6-digit product categories from 1980. These features allow me to compute labor share within an establishment across time, local la-

[1] For example, Hubmer and Restrepo (2023) studies the effect of product market concentration on automation and labor share, which is parallel to my paper.

[2] For example Gouin-Bonenfant (2022)

[3] The ECBA survey covers all establishments, including establishments in non-manufacturing sectors, but I focus on establishments in the manufacturing sector to be consistent with the CoM survey.

bor market concentration measures, and import penetration measures constructed from detailed product-level shipments at an establishment level.[4]

I also use the Comtrade data from the United Nations. I use bilateral flows of goods in HS code as reported and convert them into HS2 code. I convert all trade flows into real 2015 US dollars using the US CPI from OECD (2010).

Definition of Local Labor Markets I define a local labor market as a pair of a JSIC 3-digit manufacturing industry and a commuting zone. In the data, I have 149 unique 3-digit manufacturing industries and 259 commuting zones. To construct time-consistent commuting zones from municipalities in Japan, I first follow Kondo (2023) to convert municipalities in each year into time-consistent municipality groups.[5] I then follow Adachi et al. (2020) to convert these municipality groups into commuting zones.

2.2 Stylized Facts: Labor Market Concentration in the Japanese Manufacturing Sector

Before analyzing data at establishment-level, in this subsection, I summarize the macro time-series trends of important variables of the Japanese manufacturing sector from 1980 to 2019. For all the panels, I restrict samples to establishments with minimum of four employees to make the data time-consistent.

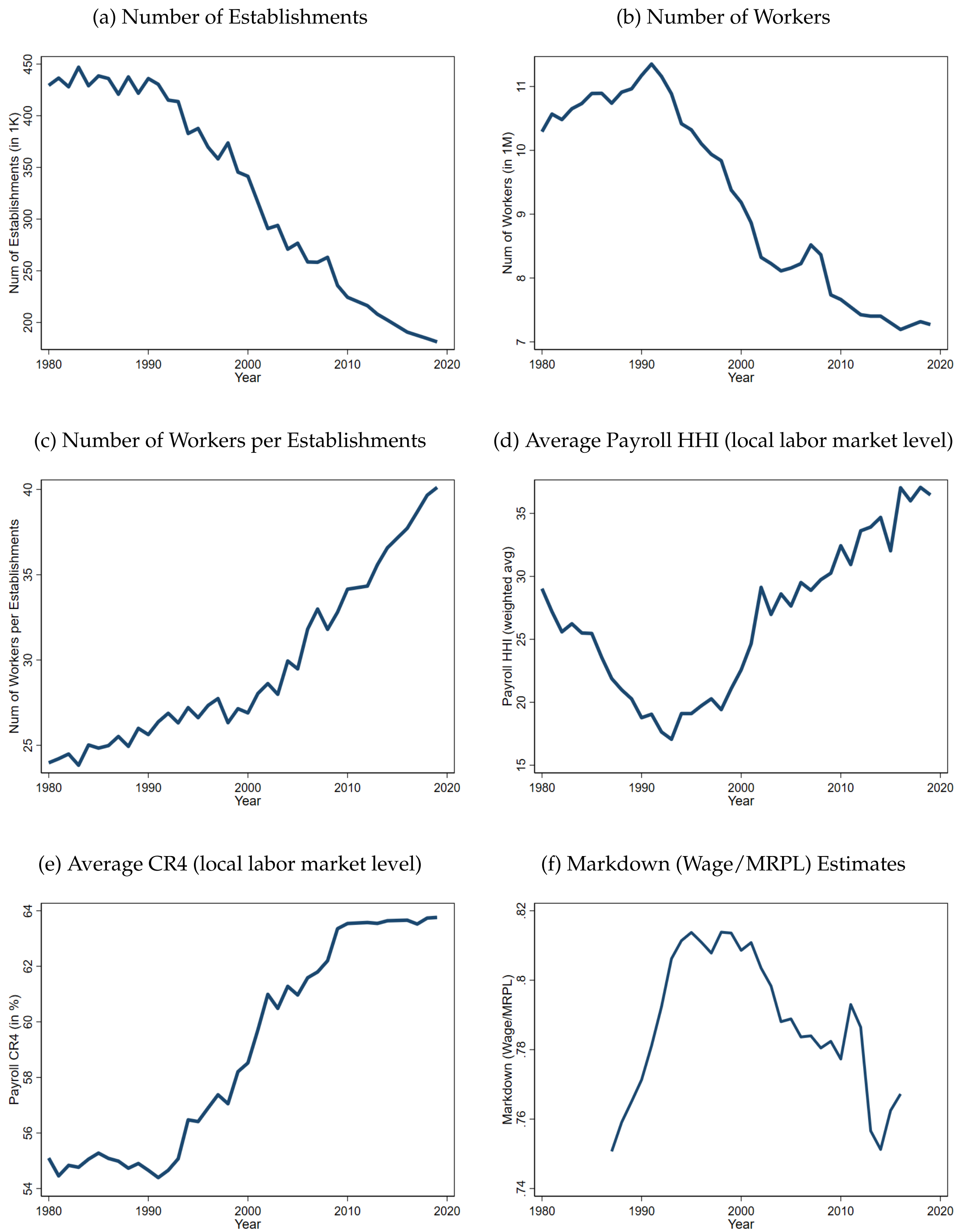
Figure 1 shows six panels of different time series, which are related to labor market concentration. Figure 1 (a) shows the number of establishments. In 1980, the Japanese manufacturing sector had over 400,000 establishments while the number decreased by more than half and has become lower than 200,000 recently. Figure 1 (b) shows the number of workers. Similar to the pattern of the number of establishments, it decreased from 10 million to about 7 million. However, as clearly shown in Figure 1 (c), the number of establishments decreased more rapidly than the number of workers. In 1980, the average number of workers in an establishment was below 25 while it is about 40 in 2019. Figure 1 (d) shows the average payroll HHI at local labor market level. For each local labor market, which is a pair of commuting zone and one of the 3-digit JSIC industrial categories, I compute payroll HHI. I then take the national average, weighing each local labor market by the total payroll. Until 1993, payroll HHI had been decreasing. Since then, it has steadily increased until 2019. Figure 1 (e) shows the average CR4, the share of the top 4 establishments' payroll in each local labor market. While there is no decline before 1993, the increasing pattern is similar to the time series of HHI. These indicate that the Japanese labor market concentration has been increasing since the mid-1990s. Finally, Figure 1 (f) shows the markdown estimate for establishments in the Japanese manufacturing sector. I follow Yeh et al. (2022) to estimate markdowns. I use trans-log specification and compute the national average using payroll share as weights. The markdown, the ratio of wage to the marginal product of labor, had once increased until the mid-1990s then decreased since then. This pattern agrees with the concentration measures in Figure (d) and (e).[6]

[4] One further advantage of this data compared to the US LBD data is that I can separately identify single establishments within each of 47 prefectures.

[5] Japan has 1,724 municipalities as of June 2023, including 6 municipalities in the Northern Territories. I drop these 6 municipalities as the CoM data does not cover them.

[6] Aoki et al. (2023) estimates markdown in Japan in the same manner but at firm-level, including non-manufacturing sectors. The sample period is 2005 to 2020, which is shorter than my paper, but it also finds the recent increasing trend of the gap between wage and the marginal product of labor.

Figure 1: Stylized Facts of the Japanese Manufacturing Sector



Note: The figures show time series of variables of the Japanese manufacturing sector. All data are from Census of Manufacturers and author's calculation. See the main text for details.

2.3 Sources of Establishment Exits in Japan

In this subsection, I study one of the potential sources of the this declining competition in labor market, a rise of Chinese import penetration.

Specification I use the following linear probability model for firm exits, where the sample is establishments in a manufacturing sector which existed in 1997.

$$\mathbb{1}\left(\text{Exit}_{i,1997,2007}\right) = \beta\Delta\text{IP}_{i,1997,2007} + X'_{i,1997}\Gamma + \varepsilon_i \tag{1}$$

where for establishment i, $\mathbb{1}\left(\text{Exit}_{i,1997,2007}\right)$ takes one if establishment i which existed in 1997 exits between 1997 and 2007, $\Delta\text{IP}_{i,1997,2007}$ is the changes in import penetration ratio at establishment level, and $X_{i,1997}$ is a vector of covariates, including employment and total shipments in 1997.

To construct establishment level trade exposure, $\Delta\text{IP}_{i,1997,2007}$, I first follow Autor et al. (2016) to construct the trade exposure measure, changes in import penetration ratio from 1997 to 2007 for each Japanese product as follows:

$$\Delta\text{IP}_{p,1997,2007} = \frac{\Delta M^{UJ}_{p,1997,2007}}{Y_{p,1997} + M_{p,1997} - E_{p,1997}}$$

where for product p, $\Delta M^{UJ}_{p,1997,2007}$ is the changes in imports from China for 1997 to 2007, and $Y_{p,1997} + M_{p,1997} - E_{p,1997}$ is initial absorption (total shipments $Y_{p,1997}$, plus total imports $M_{p,1997}$, minus total exports $E_{p,1997}$).

I then compute the average exposure for each Japanese establishment which existed in 1997, weighted by shipments of each establishment in 1997.

$$\Delta\text{IP}_{i,1997,2007} \equiv \sum_p \omega_{p,i,1997} \times \Delta\text{IP}_{p,1997,2007}$$

where $\omega_{p,i,1997}$ is the share of shipments of product p in establishment i in 1997. Since trade data at product level is available at HS code, I use the crosswalk from HS code to Standard Commodity Classification for Japan, provided by Baek et al. (2021).[7]

Sample Construction I restrict samples to the establishments with minimum of 4 employees in 1997 and those of which produced at least one product in 1997, which can be matched to trade data whether China or other countries, including Japan, reported in the Comtrade data. This restriction leaves 52,362 establishments, and 39.4% of them exited during this period. Also, for these establishments, the establishment level trade exposure, $\Delta\text{IP}_{i,1997,2007}$, has mean 0.04 (4 percentage point) with standard deviation 0.17.

Result Table 1 shows the results. Column (1) does not include any covariates. Column (2) adds initial employment in log, Column (3) adds total shipments in log. Column (4) adds 2-digit JSIC industry fixed effects, which compares different product categories within each of 2-digit industry.

In all the specification, increases in the exposure to Chinese imports leads to more establishment exits, which agrees with the finding in Aghion et al. (2022) for French manufacturing firms.[8]

[7] I thank Kazunobu Hayakawa for generously sharing the crosswalk.

[8] Aghion et al. (2022) uses firm-product level export data to define firm-level trade exposures. The advantage of the

The coefficient estimate is also economically meaningful. One standard deviation increases in the Chinese import penetration ratio, which is 17 percentage point, increases the exit rate by 2.4 percentage point ($0.17 \times 0.14 = 2.38$). This suggests that the intensifying competition in product markets due to Chinese imports leads to establishment's exits and thus hinders competition in local labor markets.

Table 1: Chinese Import Penetration and Establishment Exit

	(1)	(2)	(3)	(4)
Δ Import Penetration	0.14	0.11	0.10	0.03
	(0.05)	(0.04)	(0.04)	(0.01)
Employment (in log)		-0.09	-0.05	-0.05
		(0.01)	(0.01)	(0.01)
Shipment (in log)			-0.03	-0.03
			(0.01)	(0.01)
Observations	52,362	52,362	52,362	52,362
2-digit Industry Fixed Effects				✓

Note: The table shows the estimates of coefficients in equation (1) for the relationship between the change in Chinese import penetration and establishment exits. Column (1) does not include any covariates. Column (2) adds employment in log as a covariate, Column (3) adds total shipments, and Column (4) adds JSIC 2-digit industry fixed effects. Standard errors are clustered at JSIC 2-digit industry level and robust against heteroskedasticity.

2.4 Empirical Analysis: Local Labor Market Concentration and Labor Share

Now, I provide a set of covariance, which aligns with the theoretical predictions on manufacturing sectors in Japan where we have detailed establishment level data. I do not attempt to attribute causality. I use two specifications, across and within establishments, following Berger et al. (2023), but with different outcomes and contexts.

2.4.1 Labor Market Concentration and Labor Share: Across Establishment

Specification The goal of the analysis is first to see how labor market concentration at local labor market level correlates with labor share in establishments.

$$LS_i = \beta \ln HHI_{j,c} + \gamma \ln VA_i + X'_{j,c}\delta + \mu_j + \mu_c + \varepsilon_i \tag{2}$$

where LS_i is labor share of establishment i, $HHI_{j,c}$ is payroll HHI in an industry-cz pair (j, c), $\ln VA_i$: logged value-added of establishment i, $X_{j,c}$ is a vector of covariates at an industry-cz pair (j, c), and μ_j, μ_c are 3-digit industry FE and commuting zone FE respectively. Standard errors are clustered at industry-cz pair level (local labor market level) and robust against heteroskedasticity.

approach by Aghion et al. (2022) is that it can separate the exposure to Chinese imports in output and input markets. In fact, Aghion et al. (2022) demonstrates that the intensifying competition in output markets led to firm exits while that in input markets had positive, insignificant effects. By nature, my approach focuses on output market as I use establishment-level shipment data. The advantage of my approach is that I can connect the results to competition in local labor markets where establishments locate.

Results Table 2 shows the results for each year. All the columns include the number of establishments in each local labor market (j, c) in log, JSIC 3-digit industry fixed effects, and commuting zone fixed effects. For all the years, payroll HHI in local labor markets positively correlates with labor share of establishments. This implies that comparing two same-sized establishments in different local labor markets, the one in more concentrated local labor market has higher labor share.

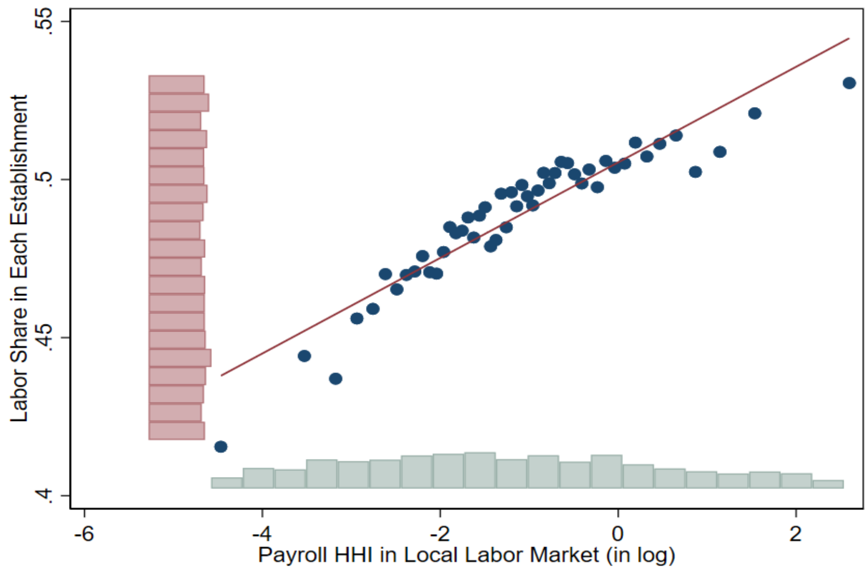
Table 2: Labor Market Concentration and Labor Share: Across Establishment

Year	1980	1990	2000	2010
	(1)	(2)	(3)	(4)
Payroll HHI (in log)	0.016	0.015	0.015	0.018
	(0.001)	(0.001)	(0.001)	(0.001)
Value Added (in log)	-0.099	-0.096	-0.102	-0.099
	(0.001)	(0.001)	(0.001)	(0.001)
Observations	50,140	56,480	47,255	38,530

Note: The table shows the estimates of coefficients in equation (2) for the relationship between payroll HHI (in log) at local labor market level and labor share at establishment level in each point time separately. Payroll HHI in local labor markets is computed by summing up the squares of the payroll share of establishments within each local labor market. Labor share in establishments is gross labor share and is computed by dividing total payroll by total shipments minus total material costs minus tax. All the columns include logged value added of establishments and the number of establishments in local labor markets as covariates. Standard errors are clustered at local labor market level and robust against heteroskedasticity.

To see that the result is not driven by outlier, Figure 2 shows the bin-scatter plots for the same specification for 2000 with histograms of both variables. Same as the regression, I control log value-added of each establishment, the number of establishments in each local labor market in log, JSIC 3-digit industry fixed effects, and commuting zone fixed effects. The log-linear relationship spans over wide regions, which implies that the result is not driven by outliers and the log-linear specification fits well in this context.

Figure 2: Bin-scatter Version: Establishment's Labor Share and LLM-level Payroll HHI in 2000



Note: The figure shows the binned scatter plots with histograms for the relationship between payroll HHI (in log) at local labor market level and labor share at establishment level in 2000.. The specification is same as equation (2), and regression estimates are same as Column (3) in Table 2.

2.4.2 Labor Market Concentration and Labor Share: Within Establishment

Specification The previous specifications compare same-sized establishments in different local labor markets in each point of time. While the interpretation of the results is transparent, unobserved heterogeneity across establishments is not controlled so that it can be the case that the regression compares establishments with different establishment characteristics affecting labor share, such as rent sharing or contracts schemes.

To mitigate these concerns, I exploit within-establishments variations of labor share across time, when local labor market concentration also changes. In particular, I run the following regression with establishment fixed effects.

$$LS_{i,t} = \beta \ln HHI_{j,c,t} + \gamma \ln VA_{i,t} + X'_{j,c,t}\delta + \mu_i + \mu_{j,t} + \mu_{c,t} + \varepsilon_i \tag{3}$$

where $LS_{i,t}$ is labor share of establishment i at time t, $HHI_{j,c,t}$ is payroll HHI in an industry-cz pair (j,c) at time t, $\ln VA_{i,t}$ is logged value-added of establishment i at time t, $X_{j,c,t}$ is a vector of covariates at an industry-cz pair (j,c) at time t, μ_t are establishment FEs, $\mu_{j,t}$ are 3-digit industry specific time trends, and $\mu_{c,t}$ are commuting zone specific time trends.

Sample Construction To analyze data in a longitudinal way, I construct samples as follows. First, I restrict samples to establishments with a minimum of 30 employees. This is necessary to construct a panel of establishments at an annual frequency with value-added consistently defined. Second, I construct a panel of establishments. While the CoM survey does not contain time-consistent establishment codes, RIETI provides a converter to enable researchers to link establishments across different years since 1986. My final sample is an unbalanced five-year panel of

55,831 unique establishments in manufacturing sectors in 1990, 1995, 2000, 2005, 2011, and 2015.

Results Table 3 shows the results.

Table 3: Labor Market Concentration and Establishment's Labor Share: Five-Year Panel

	(1)	(2)	(3)
Payroll HHI (in log)	0.009	0.008	0.012
	(0.000)	(0.000)	(0.000)
Value Added (in log)	-0.209	-0.209	-0.215
	(0.001)	(0.001)	(0.001)
Observations	232,195	232,195	232,124
Covariates		✓	✓
Establishment Fixed Effects	✓	✓	✓
Industry-Year Fixed Effects			✓
CZ-Year Fixed Effects			✓

Note: The table shows the estimates of coefficients in equation (3) for the relationship between payroll HHI (in log) at local labor market level and labor share at establishment level. Payroll HHI in local labor markets is computed by summing up the squares of the payroll share of establishments within each local labor market. Labor share in establishments is gross labor share and is computed by dividing total payroll by total shipments minus total material costs minus tax. All the columns include logged value added of establishments, the number of establishments in local labor markets as controls, with establishment fixed effects, industry-year fixed effects, and cz-year fixed effects. Standard errors are clustered at local labor market level and robust against heteroskedasticity.

Other Establishment Outcomes To study the other establishment-level outcomes, I examine how local labor market payroll HHI relates to machine-labor ratio and employment. I use the same specification as equation (3) but with different outcomes as follows:

$$Y_{i,t} = \beta \ln HHI_{j,c,t} + \gamma \ln VA_{i,t} + X'_{j,c,t}\delta + \mu_i + \mu_{j,t} + \mu_{c,t} + \varepsilon_i \tag{4}$$

where for establishment i in year t, $Y_{i,t}$ can be either machine-labor ratio or log employment. I include logged establishment-level value-added, establishment fixed effects, industry-year fixed effects, and cz-year fixed effects.

Table 4 shows the results. Column (1) uses the ratio of machine to employment, Column (2) uses the ratio of machine stock to total payroll, and Column (3) uses logged employment as outcomes. Column (1) and (2) show that machine stocks relative to labor (or payroll) are lower in more concentrated local labor markets while Column (3) shows that employment is higher in more concentrated local labor markets, comparing the same-sized establishments.

Table 4: Labor Market Concentration and Establishment Outcomes: Five-Year Panel

Dep. Var.	Machine-Labor Ratio	Machine-Labor Payment Ratio	Log Emp.
	(1)	(2)	(3)
Payroll HHI (in log)	-0.021	-0.010	0.022
	(0.003)	(0.003)	(0.001)
Value added (in log)	-0.071	0.010	0.314
	(0.006)	(0.006)	(0.002)
Observations	162,655	162,655	170,936
Covariates	✓	✓	✓
Establishment Fixed Effects	✓	✓	✓
Industry-Year Fixed Effects	✓	✓	✓
CZ-Year Fixed Effects	✓	✓	✓

Note: The table shows the estimates of coefficients in equation (4) for the relationship between payroll HHI (in log) at local labor market level and various outcomes at establishment level. Payroll HHI in local labor markets is computed by summing up the squares of the payroll share of establishments within each local labor market. Column (1) uses the ratio of machine to employment, Column (2) uses the ratio of machine stock to total payroll, and Column (3) uses logged employment as outcomes. All the columns include logged value added of establishments, the number of establishments in local labor markets as controls, with establishment fixed effects, industry-year fixed effects, and cz-year fixed effects. Standard errors are clustered at local labor market level and robust against heteroskedasticity.

3 Model of Oligopsonistic Competition in Labor Market and Automation

In this section, I develop a model of oligopsonistic competition in labor markets with endogenous automation. To do so, I combine a model of labor markets in Berger et al. (2022) with task model.

3.1 Environment

The economy consists of a representative household and a continuum of firms. The representative household consumes final goods and supplies hours worked to each firm $n_{i,j}$ given the aggregate labor $\mathcal{N}$ inelastically supplied. Firms are located in local labor market $j \in [0,1]$, each of which has finite number of firms indexed $i \in \{1, 2, .., m_j\}$. The model is static and does not allow entries or exits of firms.

3.2 Household

The household chooses the measure of workers to supply each firm $n_{i,j}$ and consumption of each good $c_{i,j}$ to maximize their static value of utility.

$$\mathcal{U} = \max_{c_{i,j}, n_{i,j}} U(\mathcal{C}, \mathcal{N})$$

The aggregate consumption and labor supply indexes are given by

$$\mathcal{C} = \int_0^1 [c_{1,j} + ... + c_{m_j,j}] dj, \quad \mathcal{N} = \left[\int_0^1 n_j^{\frac{\theta+1}{\theta}} dj\right]^{\frac{\theta}{\theta+1}}, \quad n_j = \left[\sum_{i=1}^{m_j} n_{i,j}^{\frac{\eta+1}{\eta}}\right]^{\frac{\eta}{\eta+1}}.$$

The maximization is subject to the following budget constraint.

$$\mathcal{C} = \int_0^1 [w_{1,j} n_{1,j} + ... + w_{m_j,j} n_{m_j,j}] dj + \Pi$$

where firm's profit Π is rebated lump sum to the household.

3.3 Firms

3.3.1 Production

The continuum of firms produce goods that are perfect substitutes, and I normalize the price to be one. Firms use capital $k_{i,j}$ and labor $n_{i,j}$ to produce final goods $y_{i,j}$ according to the production function:

$$y_{i,j} = z_{i,j} \left[\left(\int_0^1 y_{i,j}(x)^{\frac{\zeta-1}{\zeta}} dx \right)^{\frac{\zeta}{\zeta-1}} \right]^{\gamma}$$

where $z_{i,j}$ is firm i's productivity, $y_{i,j}(x)$ is production of task $x \in [0,1]$, $\zeta > 0$ is the elasticity of substitution across task, $\gamma \in (0,1)$ is the degree of decreasing return to scale in final good production.

As in the standard task model, task $y_{i,j}(x)$ can be produced either by labor or machines if the task is not too complex ($x \in [0, \alpha_{i,j}]$) and can only be produced by low-skill labor otherwise.

$$y_{i,j}(x) = \begin{cases} n_{i,j}(x) + k_{i,j}(x) & \text{if } x \in [0, \alpha_{i,j}] \\ n_{i,j}(x) & \text{if } x \in (\alpha_{i,j}, 1] \end{cases}$$

I assume that machines, $k_{i,j}$, are supplied at an exogenously fixed rental price R.

Firms maximize their variable profit as follows. Firms are infinitesimal with respect to the macroeconomy and take the aggregate wage $\mathbf{W}$ and labor supply $\mathcal{N}$ as given. The equilibrium concept is Cournot, and firms take as given their competitors' employment decisions, $n^*_{-i,j}$.

$$\Pi^{\text{VA}}_{ij} = \max_{n_{i,j}(x), k_{i,j}(x)} z_{i,j} \left[\left(\int_0^1 y_{i,j}(x)^{\frac{\zeta-1}{\zeta}} dx \right)^{\frac{\zeta}{\zeta-1}} \right]^{\gamma} - Rk_{i,j} - w(n_{i,j}, n^*_{-i,j}, \mathcal{N}, \mathbf{W}) n_{i,j}$$

subject to

$$w\left(n_{ij}, n^*_{-ij}, \mathcal{N}, \mathbf{W}\right) = \left(\frac{n_{ij}}{\mathbf{n}\left(n_{ij}, n^*_{-ij}\right)} \right)^{\frac{1}{\eta}} \left(\frac{\mathbf{n}\left(n_{ij}, n^*_{-ij}\right)}{\mathcal{N}} \right)^{\frac{1}{\theta}} \mathbf{W}$$

$$\mathbf{n}\left(n_{ij}, n^*_{-ij}\right) = \left[n_{ij}^{\frac{\eta+1}{\eta}} + \sum_{k \neq i} (n^*_{kj})^{\frac{\eta+1}{\eta}} \right]^{\frac{\eta}{\eta+1}}.$$

3.3.2 Automation

Before production of final goods, firms choose automation technology $\alpha_{i,j}$ to maximize their profit subject to adjustment cost, which is proportional to the variable profit of the firm.[9]

$$\Pi^{\text{TOT}}_{i,j} = \max_{\alpha_{ij \in (0,1)}} \Pi^{\text{VA}}_{i,j}(\alpha_{i,j})(1 - \kappa_{i,j}(\alpha_{i,j}))$$

3.4 Equilibrium

I take the price of final goods as a numeraire. An equilibrium is a set of wage $\{w_{ij}\}$, factor demand $\{n_{i,j}, k_{i,j}, \alpha_{i,j}\}$, and aggregate wage $\mathbf{W}$ where

- firms choose $\alpha_{i,j}$ to maximize total profit $\Pi^{\text{TOT}}_{i,j}$ given the aggregate wage $\mathbf{W}$.
- firms choose $\{n_{i,j}, k_{i,j}\}$ to maximize variable profit $\Pi^{\text{VA}}_{i,j}(\alpha_{i,j})$ given the choice of automation α_{ij}, employment decisions of other firms within each local labor market $\{n^*_{-i,j}\}$, and $\mathbf{W}$.
- labor markets clear

$$\mathbf{w}_j = \left[\sum_{i \in j} w_{ij}^{1+\eta} \right]^{\frac{1}{1+\eta}}, \mathbf{W} = \left[\int_0^1 \mathbf{w}_j^{1+\theta} dj \right]^{\frac{1}{1+\theta}}.$$

[9] I assume this proportional cost structure for simplicity in algebra.

3.5 Characterization: Firm's Decisions

3.5.1 Firm's Production

For simplicity, assume $R < \min\{w_{i,j}\}$ so that machines are always cheaper than labor. This assumption implies that firms use machines whenever possible.

$$y_{i,j}(x) = \begin{cases} k_{i,j}(x) & \text{if } x \in [0, \alpha_{i,j}] \\ n_{i,j}(x) & \text{if } x \in (\alpha_{i,j}, 1] \end{cases}$$

This leads to the reduced-form expression of the firm's production function as follows:

$$\begin{aligned} y_{i,j} &= z_{i,j} \left[\left(\int_0^{\alpha_{i,j}} k_{i,j}(x)^{\frac{\zeta-1}{\zeta}} dx + \int_{\alpha_{i,j}}^1 n_{i,j}(x)^{\frac{\zeta-1}{\zeta}} dx \right)^{\frac{\zeta}{\zeta-1}} \right]^\gamma \\ &= z_{i,j} \left[\left(\alpha_{i,j}^\zeta k_{i,j}^{\frac{\zeta-1}{\zeta}} + (1-\alpha_{i,j})^\zeta n_{i,j}^{\frac{\zeta-1}{\zeta}} \right)^{\frac{\zeta}{\zeta-1}} \right]^\gamma \end{aligned}$$

3.5.2 Firm's Employment Decisions under Oligopsonistic Competition

The firm's maximization problem becomes

$$\max_{k_{i,j}, n_{i,j}} z_{i,j} \left[\left(\alpha_{i,j}^\zeta k_{i,j}^{\frac{\zeta-1}{\zeta}} + (1-\alpha_{i,j})^\zeta n_{i,j}^{\frac{\zeta-1}{\zeta}} \right)^{\frac{\zeta}{\zeta-1}} \right]^\gamma - Rk_{i,j} - w(n_{i,j}, n^*_{-i,j}, \mathcal{N}, \mathbf{W}) n_{i,j}$$

subject to

$$w\left(n_{ij}, n^*_{-ij}, \mathcal{N}, \mathbf{W}\right) = \left(\frac{n_{ij}}{\mathbf{n}\left(n_{ij}, n^*_{-ij}\right)} \right)^{\frac{1}{\eta}} \left(\frac{\mathbf{n}\left(n_{ij}, n^*_{-ij}\right)}{\mathcal{N}} \right)^{\frac{1}{\theta}} \mathbf{W}$$

$$\mathbf{n}\left(n_{ij}, n^*_{-ij}\right) = \left[n_{ij}^{\frac{\eta+1}{\eta}} + \sum_{k \neq i} (n^*_{kj})^{\frac{\eta+1}{\eta}} \right]^{\frac{\eta}{\eta+1}}.$$

The labor demand condition yields a Lerner condition for the wage as a markdown $\mu_{i,j} \leq 1$ on the marginal product of labor, $\text{MPL}_{i,j}$ as follows:

$$w_{i.j} = \mu_{i,j} \times \text{MPL}_{i,j}, \quad \mu_{i,j} = \frac{\varepsilon_{i,j}}{\varepsilon_{i.j} + 1}, \quad \varepsilon_{i,j} = \left[\left. \frac{\partial \log w_{ij}}{\partial \log n_{ij}} \right|_{n^*_{-ij}} \right]^{-1}.$$

As in Berger et al. (2022), the elasticity and markdown have closed-form expressions as follows:

$$\varepsilon\left(s_{ij}\right) = \left[\frac{1}{\eta} + \left(\frac{1}{\theta} - \frac{1}{\eta} \right) \left. \frac{\partial \log \mathbf{n}_j}{\partial \log n_{ij}} \right|_{n^*_{-ij}} \right]^{-1} = \left[\frac{1}{\eta} + \left(\frac{1}{\theta} - \frac{1}{\eta} \right) s_{ij} \right]^{-1}$$

where payroll share $s_{i,j}$ is defined as

$$s_{ij} := \frac{w_{ij}n_{ij}}{\sum_{i=1}^{m_j} w_{ij}n_{ij}} = \frac{w_{ij}n_{ij}}{\mathbf{w}_j\mathbf{n}_j}.$$

This means that higher payroll share decreases elasticity $\varepsilon_{i,j}$ and hence markdown $\mu_{i,j}$, assuming that across-market elasticity θ is lower than within-market elasticity η.

3.5.3 Firm's Automation Decisions

Firms choose their automation technology $\alpha_{i,j}$ to maximize the total profit

$$\Pi_{i,j}^{\text{TOT}} = \max_{\alpha_{ij\in(0,1)}} \Pi_{i,j}^{\text{VA}}(\alpha_{i,j})(1-\kappa_{i,j}(\alpha_{i,j})).$$

For simplicity, assume $\zeta \to 1$ so that the elasticity of substitution across tasks to be one.[10] Then, $\Pi_{i,j}^{VA}(\alpha_{i,j})$ has closed form expression depending on α_{ij} because

$$\Pi_{i,j}^{VA}(\alpha_{i,j}) = y_{ij}(1-\alpha_{i,j}\gamma - \mu_{i,j}(s_{i,j}))(1-\alpha_{i,j})\gamma)$$

where

$$y_{i,j} = \left[\left(\frac{\alpha_{i.j}\gamma}{R}\right)^{\alpha_{i,j}}\left(\frac{(1-\alpha_{i,j})\gamma}{(1+\varepsilon_{i,j})w_{i,j}}\right)^{1-\alpha_{i,j}}\right]^{\frac{\gamma}{1-\gamma}}$$

$$w_{ij} = \left[\mu\left(s_{ij}\right)\tilde{\gamma}_{i,j}\tilde{z}_{ij}\right]^{\frac{1}{1+\eta(1-\tilde{\gamma}_{i,j})}} \times \left(w_j^{\theta-\eta}W^{-\theta}N\right)^{-\frac{1-\tilde{\gamma}_{i,j}}{1+\eta(1-\tilde{\gamma}_{i,j})}}$$

$$\tilde{z}_{i,j} = (1-\gamma\alpha_{i.j})\left(\frac{\gamma\alpha_{i,j}}{R}\right)^{\frac{\alpha_{i,j}\gamma}{1-\alpha_{i,j}\gamma}} z_{i,j}^{\frac{1}{1-\alpha_{i,j}\gamma}}$$

$$\tilde{\gamma}_{i,j} = \frac{(1-\alpha_{i,j})\gamma}{1-\alpha_{i,j}\gamma}$$

$$\varepsilon_{i,j} = \left[\frac{1}{\eta} + \left(\frac{1}{\theta} - \frac{1}{\eta}\right)s_{ij}\right]^{-1}$$

Then, I can characterize the optimal automation decisions across different degree of labor market concentration in the following proposition.

Proposition 3.1. *Suppose that $z_{i,j} = z_j$ for all $i \in j$. Then, optimal automation technology level $\alpha_{i,j}^*$ is larger (and labor share is lower) in more competitive labor market (the number of firms in the local labor market m_j is larger so that payroll HHI is lower).*

The intuition is that the tougher labor market competition leads to higher wage so that firms are more motivated to automate for more profitable cost cuts. Conversely, if the degree of labor market concentration is higher, firms can keep wages low so that there is less incentive to automate.

[10] I relax this assumption in the quantitative section.

4 Quantitative Analysis

In this section, I study how the changes in labor market competitiveness affects labor share in the Japanese manufacturing sector. In particular, I calibrate the model parameters to match the moments in 2019 and run the counterfactual experiment if the labor markets in 2019 were as competitive as those in 1990.

4.1 Calibration

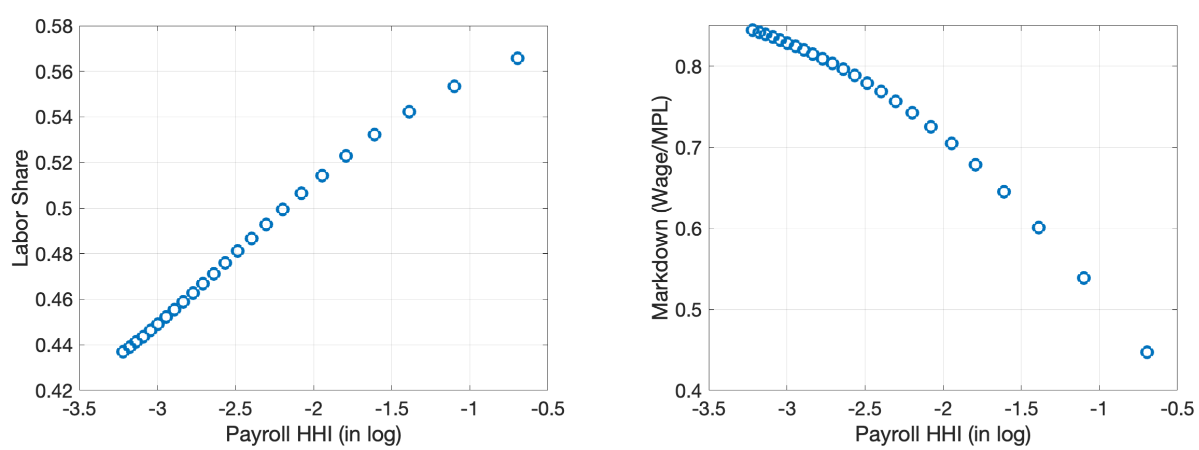
For θ and η, we take the value of 0.42 and 10.85 from Berger et al. (2022) who estimate these parameters in the US. They look at the employment response between firms across and within a 3-digit industry commuting zone pair to changes in the corporate tax at the year frequency. For machine price R, I match the median of establishment-level machine-labor ratio in 2019. For the decreasing return to scale parameter γ, I match the median labor share in 2019. For ζ, I follow Humlum (2019) to take 0.49.

Figure 3 shows the two moments generated by the model for 2019. The left panel shows the average labor share, and the right panel shows the average markdown across local labor markets with different payroll HHI (different number of establishments) in 2019. The left panel is directly comparable to the pattern in Figure 2, which is roughly comparable.[11] The right panel shows the markdown, the ratio of wage to the marginal revenue product of labor. As the payroll HHI increases, markdown decreases.

Figure 3: Moments Generated by the Model in 2019

(a) Labor Share and Payroll HHI

(b) Markdown (Wage/MRPL) and Payroll HHI



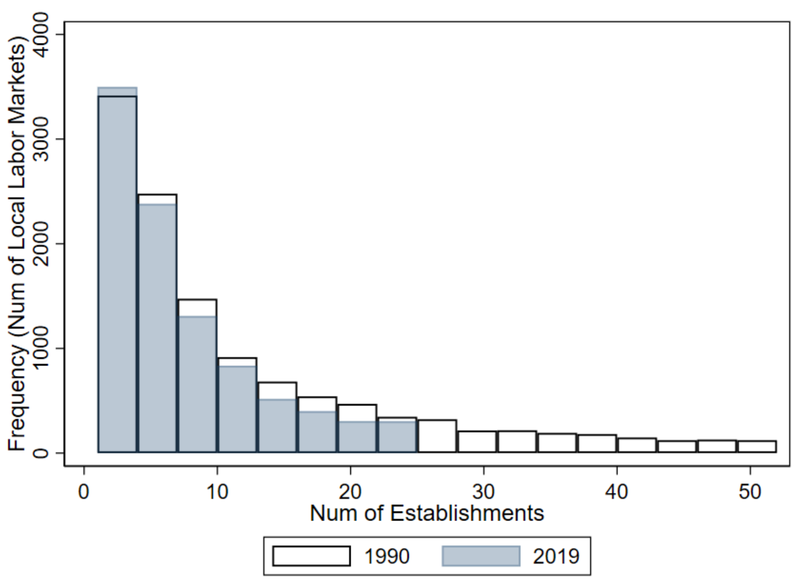
Note: The figures show the moments generated by the model in 2019. The left panel shows the labor share against payroll HHI (in log), and the right panel shows the markdown, the ratio of wage to marginal product of labor, against payroll HHI (in log).

[11] I am working on the disclosure process to directly compare these two figures.

4.2 Counterfactual Experiment

My counterfactual experiment is to keep the parameters to match the moments in 2019 but feed the distribution of the number of firms across local labor markets in 1990 rather than those in 2019. Figure 4 shows the histograms for the distribution of the number of establishments across local labor markets in Japan in 1990 and 2019. I drop top 10% and bottom 10% of the distribution in each year. From 1990 to 2019, the distribution has shifted to the left, which means that local labor markets have become less competitive.

Figure 4: Distribution of the Number of Establishments across Local Labor Markets



Note: The figure the histograms for the distribution of the number of establishments across local labor markets in Japan in 1990 and 2019. I drop top 10% and bottom 10% of the distribution in each year. Data is from Census of Manufacturers

I then simulate the model and get the counterfactual distribution of equilibrium outcomes, including labor share in each establishment and aggregate labor share. The difference between the counterfactual values under more competitive labor markets and the actual values under more concentrated labor markets indicate the effect of labor market concentration on labor share.

Table 5 shows the results. Column (1) shows the actual data, perfectly matched in the model. Column (2) shows the counterfactual. The first row shows the average number of establishments in the actual data in 1990, which I feed in the model. The second row shows the median labor share in the counterfactual experiment. Column (3) shows the differences between the counterfactual and the data in 2019. If the labor market in 2019 were kept as competitive as in 1990, the median labor share in the Japanese manufacturing sector would have been 1.7pt lower.

Table 5: Counterfactual Labor Share

	(1) Actual	(2) Counterfactual	(3) Difference ((2)-(1))
Median Num. of Firms	7.0	11.4	4.4
Median Labor Share	53.2%	51.5%	-1.7pt

Note: The table shows the results of the counterfactual experiments where I feed the distribution of the number of establishments across local labor markets in 1990 to the model calibrated to the data in 2019. Column (1) shows the actual data, perfectly matched in the model. Column (2) shows the counterfactual. The first row shows the average number of establishments in the actual data in 1990, which I feed in the model. The second row shows the median labor share in the counterfactual experiment. Column (3) shows the differences between the counterfactual and the data in 2019.

5 Conclusion

In this paper, I show that the implications of labor market power on labor share can be different if one considers endogenous responses of automation technology. Focusing on the comparison between same-sized establishments in different local labor markets, one in a more concentrated local labor market has a higher labor share and lower degrees of automation.

This is far from the last word on the implication of labor market power: empirically or theoretically. I focus on comparing the same-sized establishments in the empirical section and do not allow them to be heterogeneous in productivity in the quantitative section. As the empirical results show, larger establishments have lower labor shares. Thus, I suspect that the composition effects counteract the within effect—comparing same-sized establishments—, and the aggregate effects of labor market concentration on labor share can go either way. This is a clear next step in the quantitative model to allow productivity heterogeneity.[12]

I also suspect that my mechanism can have implications for economic stagnation in Japan. Previous studies argue that the stagnation is due to either low TFP growth and/or low capital investment (Hayashi and Prescott, 2002; Fukao et al., 2021). In fact, there is no growth in robot investment since 2000 despite the demographic trends towards labor shortage. These can be consequences of the rising labor market concentration as labor market concentration can slow down the reallocation of resources and hinder capital investment motivated by high wage pressure.

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[12]This is challenging in practice as I have to solve J ($\approx 10,000$) Nash equilibrium to get the payroll share within each local labor market with endogenous technology in each iteration of the outer loop to pin down aggregate prices.

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A Theory Appendix

A.1 Proof of Proposition 3.1

$$\Pi_{i,j}^{VA}(\alpha_{i,j}) = y_{ij}(1-\alpha_{i,j}\gamma - \mu_{i,j}(s_{i,j}))(1-\alpha_{i,j})\gamma)$$

where

$$y_{i,j} = \left[\left(\frac{\alpha_{i.j}\gamma}{R}\right)^{\alpha_{i,j}}\left(\frac{(1-\alpha_{i,j})\gamma}{(1+\varepsilon_{i,j})w_{i,j}}\right)^{1-\alpha_{i,j}}\right]^{\frac{\gamma}{1-\gamma}}$$

$$w_{ij} = \left[\mu\left(s_{ij}\right)\tilde{\gamma}_{i,j}\tilde{z}_{ij}\right]^{\frac{1}{1+\eta(1-\tilde{\gamma}_{i,j})}} \times \left(w_j^{\theta-\eta}W^{-\theta}N\right)^{-\frac{1-\tilde{\gamma}_{i,j}}{1+\eta(1-\tilde{\gamma}_{i,j})}}$$

$$\tilde{z}_{i,j} = (1-\gamma\alpha_{i.j})\left(\frac{\gamma\alpha_{i,j}}{R}\right)^{\frac{\alpha_{i,j}\gamma}{1-\alpha_{i,j}\gamma}} z_{i,j}^{\frac{1}{1-\alpha_{i,j}\gamma}}$$

$$\tilde{\gamma}_{i,j} = \frac{(1-\alpha_{i,j})\gamma}{1-\alpha_{i,j}\gamma}$$

$$\varepsilon_{i,j} = \left[\frac{1}{\eta} + \left(\frac{1}{\theta} - \frac{1}{\eta}\right)s_{ij}\right]^{-1}$$

Define $\pi_{i,j}(\alpha_{i,j}) \equiv \ln \Pi^{VA}_{i,j}(\alpha_{i,j})$. Since $s_{ij} = 1/m_j$ in the symmetric case, it is sufficient to show

$$\frac{\partial^2 \pi_{i,j}(\alpha_{i,j})}{\partial \alpha_{i,j} \partial s_{i,j}} < 0.$$

Since I can linearly decompose $\pi_{i,j}(\alpha_{i,j})$ into the following two components

$$\pi_{i,j}(\alpha_{i,j}) = \ln y_{i,j} + \ln(1 - \alpha_{i,j}\gamma - \mu_{i,j}(s_{i,j})(1 - \alpha_{i,j})\gamma),$$

which I can evaluate the cross derivatives one by one.

Effects via Output Focus on $\ln y_{i,j}$.

$$\ln y_{i,j} = \frac{\gamma}{1-\gamma}\alpha_{i,j} \ln\left(\frac{\alpha_{i,j}\gamma}{R}\right) + \frac{\gamma}{1-\gamma}(1-\alpha_{i,j}) \ln\left(\frac{(1-\alpha_{i,j})\gamma)}{(1+\varepsilon_{i,j})w_{i,j}}\right)$$

Then

$$\begin{aligned}
\frac{\partial^2 \ln y_{i,j}}{\partial \alpha_{i,j} \partial s_{i,j}} &= -\frac{\gamma}{1-\gamma}\frac{\partial^2}{\partial \alpha_{i,j}\partial s_{i,j}}\left[(1-\alpha_{i,j})\ln \varepsilon_{i,j}\right] - \frac{\gamma}{1-\gamma}\frac{\partial^2}{\partial \alpha_{i,j}\partial s_{i,j}}\left[(1-\alpha_{i,j})\ln w_{i,j}\right] \\
&= \frac{\gamma}{1-\gamma}\frac{\partial \ln \varepsilon_{i,j}}{\partial s_{i,j}} + \frac{\gamma}{1-\gamma}\frac{\partial \ln w_{i,j}}{\partial s_{i,j}} - \frac{\gamma}{1-\gamma}(1-\alpha_{i,j})\frac{\partial^2 \ln w_{i,j}}{\partial \alpha_{i,j}\partial s_{i,j}} < 0
\end{aligned}$$

because

$$\begin{aligned}
\frac{\partial \ln \varepsilon_{i,j}}{\partial s_{i,j}} &= -\left[\frac{1}{\eta} + \left(\frac{1}{\theta} - \frac{1}{\eta}\right)s_{ij}\right]^{-2}\left(\frac{1}{\theta} - \frac{1}{\eta}\right) < 0, \\
\frac{\partial \ln w_{i,j}}{\partial s_{i,j}} &= \frac{-(\theta^{-1} - \eta^{-1})}{1 + \theta(1 - \widetilde{\gamma}_{i,j})}\left[s_{i,j}(\theta^{-1} - \eta^{-1}) + \eta^{-1}\right]^{-2} < 0
\end{aligned}$$

and

$$\frac{\partial^2 \ln w_{i,j}}{\partial \alpha_{i,j}\partial s_{i,j}} = \frac{(\theta^{-1} - \eta^{-1})\theta\gamma\frac{1-\gamma}{(1-\alpha\gamma)^2}}{\left(1 + \theta(1 - \widetilde{\gamma}_{i,j})\right)^2}\left[s_{i,j}(\theta^{-1} - \eta^{-1}) + \eta^{-1}\right]^{-2} > 0$$

because $\theta < \eta$.

Effects via Profit Margin

$$\begin{aligned}
&\frac{\partial^2 \ln(1 - \alpha_{i,j}\gamma - \mu_{i,j}(s_{i,j})(1-\alpha_{i,j})\gamma)}{\partial \alpha_{i,j}\partial s_{i,j}} \\
&= \frac{\partial}{\partial s_{i,j}}\left(\frac{-\gamma(1 - \mu_{i,j}(s_{i,j}))}{(1 - \alpha_{i,j}\gamma - \mu_{i,j}(s_{i,j})(1-\alpha_{i,j})\gamma)}\right) \\
&= \frac{\gamma(1 - \mu_{i,j}(s_{i,j}))}{(1 - \alpha_{i,j}\gamma - \mu_{i,j}(s_{i,j})(1-\alpha_{i,j})\gamma)^2}\frac{\partial \mu_{i,j}(s_{i,j})}{\partial s_{i,j}}(1-\alpha_{i,j})\gamma + \frac{\gamma}{(1 - \alpha_{i,j}\gamma - \mu_{i,j}(s_{i,j})(1-\alpha_{i,j})\gamma)}\frac{\partial \mu_{i,j}(s_{i,j})}{\partial s_{i,j}} < 0
\end{aligned}$$

because $\mu_{i,j}(s_{i,j}) < 1$ and $\frac{\partial \mu_{i,j}(s_{i,j})}{\partial s_{i,j}} < 0$. ■

B Data Appendix

The purpose of this section is to provide aggregate trends of labor share and robot stocks for the Japanese manufacturing sector.

B.1 Data Sources for Appendix

JARA Data One additional 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 Restrepo (2020)). JARA data consists of robot shipments (both in units and sales value) by destination industry and robot application from 1978 to 2017.[13]

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

Figure B.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.

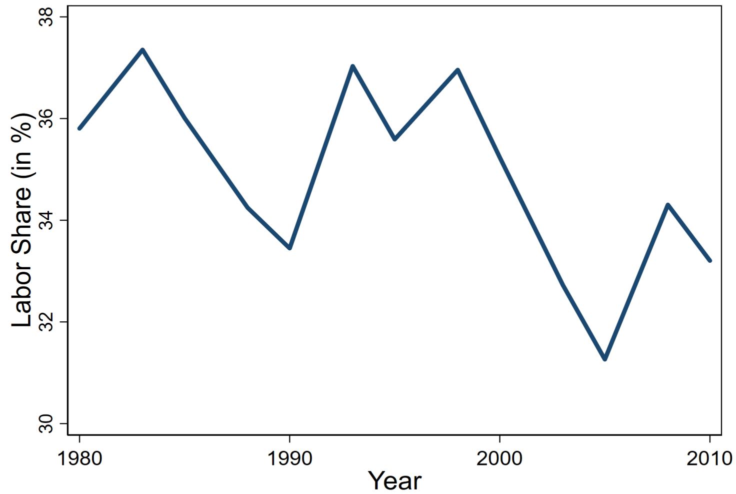
The overall picture is similar to that of the labor share calculated using National Accounts. According to the trend of the labor share, as reported by the Cabinet Office[14], the decline has been about the same, down 4 percentage points from its peak in the early 1980s. The developments of continuing 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 B.2.[15]

[13]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.

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

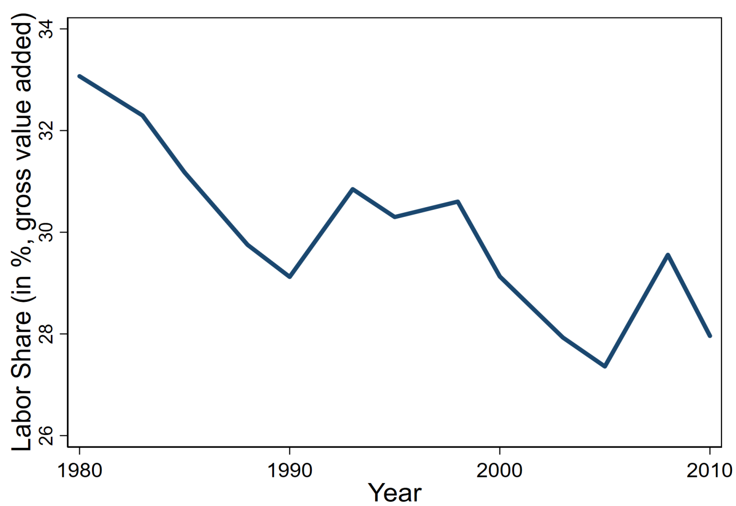
[15]**?** argues that the labor share in the US did not decrease if using net value added instead of gross value added.

Figure B.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.

Figure B.2: Labor Share of Gross Value Added in the Japanese Manufacturing Sectors



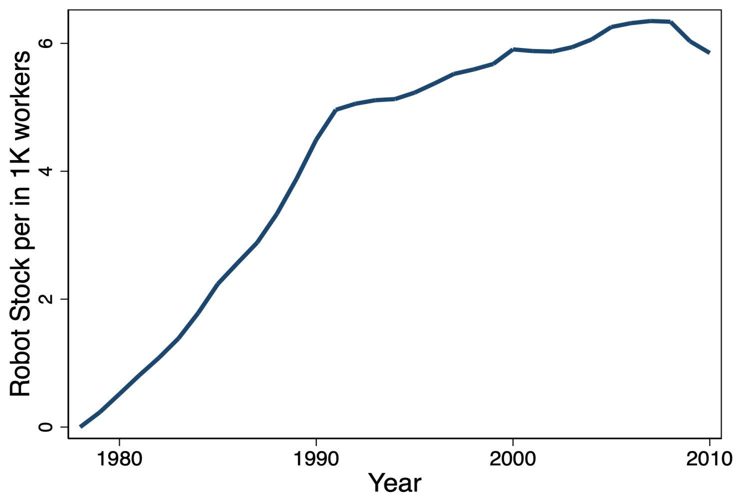
Note: This figure shows the labor share of gross value added in the Japanese manufacturing sector from 1980 to 2010. Labor share is computed as the share of total payroll to net value added (from the Japanese Census of Manufactures). The samples are establishments with more than or equal to 30 employees,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

Fact 2. *Robot stocks have slowed significantly since about 1990.*

Figure B.3 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 B.3: 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.