Labor Market Concentration, Automation, and Labor Share *

Shinnosuke Kikuchi†
MIT

July 30, 2023

Preliminary and Incomplete.

Please click HERE for the most recent version.

Abstract

I study how labor market concentration affects labor share with endogenous technology. I develop a model with oligopsonistic competition in labor markets with endogenous automation, which rationalizes the empirical patterns. Higher labor market concentration keeps wages low, discourages automation, and increases labor share. I provide new empirical evidence on the relationship between local labor market power, labor share, and automation, using longitudinal establishment-level data in the Japanese manufacturing sector. Contrary to popular belief, I show that *higher* labor market power correlates with *higher* labor share and lower automation, comparing same-sized establishments. This supports the theoretical predictions. 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.

*I thank Daron Acemoglu, Kosuke Aoki, David Autor, Chris Edmond, Ippei Fujiwara, and Toyoichiro Shirota for their helpful comments. This study is a part of the project "Macroeconomy and Automation" undertaken at the Research Institute of Economy, Trade and Industry (RIETI). I acknowledge permission to access the microdata of the Census of Manufacture and the Economic Census of Business Activity (for manufacturing sectors), granted by the Ministry of Economy, Trade and Industry in Japan. I am grateful for Keio University, where I worked on the empirical analyses using the microdata, for its hospitality during my visits. I deeply thank RIETI for providing their help for the data access.

†Email: skikuchi@mit.edu

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 and labor share 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 also present the fact that increases in the exposure to Chinese imports seem to be one of the sources of this changes in local labor market concentration.

In Section 3, I present a model to connect labor market power and labor share. I extend a model of oligopsonistic competition in labor market as in Berger et al. (2022) by adding endogenous automation as in 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 tests the theory using the establishment-level data in the Japanese manufacturing sector. Using both cross-sectional and longitudinal variations, I show that payroll share within a local labor market is positively correlated with labor share and negatively correlated with machine-labor ratio, comparing same-sized establishments. These are consistent with the theoretical prediction where labor market power leads to higher labor share due to endogenous (no-)automation.

Section 5 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 6.

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, which alters the common belief on the implication of labor market power on labor share. 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. This is important to assess the theoretical prediction in a consistent manner.

This paper also 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, 2022), 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). This paper focuses on automation and labor market concentration as well, but I show that the implication of these factors should be jointly examined, and the implication of labor market concentration can be different.

2 Facts on Labor Market Concentration and Labor Share in the Japanese Manufacturing Sector

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

[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) runs regression across countries and across industries.

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 labor 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

In this subsection, I summarize the macro time-series trends of labor market concentration in 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

[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.

[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.

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]

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.

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

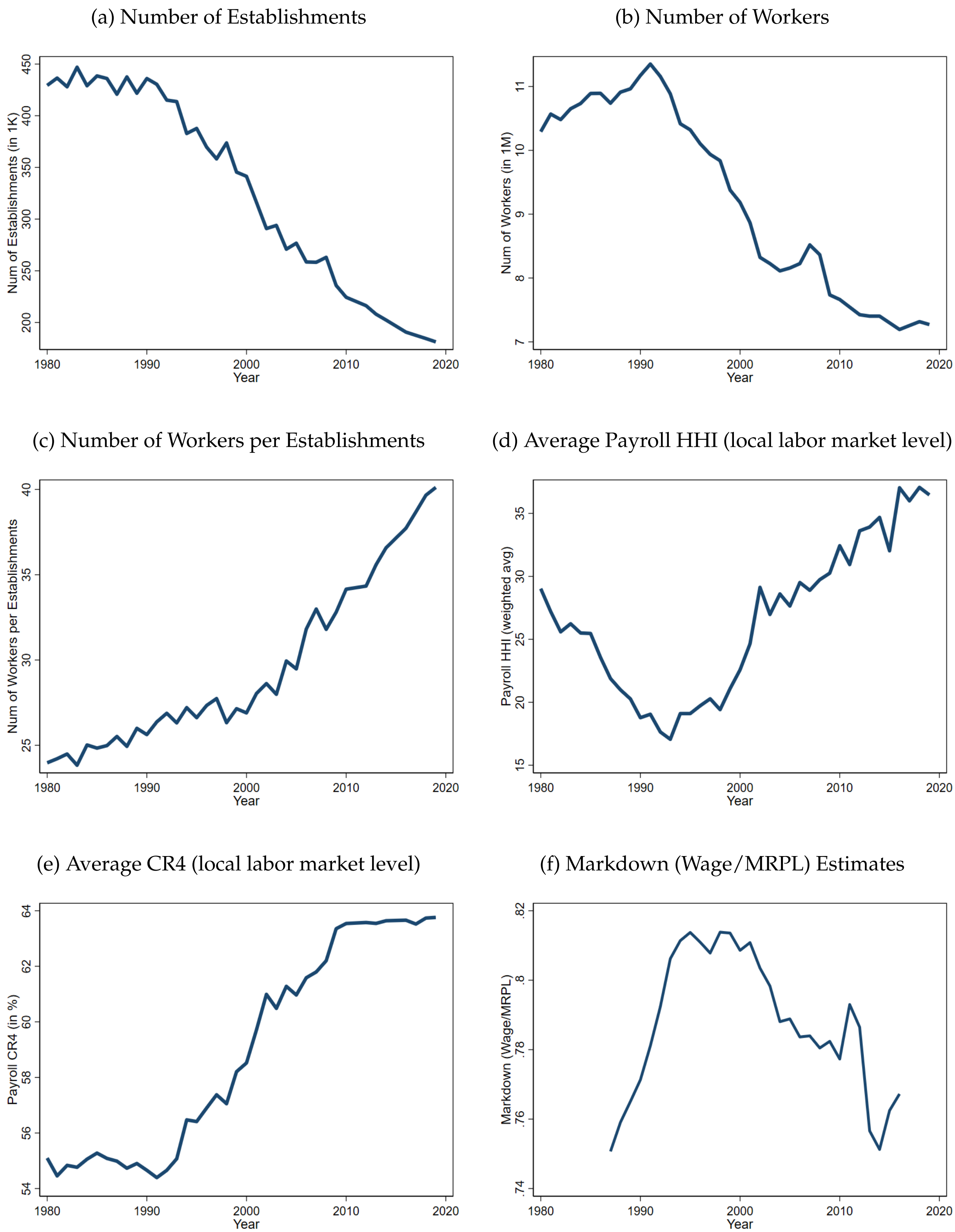
where $\omega_{p,i,1997}$ is the share of shipments of product p in establishment i in 1997. Since trade data at product level is available at HS code, I use the crosswalk from HS code to the product categories used in the Census of Manufacturer in Japan, provided by Baek et al. (2021).[7]

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

[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.

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

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.

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, $\Delta \mathrm{IP}_{i,1997,2007}$, 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] 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 Stylized Facts: Labor Share in the Japanese Manufacturing Sector

Aggregate Labor Share I first show the aggregate labor share. I compute the aggregate labor share as the average of establishment-level labor share, weighted by establishment's payroll.[9]

$$LS_t = \sum_i \omega_{i,t} LS_{i,t}$$

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

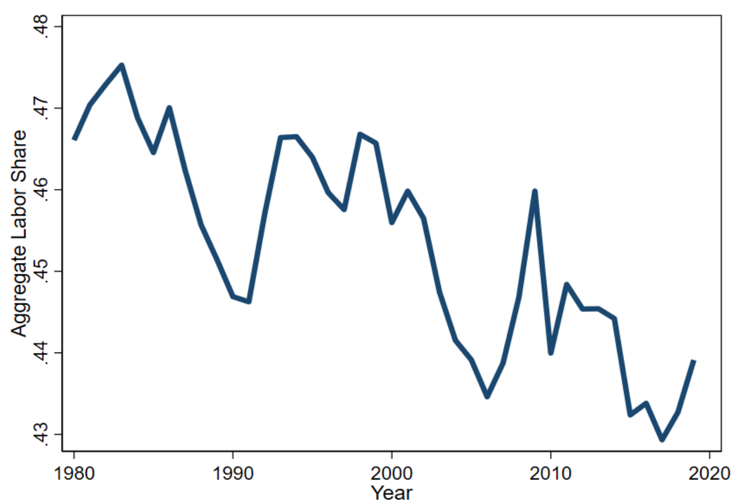
[9] I do this rather than dividing the economy-wide sum of payroll by economy-wide sum of value-added to be consistent with the decomposition later. Nevertheless, the time-series pattern is similar when I take that alternative approach while the level becomes lower.

where $\omega_{i,t} \equiv \frac{\text{payroll}_{i,t}}{\sum_k \text{payroll}_{k,t}}$ is the payroll share of establishment i in year t out of the sum of the payroll of all the establishments in the Japanese manufacturing sector, and $LS_{i,t} \equiv \frac{\text{payroll}_{i,t}}{\text{payroll}_{i,t}}$ is the labor share of establishment i in year t.

Figure 2 shows the labor share of gross value added in the manufacturing sector at establishment level in Japan since 1980. Labor share of gross value added in manufacturing sectors has decreased by about 4% point since 1980. In 1980, the labor share of gross value added was high at around 47%, but it decreased by 4% points to reach 43% in 2017, then rose to 44% in 2019.[10]

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 Fukao and Perugini (2021) or the Cabinet Office[11], the decline has been about the same, down 4 percentage points from its peak in the early 1980s.[12] 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.

Figure 2: Labor Share of 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 gross value added (from the Japanese Census of Manufactures). Each establishment is weighted by its total payroll. The samples are establishments with more than or equal to 30 employees, in manufacturing sectors.

Decomposition I now follow Kehrig and Vincent (2021) to decompose the change in the aggregate labor share. For some time t_0 and t_1, I divide establishments into three groups—survivors $i \in S$, entrants $i \in E$, and exits $i \in X$. I then decompose the aggregate change $\Delta LS_{t_0,t_1}$ into five

[10]The level of the labor share may sound low compared to the conventional value, 2/3. The difference comes from the fact that I use establishment-level labor share, rather than firm-level labor share. In fact, Kehrig and Vincent (2021) reports that the aggregate labor share at establishment level is around 0.4 for the US manufacturing sector in 2012.

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

[12]See Figure 3 in Fukao and Perugini (2021) for example.

terms as follows.

$$\Delta LS_{t_0,t_1} = \sum_{i\in S}\omega_{i,t_0}\times \Delta LS_{i,t_0,t_1} + \sum_{i\in S}\Delta\omega_{i,t_0,t_1}\times\left(LS_{i,t_0}-\overline{LS_{t_0}}\right) + \sum_{i\in S}\Delta\omega_{i,t_0,t_1}\times\Delta LS_{i,t_0,t_1} \tag{2}$$

$$+ \sum_{i\in E}\omega_{i,t_1}\times\left(LS_{i,t_1}-\overline{LS_{t_0}}\right) + \sum_{i\in X}\omega_{i,t_0}\times\left(\overline{LS_{t_0}}-LS_{i,t_0}\right) \tag{3}$$

where $\omega_{i,t}$ is the payroll share of establishment i in the sum of the payroll of all the establishments in year t. $LS_{i,t}$ is the labor share of establishment i in year t, and $\overline{LS_t}$ is the unweighted average of labor share of all the establishments in year t.

The first term is the within effect, fixing the payroll share of each establishment and reflect the changes in the labor share of establishments which survive between the two periods. The second term is the share effect, fixing the labor share of each establishment and reflect the changes in the payroll share of establishments which survive.[13] The third term is the covariance effect of survivors. This term captures the contribution of establishments which expand and change labor share during the period. The fourth and fifth terms are the contribution from entrants and exits, respectively.

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 ten-year panel of establishments in manufacturing sectors in 1986, 1996, 2006, and 2016.

Figure 3 shows the results. For the first two decades, the pattern is clear. The first and second terms contribute to decrease labor share while the third term contributes to increase labor share. For example, between 1996 and 2006, the aggregate labor share declined by 2.0% pt. This decline is driven by those of which were initially large and decreased labor share and by those of which initially had low labor share and increased value-added share. The third term, which contributed positively to aggregate labor share, captures the role of expanding (in terms of payroll share) establishments in *increasing* labor share.

[13] I need to subtract the average $\overline{LS_t}$ to adjust the fourth and fifth terms explained later.

Figure 3: Decomposition of Labor Share Changes

Note: The figures show the result of the decomposition of the change in aggregate labor share following equation (2) for each decade. The sample is the establishments with minimum of 30 employees every year, and I further restrict the samples to those of which can be matched across time at least for two years consecutively. Data is from the Census of Manufacturers in Japan.

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.[14]

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

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 $\mathbf{W}$ and labor $\mathcal{N}$ where

- households choose hours worked to each firm and aggregate labor to maximize utility
- 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

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

[14] 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:

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

3.5.2 Firm's Employment Decisions under Oligopsonistic Competition

The firm's maximization problem becomes

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

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.[15] Then, $\Pi_{i,j}^{VA}(\alpha_{i,j})$ has closed form expression depending on α_{ij}. 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 for establishments with higher payroll share $s_{i,j}$ if the elasticity of substitution across labor markets, θ, is smaller than 2.*

The proof is in Appendix A. 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. [16]

Implication for Labor Share Since the labor share of establishment i can be expressed as follows

$$LS_{i,j} \equiv \frac{w_{i,j}n_{i,j}}{y_{i,j}} = \mu_{i,j}\gamma(1-\alpha_{i,j}),$$

Comparing the same-sized establishment across different payroll share $s_{i,j}$, the relationship between labor share and payroll share is characterized as follows.

$$\frac{d\ln LS_{i,j}}{d\ln s_{i,j}} = \underbrace{\frac{d\ln \mu_{i,j}}{d\ln s_{i,j}}}_{<0\text{: Labor Market Power}} + \underbrace{\frac{d\ln(1-\alpha_{i,j})}{d\ln s_{i,j}}}_{>0\text{: Less Automation}} \tag{4}$$

The first term captures the standard labor market power; higher payroll share means more labor market power and lower wage. The second term captures a new mechanism of endogenous automation: higher payroll share leads to less automation. If there is no endogenous automation response, establishments with higher payroll share will have lower labor share. However, with endogenous automation, the relationship can be reversed. I test this empirical prediction using the Japanese data in the next section.

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

[16] The assumption is on the labor supply elasticity across local labor markets, θ, and Berger et al. (2022) estimates θ to be 0.42, which is below 2.

4 Empirical Analysis

In this section, I test the prediction of equation (4) using the establishment-level data in the Japanese manufacturing sector.

4.1 Samples and Summary Statistics

I first present summary statistics for the variables to be used in the analysis. Due to the data availability for machine stock, I use years of 1980, 1990, 2000, 2011, and 2015. Table 2 shows the summary statistics for 1980, 2000, and 2015. For 1990 and 2011, see Table C.1 in Appendix C. I show unweighted average, standard deviation, and selected percentiles for labor share, payroll share, log value-added, machine to labor factor ratio, and employment for establishments in the sample each year. I restrict samples to those with minimum of 30 employees, with positive values for labor share, payroll, value-added, and machine stocks. I further restrict samples to establishments with labor share between 0 and 1.

4.2 Cross Sectional Analysis

Labor Share I first start with the following specification to study the relationship between labor share of value-added and payroll share within local labor market.

$$\ln LS_{i,j} = \beta \ln s_{i,j} + \gamma \ln \mathrm{VA}_{i,j} + \psi_{\mathrm{IND}(i,j)} + \psi_{\mathrm{CZ}(i,j)} + u_{i,j} \tag{5}$$

where $LS_{i,j}$ is the labor share of establishment i in local labor market j, $s_{i,j}$ is the payroll share, $VA_{i,j}$ is the productivity proxied by the valued-added, $\psi_{\mathrm{IND}(i,j)}$ is JSIC 3-digit industry fixed effects, $\psi_{\mathrm{CZ}(i,j)}$ is commuting zone fixed effects, and $u_{i,j}$ is the residual.

Table 3 shows the results. Each column shows the result for each year respectively. Standard errors are clustered at local labor market level and robust against heteroskedasticity. It is clear that, for all the years, payroll share associates with higher labor share, so that the second term—automation or something else not captured in the model—in equation (4) dominates the first term—static labor market power effect.

To facilitate the interpretation of the magnitude, Table 4 shows the results for the version of (5) but with level of labor share instead of log labor share as an outcome. For instance, the estimate of 0.04 in 1980 means that an 20% increase in payroll share within a local labor market associates with 0.8%pt increases in labor share. To put it more concretely, consider the following situation. Comparing two same-sized establishments in two different local labor markets with initial payroll shares 10% within each local labor markets. Suppose there is a mass layoff by a competitor in one of the local labor markets so that the one establishment increases its payroll share to 12%, which is a 20% increase—or an 2% pt increase, while keeping its size. The estimate of 0.04 implies that the labor share of the establishment will increase by 0.8%pt, which is economically sizable.

Machine-Labor Ratio To relate this pattern to automation, I then estimate the same equation but with the machine-labor ratio as an outcome as follows:

$$\ln\left(\frac{K_{i,j}}{L_{i,j}}\right) = \beta \ln s_{i,j} + \gamma \ln \mathrm{VA}_{i,j} + \psi_{\mathrm{IND}(i,j)} + \psi_{\mathrm{CZ}(i,j)} + u_{i,j} \tag{6}$$

Table 2: Summary Statistics

Variables	Average	Std. Dev	p10	p25	p50	p75	p90
Panel A: Data in 1980							
Labor Share	0.50	0.20	0.24	0.35	0.49	0.64	0.77
Payroll Share $\times$ 100	0.96	5.35	0.01	0.03	0.10	0.41	1.42
Log Value Added	10.45	1.19	9.15	9.67	10.27	11.04	12.01
Log Machine Labor Ratio	-1.49	1.28	-3.09	-2.18	-1.36	-0.67	-0.05
Machine Labor Payment Ratio	0.47	1.18	0.05	0.11	0.26	0.51	0.95
Num. of Workers	124.16	326.98	34.00	41.00	58.00	104.00	215.00
N	49,295						
Panel B: Data in 2000							
Labor Share	0.48	0.20	0.22	0.34	0.48	0.62	0.75
Payroll Share $\times$ 100	0.72	2.55	0.02	0.05	0.17	0.62	1.83
Log Value Added	11.11	1.20	9.81	10.30	10.90	11.72	12.72
Log Machine Labor Ratio	-1.25	1.49	-3.15	-2.01	-1.07	-0.29	0.40
Machine Labor Payment Ratio	0.69	1.36	0.04	0.13	0.34	0.75	1.49
Num. of Workers	121.85	274.07	34.00	42.00	61.00	110.00	223.00
N	45,025						
Panel C: Data in 2015							
Labor Share	0.46	0.20	0.19	0.31	0.45	0.59	0.73
Payroll Share $\times$ 100	0.73	3.91	0.01	0.03	0.11	0.41	1.32
Log Value Added	11.20	1.22	9.88	10.35	10.98	11.85	12.85
Log Machine Labor Ratio	-1.41	1.66	-3.46	-2.23	-1.24	-0.37	0.44
Machine Labor Payment Ratio	0.74	3.28	0.03	0.11	0.29	0.69	1.56
Num. of Workers	127.41	319.03	34.00	42.00	63.00	116.00	240.00
N	37,139						

Note: The table shows the summary statistics of the unweighted average, standard deviation, and selected percentiles for labor share, payroll share within local labor market, log value-added, machine-labor ratio (in log), machine to labor factor ratio, and employment for establishments in the sample in each year. Samples are restricted to those with minimum of 30 employees, with positive values for labor share, payroll, value-added, and machine stocks. They are further restricted to establishments with labor share between 0 and 1. Labor share is a gross labor share of value-added, where total labor payment is divided gross value added. Payroll share is the share of establishment's payroll in the sum of the payroll in local labor markets. A local labor market is defined as a pair of a 3-digit JSIC industry category and a commuting zone. Machine-labor ratio is the ratio between real machine stock deflated using price in 2015 to number of workers. Machine labor payment ratio is the ratio between machine stock and payroll.

Table 3: Log Labor Share and Payroll Share: Cross Section

Year	1980	1990	2000	2011	2015
	(1)	(2)	(3)	(4)	(5)
Log Payroll Share	0.112	0.128	0.136	0.152	0.176
	(0.003)	(0.003)	(0.004)	(0.005)	(0.007)
Log Value Added	-0.306	-0.329	-0.348	-0.367	-0.384
	(0.004)	(0.004)	(0.004)	(0.005)	(0.008)
N	49,288	54,962	45,010	36,724	37,131
Industry FEs	✓	✓	✓	✓	✓
CZ FEs	✓	✓	✓	✓	✓

Note: The table shows the estimates of coefficients in equation (5) for the relationship between establishment's payroll share (in log) within local labor markets and labor share (in log) in each year separately. 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 as a proxy for productivity. Standard errors are clustered at local labor market level and robust against heteroskedasticity.

Table 4: Labor Share and Payroll Share: Cross Section

Year	1980	1990	2000	2011	2015
	(1)	(2)	(3)	(4)	(5)
Log Payroll Share	0.043	0.045	0.046	0.046	0.055
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Log Value Added	-0.118	-0.118	-0.123	-0.120	-0.126
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
N	49,288	54,962	45,010	36,724	37,131
Industry FEs	✓	✓	✓	✓	✓
CZ FEs	✓	✓	✓	✓	✓

Note: The table shows the estimates of coefficients in equation (5) for the relationship between establishment's payroll share (in log) within local labor markets and labor share in each year separately. Instead of using log labor share, this table's regression uses the level of labor share, which is between 0 and 1. 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 as a proxy for productivity. Standard errors are clustered at local labor market level and robust against heteroskedasticity.

where $\frac{K_{i,j}}{L_{i,j}}$ is the ratio of nominal machine stock to total payroll of establishment i in local labor market j.

Table 5 shows the results. Same as before, each column shows the result for each year respectively. Standard errors are clustered at local labor market level and robust against heteroskedasticity. Again, in all the years, higher payroll share correlates with lower machine to labor ratio, comparing same-sized establishments in different local labor markets.

Table 5: Log Machine-Labor Ratio and Payroll Share: Cross Section

Year	1980	1990	2000	2011	2015
	(1)	(2)	(3)	(4)	(5)
Log Payroll Share	-0.073	-0.058	-0.057	-0.095	-0.078
	(0.006)	(0.006)	(0.008)	(0.009)	(0.010)
Log Value Added	0.269	0.348	0.355	0.373	0.373
	(0.007)	(0.007)	(0.008)	(0.009)	(0.011)
N	49,288	54,962	45,010	36,724	37,131
Industry FEs	✓	✓	✓	✓	✓
CZ FEs	✓	✓	✓	✓	✓

Note: The table shows the estimates of coefficients in equation (6) for the relationship between establishment's payroll share (in log) within local labor markets and machine to labor ratio in each year separately. Machine to labor ratio in establishments is computed by dividing nominal machine stock divided by payroll. All the columns include logged value added of establishments as a proxy for productivity. Standard errors are clustered at local labor market level and robust against heteroskedasticity.

Limitation Here, I present results using OLS. If wages were used as an outcome variable, the endogeneity issue would have been severe, and the sign could have been opposite as shown in Azkarate-Askasua and Zerecero (2023). The intuition is that while higher payroll share means larger labor market power to suppress wages, the higher wages makes establishments larger as establishments offering higher wages can naturally attract more workers.

In the current version, I offer two additional specifications, one in Section 4.3 and one in Appendix C. Section 4.3 uses a panel structure of the data to validate that the results remain the same if I use the changes in payroll share across time within establishments also associate with increases in labor share. Appendix C uses local labor market payroll HHI as a running variable instead of establishment-level payroll share. While there is an issue of using market equilibrium outcomes as running variables, it shows that higher market-level labor market power associates with higher labor share for same-sized establishments in different local labor markets.[17]

4.3 Longitudinal Analysis

In this subsection, I use the panel structure of the data to include establishment fixed effects and exploit the variation across time within establishments.

[17] In addition to these two approaches, I am currently working on an IV strategy using competitor's exits as an instrument for increases in payroll share as in Azkarate-Askasua and Zerecero (2023).

The specification is as follows

$$\ln LS_{i,j,t} = \beta \ln s_{i,j,t} + \gamma \ln VA_{i,j,t} + \psi_{\text{IND}(i,j),t} + \psi_{\text{CZ}(i,j),t} + \psi_i + u_{i,j,t} \tag{7}$$

where $LS_{i,j,t}$ is the labor share of establishment i in local labor market j in year t, $s_{i,j,t}$ is the payroll share, $VA_{i,j}$ is the productivity proxied by the valued-added, $\psi_{\text{IND}(i,j),t}$ is JSIC 3-digit industry and time fixed effects, $\psi_{\text{CZ}(i,j),t}$ is commuting zone and time fixed effects, ψ_i is establishment fixed effects, and $u_{i,j,t}$ is the residual.

Table 6 shows the results. Columns (1) and (2) use 1-year panel data. Columns (3) and (4) use 5-year panel data, every five years from 1990 to 2015. The number of unique establishments during the period is 888,965. Columns (1) and (3) include establishment fixed effects. Columns (2) and (4) add industry-year fixed effects and cz-year fixed effects to control industry-specific trends and commuting-zone-specific trends.

Table 6: Log Labor Share and Payroll Share: Across Time

Year	Annual		5-Year Panel	
	(1)	(2)	(3)	(4)
Log Payroll Share	0.204	0.373	0.152	0.336
	(0.004)	(0.005)	(0.005)	(0.006)
Log Value Added	-0.639	-0.735	-0.605	-0.702
	(0.003)	(0.003)	(0.004)	(0.004)
Observations	1,417,971	1,417,662	232,195	232,124
Establishment FEs	✓	✓	✓	✓
Industry-Year FEs		✓		✓
CZ-Year FEs		✓		✓

Note: The table shows the estimates of coefficients in equation (7) for the relationship between establishment's payroll share (in log) within local labor markets and labor share. All the columns include logged value added of establishments as a proxy for productivity. Columns (1) and (2) use 1-year panel data. Columns (3) and (4) use 5-year panel data, every five years from 1990 to 2015. Columns (1) and (3) include establishment fixed effects. Columns (2) and (4) add industry-year fixed effects and cz-year fixed effects to control industry-specific trends and commuting-zone-specific trends. Standard errors are clustered at local labor market level and robust against heteroskedasticity.

Using the following specification, I also study the relationship between machine-labor ratio and payroll share in this setting

$$\ln\left(\frac{K_{i,j,t}}{L_{i,j,t}}\right) = \beta \ln s_{i,j,t} + \gamma \ln VA_{i,j,t} + \psi_{\text{IND}(i,j),t} + \psi_{\text{CZ}(i,j),t} + \psi_i + u_{i,j,t} \tag{8}$$

where $\frac{K_{i,j,t}}{L_{i,j,t}}$ is the ratio of machine stock to labor in establishment i in local labor market j in year t.

Table 7 shows the results. Columns (1) includes establishment fixed effects. Columns (2) adds industry-year fixed effects and cz-year fixed effects to control industry-specific trends and commuting-zone-specific trends. Standard errors are clustered at local labor market level and robust against heteroskedasticity. Same as the cross-sectional analysis, Higher payroll share associates with lower machine to labor ratio, which is consistent with the theoretical prediction.

Table 7: Log Machine-Labor Ratio and Payroll Share: Across Time

	(1)	(2)
Log Payroll Share	-0.059	-0.205
	(0.006)	(0.005)
Log Value Added	-0.010	0.034
	(0.008)	(0.005)
Observations	219,509	219,433
Establishment FEs	✓	✓
Industry-Year FEs		✓
CZ-Year FEs		✓

Note: The table shows the estimates of coefficients in equation (8) for the relationship between establishment's payroll share (in log) within local labor markets and labor share. All the columns include logged value added of establishments as a proxy for productivity and use 5-year panel data, every five years from 1990 to 2015 with 2010 data replaced with 2011 data due to the availability of machine stock data. Columns (1) includes establishment fixed effects. Columns (2) adds industry-year fixed effects and cz-year fixed effects to control industry-specific trends and commuting-zone-specific trends. Standard errors are clustered at local labor market level and robust against heteroskedasticity.

5 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.

5.1 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.

For households' preference, I follow Berger et al. (2022) to use the following GHH preference

$$U(\mathcal{C}, \mathcal{N}) = \log\left(C - \bar{\phi}^{-\frac{1}{\phi}} \frac{\mathcal{N}^{1+\frac{1}{\phi}}}{1+\frac{1}{\phi}}\right)$$

I use $\bar{\phi} = 2.17$ and $\phi = 0.50$ for now.[18]

Table 8 summarizes the parameters calibrated.

Figure 4 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

[18] I am working on estimating these parameters.

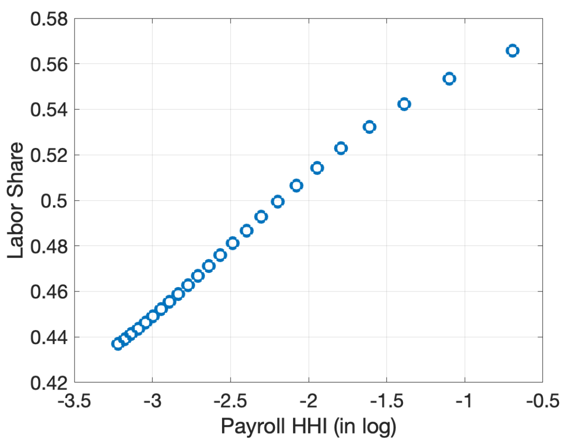
Table 8: Summary of Parameters

Parameters		Value	Source/Target
θ	Across-market substitutability	0.42	Berger et al. (2022)
η	Within-market substitutability	10.85	Berger et al. (2022)
R	Machine price	0.10	Machine-labor ratio
γ	Decreasing return	0.95	Median labor share
ζ	Substitutability across task	0.49	Humlum (2019)
$\bar{\phi}$	Labor disutility sifter	2.17	Berger et al. (2022)
ϕ	Labor supplu elasticity	0.5	Berger et al. (2022)

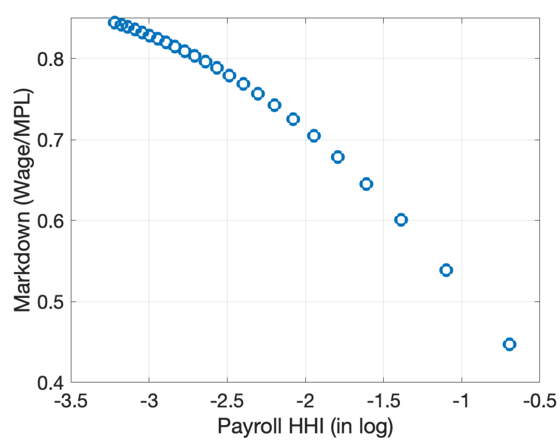
comparable to the pattern in Figure C.2, which is roughly comparable.[19] The right panel shows the markdown, the ratio of wage to the marginal revenue product of labor. As the payroll HHI increases, markdown decreases.

Figure 4: 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).

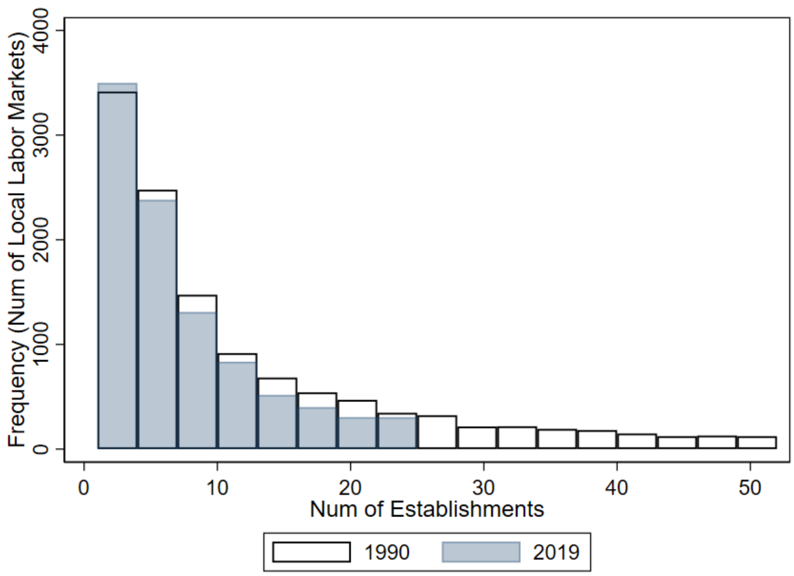
5.2 Counterfactual Experiment

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 5 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

[19] I am working on the disclosure process to directly target this moments to estimate parameters.

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 5: 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 9 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 9: 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.

6 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.[20]

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 as shown in Figure B.1. 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.

References

Acemoglu, D. and P. Restrepo (2018). The race between man and machine: Implications of technology for growth, factor shares, and employment. *American economic review 108*(6), 1488–1542.

Acemoglu, D. and P. Restrepo (2019). Automation and new tasks: How technology displaces and reinstates labor. *Journal of Economic Perspectives 33*(2), 3–30.

[20]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.

Acemoglu, D. and P. Restrepo (2022). Tasks, automation, and the rise in us wage inequality. *Econometrica 90*(5), 1973–2016.

Adachi, D., T. Fukai, D. Kawaguchi, and Y. U. Saito (2020). Commuting zones in Japan. *Research Institute of Economy, Trade and Industry (RIETI) Discussion Paper*.

Aghion, P., A. Bergeaud, M. Lequien, M. Melitz, and T. Zuber (2022). Opposing firm level responses to the china shock: Output competition versus input supply.

Aoki, K., Y. Hogen, and K. Takatomi (2023). Price markups and wage setting behavior of japanese firms. Technical report, Bank of Japan.

Autor, D., D. Dorn, L. F. Katz, C. Patterson, and J. V. Reenen (2020). The Fall of the Labor Share and the Rise of Superstar Firms . *The Quarterly Journal of Economics 135*(2), 645–709.

Autor, D. H., D. Dorn, and G. H. Hanson (2016). The china shock: Learning from labor-market adjustment to large changes in trade. *Annual review of economics 8*, 205–240.

Azar, J., I. Marinescu, and M. Steinbaum (2022, April). Labor Market Concentration. *Journal of Human Resources 57*(S), S167–S199.

Azkarate-Askasua, M. and M. Zerecero (2023). The Aggregate Effects of Labor Market Concentration. *SSRN Electronic Journal*.

Baek, Y., K. Hayakawa, K. Tsubota, S. Urata, and K. Yamanouchi (2021). Tariff pass-through in wholesaling: Evidence from firm-level data in japan. *Journal of the Japanese and International Economies 62*, 101164.

Barkai, S. (2020). Declining Labor and Capital Shares. *Journal of Finance 75*(5), 2421–2463.

Berger, D., K. Herkenhoff, A. R. Kostol, and S. Mongey (2023). An Anatomy of Monopsony: Search Frictions, Amenities and Bargaining in Concentrated Markets.

Berger, D., K. Herkenhoff, and S. Mongey (2022). Labor market power. *American Economic Review 112*(4), 1147–93.

Brooks, W. J., J. P. Kaboski, Y. A. Li, and W. Qian (2021). Exploitation of labor? classical monopsony power and labor's share. *Journal of Development Economics 150*, 102627.

De Loecker, J., J. Eeckhout, and G. Unger (2020). The Rise of Market Power and the Macroeconomic Implications . *The Quarterly Journal of Economics 135*(2), 561–644.

Dinlersoz, E., Z. Wolf, et al. (2018). Automation, labor share, and productivity: Plant-level evidence from us manufacturing. Technical report.

Elsby, M., B. Hobijn, and A. Sahin (2013). The Decline of the U.S. Labor Share. *Brookings Papers on Economic Activity 44*(2 (Fall)), 1–63.

Engbom, N. (2022). Labor market fluidity and human capital accumulation. Technical report, National Bureau of Economic Research.

Feenstra, R. C., R. Inklaar, and M. P. Timmer (2015). The next generation of the penn world table. *American Economic Review 105*(10), 3150–82.

Fukao, K., Y. G. Kim, and H. U. Kwon (2021). The causes of japan's economic slowdown: an analysis based on the japan industrial productivity database. *International Productivity Monitor* (40), 56–88.

Fukao, K. and C. Perugini (2021). The long-run dynamics of the labor share in japan. *Review of Income and Wealth 67*(2), 445–480.

Gouin-Bonenfant, É. (2022). Productivity dispersion, between-firm competition, and the labor share. *Econometrica 90*(6), 2755–2793.

Hayashi, F. and E. C. Prescott (2002). The 1990s in japan: A lost decade. *Review of Economic Dynamics 5*(1), 206–235.

Hubmer, J. and P. Restrepo (2023). Not a typical firm.

Humlum, A. (2019). Robot adoption and labor market dynamics. *Princeton University*.

Jarosch, G., J. S. Nimczik, and I. Sorkin (2019). Granular search, market structure, and wages. Technical report, National Bureau of Economic Research.

Kehrig, M. and N. Vincent (2021). The micro-level anatomy of the labor share decline. *The Quarterly Journal of Economics 136*(2), 1031–1087.

Kondo, K. (2023). Municipality-level panel data and municipal mergers in japan. Technical report, Research Institute of Economy, Trade and Industry (RIETI).

Lamadon, T., M. Mogstad, and B. Setzler (2022). Imperfect competition, compensating differentials, and rent sharing in the us labor market. *American Economic Review 112*(1), 169–212.

Miller, N., S. Berry, F. Scott Morton, J. Baker, T. Bresnahan, M. Gaynor, R. Gilbert, G. Hay, G. Jin, B. Kobayashi, et al. (2022). On the misuse of regressions of price on the hhi in merger review. *Journal of Antitrust Enforcement 10*(2), 248–259.

OECD (2010). "main economic indicators - complete database", main economic indicators (database) consumer price index: All items for the united states [usacpiallainmei]. http://dx.doi.org/10.1787/data-00052-en. Retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/USACPIALLAINMEI, February 18, 2023.

Rubens, M. (2023a). Market structure, oligopsony power, and productivity. *American Economic Review*.

Rubens, M. (2023b). Oligopsony Power and Factor-Biased Technology Adoption.

Stansbury, A. and L. H. Summers (2020). The Declining Worker Power Hypothesis: An explanation for the recent evolution of the American economy. NBER Working Papers 27193.

vom Lehn, C. (2018). Understanding the decline in the U.S. labor share: Evidence from occupational tasks. *European Economic Review 108*(C), 191–220.

Yeh, C., C. Macaluso, and B. Hershbein (2022). Monopsony in the us labor market. *American Economic Review 112*(7), 2099–2138.

A Theory Appendix

A.1 Proof of Proposition 3.1

Here, I reprint the proposition 3.1.

Proposition A.1. *Suppose that $z_{i,j} = z_j$ for all $i \in j$. Then, optimal automation technology level $\alpha^*_{i,j}$ is larger (and hence labor share is lower) in more competitive labor markets (where the number of firms m_j is larger) if the elasticity of substitution across labor markets, θ, is smaller than 2.*

Remember that the profit is

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

where

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

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

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

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

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

$$\frac{\partial^2 \pi_{i,j}(\alpha_{i,j})}{\partial\alpha_{i,j}\partial s_{i,j}} = \frac{\partial^2 \ln y_{i,j}}{\partial\alpha_{i,j}\partial s_{i,j}} + \frac{\partial^2 \ln(1-\alpha_{i,j}\gamma - \mu_{i,j}(s_{i,j})(1-\alpha_{i,j})\gamma)}{\partial\alpha_{i,j}\partial s_{i,j}} < 0.$$

This is equivalent to show that

$$\frac{\partial^2 \pi_{i,j}(\alpha_{i,j})}{\partial\alpha_{i,j}\partial \mu_{i,j}} = \frac{\partial^2 \ln y_{i,j}}{\partial\alpha_{i,j}\partial \mu_{i,j}} + \frac{\partial^2 \ln(1-\alpha_{i,j}\gamma - \mu_{i,j}(1-\alpha_{i,j})\gamma)}{\partial\alpha_{i,j}\partial \mu_{i,j}} > 0.$$

A.1.1 Effects via Output

I first derive

$$\frac{\partial^2 \ln y_{i,j}}{\partial\alpha_{i,j}\partial \mu_{i,j}}.$$

Marginal Revenue Product of Labor To begin with, I express the marginal revenue product of labor as a function of $\mu_{i,j}$ and the aggregates, W and N, which firms take as given.

I can show the following

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

because

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

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

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

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

Computing Derivative

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

Substituting the following,

$$\ln\left(\frac{w_{i,j}}{\mu_{i,j}}\right) = \frac{-\theta(1-\widetilde{\gamma}_{i,j})}{1+\theta(1-\widetilde{\gamma}_{i,j})}\ln\mu_{i,j} + \frac{1}{1+\theta(1-\widetilde{\gamma}_{i,j})}\ln\tilde{\gamma}_{i,j}\tilde{z}_{ij} - \frac{1-\tilde{\gamma}_{i,j}}{1+\theta(1-\widetilde{\gamma}_{i,j})}\ln\left(M_j^{\frac{\theta-\eta}{1+\eta}} W^{-\theta} N\right)$$

I can have the cross-derivative as follows.

$$\begin{aligned}
\frac{\partial^2 \ln y_{i,j}}{\partial\alpha_{i,j}\partial\mu_{i,j}} &= -\frac{\partial}{\partial\alpha_{i,j}}\left(\frac{\gamma}{1-\gamma}(1-\alpha_{i,j})\frac{-\theta(1-\widetilde{\gamma}_{i,j})}{1+\theta(1-\widetilde{\gamma}_{i,j})}\frac{1}{\mu_{i,j}}\right) \\
&= -\frac{\gamma}{1-\gamma}\frac{1}{\mu_{i,j}}\frac{\partial}{\partial\alpha_{i,j}}\left((1-\alpha_{i,j})\frac{-\theta(1-\widetilde{\gamma}_{i,j})}{1+\theta(1-\widetilde{\gamma}_{i,j})}\right) \\
&= \frac{\gamma}{1-\gamma}\frac{1}{\mu_{i,j}}\frac{-\theta(1-\widetilde{\gamma}_{i,j})}{1+\theta(1-\widetilde{\gamma}_{i,j})} + \frac{\gamma}{1-\gamma}\frac{(1-\alpha_{i,j})}{\mu_{i,j}}\frac{\partial}{\partial\alpha_{i,j}}\left(\frac{\theta(1-\widetilde{\gamma}_{i,j})}{1+\theta(1-\widetilde{\gamma}_{i,j})}\right) \\
&= -\frac{\gamma}{1-\gamma}\frac{1}{\mu_{i,j}}\frac{\theta(1-\gamma)}{1-\alpha_{i,j}\gamma+\theta(1-\gamma)} + \frac{\gamma}{1-\gamma}\frac{(1-\alpha_{i,j})}{\mu_{i,j}}\frac{\theta(1-\gamma)\gamma}{(1-\alpha_{i,j}\gamma+\theta(1-\gamma))^2} \\
&= \frac{\gamma}{1-\gamma}\frac{1}{\mu_{i,j}}\frac{\theta(1-\gamma)}{(1-\alpha_{i,j}\gamma+\theta(1-\gamma))^2}\left((1-\alpha_{i,j})\gamma-(1-\alpha_{i,j}\gamma+\theta(1-\gamma))\right)
\end{aligned}$$

$$= \quad -\frac{\gamma}{1-\gamma}\frac{1}{\mu_{i,j}}\frac{(\theta(1-\gamma))^2}{(1-\alpha_{i,j}\gamma+\theta(1-\gamma))^2} < 0$$

Now,

$$\begin{aligned}
\frac{\partial^2 \ln y_{i,j}}{\partial\alpha_{i,j}\partial\mu_{i,j}} &= -\frac{\gamma}{1-\gamma}\frac{1}{\mu_{i,j}}\frac{(\theta(1-\gamma))^2}{(1-\alpha_{i,j}\gamma+\theta(1-\gamma))^2} \\
&> -\frac{\gamma}{1-\gamma}\frac{1}{\inf(\mu_{i,j})}\frac{(\theta(1-\gamma))^2}{(1-\alpha_{i,j}\gamma+\theta(1-\gamma))^2} \\
&= -\frac{\gamma}{1-\gamma}\frac{1+\theta}{\theta}\frac{(\theta(1-\gamma))^2}{(1-\alpha_{i,j}\gamma+\theta(1-\gamma))^2}
\end{aligned} \tag{9}$$

A.2 Effect via Variable Profit

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

Now, evaluating it

$$\begin{aligned}
\frac{\partial^2 \ln(1-\alpha_{i,j}\gamma-\mu_{i,j}(1-\alpha_{i,j})\gamma)}{\partial\mu_{i,j}\partial\alpha_{i,j}} &= \frac{(1-\alpha_{i,j})\gamma}{(1-\alpha_{i,j}\gamma-\mu_{i,j}(1-\alpha_{i,j})\gamma)^2} + \frac{\gamma}{1-\alpha_{i,j}\gamma-\mu_{i,j}(1-\alpha_{i,j})\gamma} \\
&> \frac{(1-\alpha_{i,j})\gamma}{(1-\alpha_{i,j}\gamma-\inf(\mu_{i,j})(1-\alpha_{i,j})\gamma)^2} + \frac{\gamma}{1-\alpha_{i,j}\gamma-\inf(\mu_{i,j})(1-\alpha_{i,j})\gamma}
\end{aligned} \tag{10}$$

A.3 Total Effects

Now, we can study the sum of these two effects. In particular, from equation (9) and (10),

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

Since the denominator is positive, I focus on the sign of the numerator as follows:

$$\begin{aligned}
&-(\theta(1-\gamma))^2(1-\alpha_{i,j}\gamma-\mu_{i,j}(1-\alpha_{i,j})\gamma)^2 + \left((1-\alpha_{i,j})+(1-\alpha_{i,j}\gamma-\mu_{i,j}(1-\alpha_{i,j})\gamma)\right)(1-\gamma)\mu_{i,j}(1-\alpha_{i,j}\gamma+\theta(1-\gamma))^2 \\
=&(1-\alpha_{i,j}\gamma-\mu_{i,j}(1-\alpha_{i,j})\gamma)\times\left((1-\gamma)\mu_{i,j}(1-\alpha_{i,j}\gamma+\theta(1-\gamma))^2-(\theta(1-\gamma))^2(1-\alpha_{i,j}\gamma-\mu_{i,j}(1-\alpha_{i,j})\gamma)\right) \\
&+(1-\alpha_{i,j})(1-\gamma)\mu_{i,j}(1-\alpha_{i,j}\gamma+\theta(1-\gamma))^2
\end{aligned}$$

Then, it is sufficient to show that the following term is positive because the remaining parts are clearly positive

$$(1-\gamma)\mu_{i,j}(1-\alpha_{i,j}\gamma+\theta(1-\gamma))^2-(\theta(1-\gamma))^2(1-\alpha_{i,j}\gamma-\mu_{i,j}(1-\alpha_{i,j})\gamma)$$

Since this is increasing in $\mu_{i,j}$,

$$\begin{aligned}&(1-\gamma)\mu_{i,j}(1-\alpha_{i,j}\gamma+\theta(1-\gamma))^2-(\theta(1-\gamma))^2(1-\alpha_{i,j}\gamma-\mu_{i,j}(1-\alpha_{i,j})\gamma)\\ &>(1-\gamma)\inf(\mu_{i,j})(1-\alpha_{i,j}\gamma+\theta(1-\gamma))^2-(\theta(1-\gamma))^2(1-\alpha_{i,j}\gamma-\inf(\mu_{i,j})(1-\alpha_{i,j})\gamma)\end{aligned}$$

Then, it is sufficient to show that the right hand side is positive. Let's define the right hand side as a function of $\alpha_{i,j}$ as follows.

$$F(\alpha_{i,j})=(1-\gamma)\inf(\mu_{i,j})(1-\alpha_{i,j}\gamma+\theta(1-\gamma))^2-(\theta(1-\gamma))^2(1-\alpha_{i,j}\gamma-\inf(\mu_{i,j})(1-\alpha_{i,j})\gamma)$$

We want to show $F(\alpha_{i,j})>0$ for $\alpha_{i,j}\in(0,1)$. Since $\alpha_{i,j}\in(0,1)$, it is sufficient to show that $F'(\alpha_{i,j})<0$ and $F(1)>0$.

Evaluate F Function First, we show it is decreasing in $\alpha_{i,j}$. Now let's drop subscripts for spaces.

$$F'(\alpha)=(1-\gamma)\gamma\left[2\inf(\mu)\gamma\alpha-2\inf(\mu)-2(1-\gamma)\inf(\mu)\theta+\theta^2(1-\gamma)-\theta^2(1-\gamma)\inf(\mu)\right]$$

As $\alpha<1$,

$$\begin{aligned}F'(\alpha)<&(1-\gamma)\gamma\left[2\inf(\mu)\gamma-2\inf(\mu)-2(1-\gamma)\inf(\mu)\theta+\theta^2(1-\gamma)-\theta^2(1-\gamma)\inf(\mu)\right]\\ =&(1-\gamma)^2\gamma\left[-2\inf(\mu)(1+\theta)+\theta^2(1-\inf(\mu))\right]\\ =&(1-\gamma)^2\gamma\left[-2\frac{\theta}{1+\theta}(1+\theta)+\theta^2(1-\frac{\theta}{1+\theta})\right]\\ =&(1-\gamma)^2\gamma\left[-2\theta+\theta^2\frac{1}{1+\theta}\right]\\ =&(1-\gamma)^2\gamma\frac{\theta}{1+\theta}\left[-2(1+\theta)+\theta\right]\\ =&(1-\gamma)^2\gamma\frac{\theta}{1+\theta}\left[-2-\theta\right]\end{aligned}$$

If $\theta<2$, this is negative.
Second, we evaluate $F(1)$.

$$\begin{aligned}F(1)&=(1-\gamma)\inf(\mu)(1-\gamma+\theta(1-\gamma))^2-(\theta(1-\gamma))^2(1-\gamma)\\ &=(1-\gamma)^3\left(\inf(\mu)(1+\theta)^2-\theta^2\right)\\ &=(1-\gamma)^3\left(\frac{\theta}{1+\theta}(1+\theta)^2-\theta^2\right)\\ &=(1-\gamma)^3\left(\theta(1+\theta)-\theta^2\right)\\ &=(1-\gamma)^3\theta>0\end{aligned}$$

Therefore, $F(\alpha_{i,j})>0$ for $\alpha_{i,j}\in(0,1)$.

Conclusion This means that if $\theta < 2$,

$$\frac{\partial \ln \Pi_{i,j}^{VA}(\alpha_{i,j})}{\partial \alpha_{i,j} \partial \mu_{i,j}} = \frac{\partial^2 \ln y_{i,j}}{\partial \alpha_{i,j} \partial \mu_{i,j}} + \frac{\partial^2 \ln(1 - \alpha_{i,j}\gamma - \mu_{i,j}(1-\alpha_{i,j})\gamma)}{\partial \mu_{i,j} \partial \alpha_{i,j}} > 0$$

and thus

$$\frac{\partial \ln \Pi_{i,j}^{VA}(\alpha_{i,j})}{\partial \alpha_{i,j} \partial s_{i,j}} < 0$$

Therefore, if labor markets are more concentrated, there is less automation, and the labor share, $(1 - \alpha_{i,j})$ is higher.
■

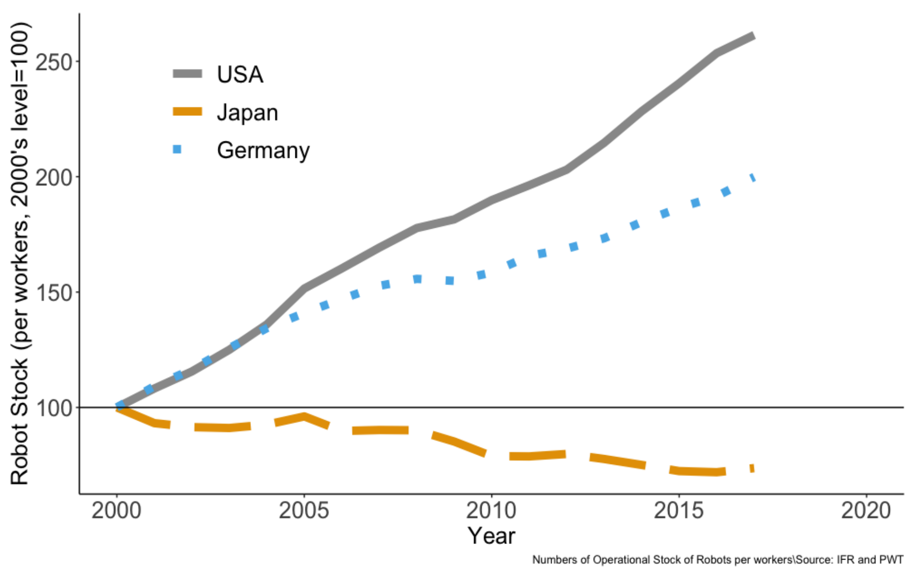
B Data Appendix

B.1 Robot Trends

Figure B.1 illustrates that the evolution of the number of operational robots per workers in Japan, comparing those in the US and Germany. The values are normalized by the values in 2000 for each country. I use a 10% annual discounted rate to construct stock in quantity. For robot stock, I use data from IFR. For the number of workers, I use data from Feenstra et al. (2015).

Despite continuing to be one of the world's top robot manufacturing countries, it is surprising that the growth rate of robot stock has been negative since 2000. This trend in robot stock looks very different from that of other countries, including the US and Germany, where robot stocks have continued to rise.

Figure B.1: Robot Stock



Note: The figure shows the robot stock per workers for US, Japan, and Germany since 2000. The values are normalized by the values in 2000 for each country. I use a 10% annual discounted rate to construct stock in quantity. For robot stock, I use data from IFR. For the number of workers, I use data from Feenstra et al. (2015).

C Empirical Appendix

C.1 Summary Statistics for 1990 and 2011

Table C.1: Summary Statistics

Variables	Average	Std. Dev	p10	p25	p50	p75	p90
Panel A: Data in 1990							
Labor Share	0.48	0.20	0.22	0.34	0.47	0.62	0.75
Payroll Share $\times$ 100	0.69	2.29	0.01	0.04	0.15	0.54	1.68
Log Value Added	10.91	1.22	9.54	10.10	10.73	11.52	12.50
Log Machine Labor Ratio	-1.40	1.41	-3.22	-2.18	-1.23	-0.47	0.19
Machine Labor Payment Ratio	0.55	0.99	0.04	0.11	0.29	0.62	1.21
Num. of Workers	125.30	301.80	34.00	42.00	61.00	108.00	220.00
N	54,974						
Panel B: Data in 2011							
Labor Share	0.47	0.21	0.19	0.32	0.47	0.61	0.74
Payroll Share $\times$ 100	0.91	4.77	0.01	0.04	0.16	0.58	1.75
Log Value Added	11.12	1.22	9.79	10.26	10.89	11.76	12.76
Log Machine Labor Ratio	-1.35	1.63	-3.40	-2.17	-1.16	-0.32	0.46
Machine Labor Payment Ratio	0.77	5.00	0.03	0.11	0.31	0.72	1.59
Num. of Workers	122.49	266.11	34.00	41.00	61.00	112.00	227.00
N	36,730						

Note: The table shows the summary statistics of the unweighted average, standard deviation, and selected percentiles for labor share, payroll share within local labor market, log value-added, machine-labor ratio (in log), machine to labor factor ratio, and employment for establishments in the sample in each year. Samples are restricted to those with minimum of 30 employees, with positive values for labor share, payroll, value-added, and machine stocks. They are further restricted to establishments with labor share between 0 and 1. Labor share is a gross labor share of value-added, where total labor payment is divided gross value added. Payroll share is the share of establishment's payroll in the sum of the payroll in local labor markets. A local labor market is defined as a pair of a 3-digit JSIC industry category and a commuting zone. Machine-labor ratio is the ratio between real machine stock deflated using price in 2015 to number of workers. Machine labor payment ratio is the ratio between machine stock and payroll.

C.2 Empirical Analysis: Local Labor Market Concentration and Labor Share

In the main text, I provide empirical evidence where I use establishment's payroll share as a proxy for labor market power. In this section, I instead use payroll HHI as a proxy for labor market power. Having payroll HHI at local labor market level as a running variable has two caveats. First, I am comparing the same-sized establishments across local labor markets, faced with different payroll HHI at local labor market level. Therefore, the treatment is not at establishment level. Second, running regressions using concentration measures, including HHI, has been criticized as it is not informative in causal sense (Miller et al., 2022). Thus, the goal here is to provide a set of covariance, which is consistent with the theoretical predictions, following Berger et al. (2023).

Below, 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.

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 use two specifications, across and within establishments, following Berger et al. (2023), but with different outcomes and contexts.

C.2.1 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.

$$LS_i = \beta \ln HHI_{j,c} + \gamma \ln VA_i + \mu_j + \mu_c + \varepsilon_i \tag{11}$$

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

The parameter of interest is β. The interpretation is, how labor shares of same-sized establishments differ in local labor markets with different degree of labor market concentration. I compare same-sized establishments by controlling the value-added of establishments.

Results Table C.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.

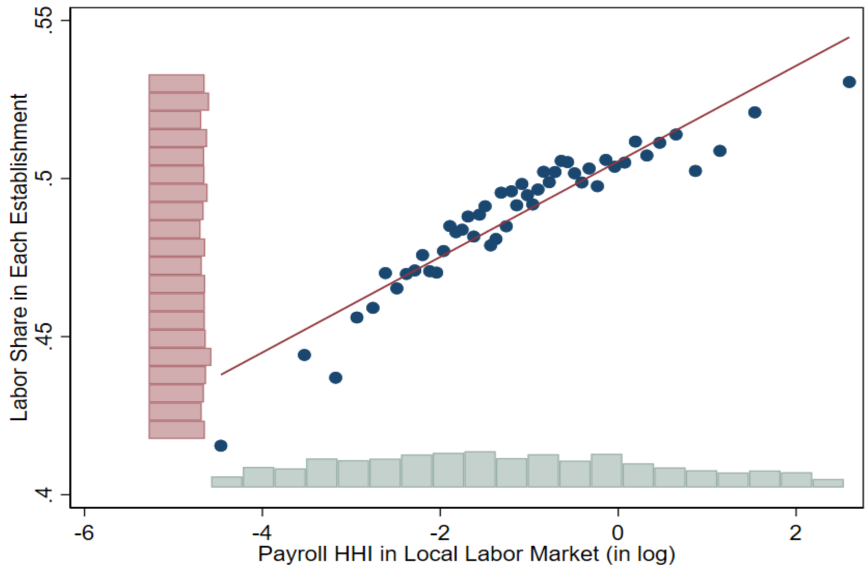
Table C.2: Labor Market Concentration and Labor Share: Across Establishment

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 (11) 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 C.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 C.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 (11), and regression estimates are same as Column (3) in Table C.2.

C.2.2 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.

$$LS_{i,t} = \beta \ln HHI_{j,c,t} + \gamma \ln VA_{i,t} + X'_{j,c,t}\delta + \mu_i + \mu_{j,t} + \mu_{c,t} + \varepsilon_i \tag{12}$$

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 C.3 shows the results.

Table C.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 (12) 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 (12) but with different outcomes as follows:

$$Y_{i,t} = \beta \ln HHI_{j,c,t} + \gamma \ln VA_{i,t} + X'_{j,c,t}\delta + \mu_i + \mu_{j,t} + \mu_{c,t} + \varepsilon_i \tag{13}$$

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 C.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 C.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 (13) 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.