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Trends in National and Local Market Concentration in Japan: 1980-2020[1]

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Abstract

I document trends of concentration in national and local markets in Japan since 1980. First, national market concentration within industries or product categories has increased since the mid-1990s regardless of sectors, data sources, or measurements. This is consistent with the findings in other developed countries, including the US. Second, local market concentration has also increased since the late 1990s, which contrasts with the findings in the US that local market concentration has been decreasing recently. The increase in local market concentration is associated with the decline in the number of establishments and is concentrated in areas outside large cities.

Keywords: Concentration, Product Market, Labor Market
JEL classification: E2, D2, D4, J3, K2, L1.

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1 Introduction

In this paper, I document trends of concentration in national and local markets in Japan since 1980. I focus on the manufacturing sector, which is the most important sector in Japan in terms of employment and output. I use establishment-level data from the Census of Manufacture (CoM) and the Basic Survey of Japanese Business Structure and Activities (BSBSA) to construct measures of concentration in product and labor markets. I also use the TSR data to relate geographical concentration to firm-to-firm transactions.

The main findings of the paper are as follows. First, I find that the concentration in industry-level national markets has been increasing since the mid-1990s both in manufacturing sectors and non-manufacturing sectors, across different measures of concentration. This increase in concentration is not correlated with the rise in markups across industries.

Second, I show that the concentration in 6-digit product-level national markets has also been increasing over the last 40 years. The increase is the most rapid between 1998 and 2006. For instance, CR4 at 6-digit product categories increased from 32% to 40% during these 8 years.

Third, I show that the concentration in the local market is also on an increasing trend. HHI for payroll and shipment within local labor markets has increased since the mid-1990s. This contrasts with the findings in the US that the local market concentration has been decreasing recently.

This paper contributes to several strands of the literature. First, this paper relates to the papers that document trends in concentration in Japan. There are several papers that study the trends in concentration at the industry level, including Fukao et al. (2021), Honda and Igarashi (2021), Miyakawa and Takizawa (2022), Nakamura and Ohashi (2019). Compared to these papers, this paper newly constructed a crosswalk across different product categories within manufacturing sectors over time. None of them provides long-run trends in product market concentration, particularly using product categories as a unit as opposed to industry categories. The crosswalk enables me to show the trends in national, product market concentration since 1980.

Second, I provide trends in local market concentration, in addition to national product market concentration.[1] As shown in Rossi-Hansberg et al. (2021) and Berger et al. (2022), the trends in product and labor market concentration differ in the US—national market concentration rises while local market concentration declines. My findings in Japan of rising both national and local market concentration contrast with these findings in the US.

I note that this paper does not provide estimates for markups or markdowns using production function estimation unlike previous papers estimating markups (The Cabinet Office, Japan, 2023; Diez et al., 2018; Fukao et al., 2021; Matsukawa, 2018; Nakamura, 2018; Nakamura and Ohashi, 2019; Miyakawa and Takizawa, 2022; Honda and Igarashi, 2021) or estimating markdowns (Aoki et al., 2023). I do not estimate these using production function estimation because there are several issues in their estimation procedures. First, as pointed out by Bond et al. (2021) and Kasahara and Sugita (2020), the production estimations based on the method by Ackerberg et al. (2015) are biased. Second, the identification of markdown using the method in Yeh et al. (2022), as in Aoki et al. (2023), requires several assumptions as listed in Yeh et al. (2022), including (i) there is no labor adjustment cost, (ii) labor is chosen statically, (iii) labor is used only for production purposes, not for other purposes such as marketing. While Yeh et al. (2022) justify them when analyzing the US labor market, it is unclear if these assumptions apply to the Japanese labor market where

[1] Some papers use cross-sectional variations to study the role of labor market concentration in Japan, including Izumi et al. (2023), Kawaguchi (2018).

protection of permanent workers against individual dismissals is higher than other developed countries, in particular the US (Hashimoto and Raisian, 1985; Jones and Seitani, 2019).

2 Data and Measurement

2.1 Data

2.1.1 Basic Survey of Japanese Business Structure and Activities

The first data I use is the Basic Survey of Japanese Business Structure and Activities (BSBSA) conducted by the Ministry of Economy, Trade and Industry (METI). All firms with more than 50 employees and JPY 30 million (USD 0.3 million) initial funds are asked to fill out and submit the questionnaire. The BSBSA contains information on the number of employees, sales, and other firm-level information. The BSBSA is conducted every year since 1995. I use the data from 1992, and 1995 to 2020. The BSBSA does not cover all of the industries. In particular, the BSBSA only covers selected sectors, including the mining, manufacturing, wholesale and retail trade, eating and drinking services (excluding "Other eating and drinking places"), and other industries such as Electricity and gas service, information service, etc., controlled by METI.

2.1.2 Census of Manufacture

My second data source is the Japanese Census of Manufacture (CoM) for the manufacturing sector. The Ministry of Economy, Trade, and Industry (METI) conducts the Japanese Census of Manufacture annually to gather information on the current status of establishments in the manufacturing sector. Specifically, this census covers all manufacturing establishments in years whose last digits are 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 for Business Activity (ECBA) was conducted.[2] 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.[3]

2.1.3 TSR Data

The third data I use is firm-level balance sheet data from Tokyo Shoko Research (TSR). The TSR is a private firm that collects information on firms in Japan. The TSR data also contains information on the number of employees, sales, and other firm-level information. It also reports

[2] 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.

[3] 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.

up to 24 main suppliers and buyers. I use this dataset to track the dynamic evolution of supplier-to-buyer linkages. I use the data from 2007 to 2020.[4]

2.2 Measurement

In this section, I explain the measurement I use for concentration. I mainly use the Herfindahl-Hirschman Index (HHI). In particular, I use the following definition of national-level HHI. First, I calculate industry-level or product-level HHI as follows:

$$\text{HHI}_i = \sum_{f=1}^{n} s_f^2 \tag{1}$$

where s_f is sales of firm f in industry i divided by total sales in industry i. I use values of shipment, payroll, or employment instead of sales when needed, but the definitions are the same. Then, I calculate national-level HHI by taking a weighted average of industry-level or product-level HHI:

$$\text{HHI} = \sum_{i=1}^{m} \text{HHI}_i \cdot \frac{\text{Sales}_i}{\text{Sales}} \tag{2}$$

where Sales_i is total sales in industry i and Sales is total sales in the economy.

I also use CR4, the sum of the share of sales for the top four firms within each industry. I use the sales share of the industry relative to the total sales in the economy in each year as weights to take an average.

$$\text{CR4} = \sum_{i=1}^{m} \text{CR4}_i \cdot \frac{\text{Sales}_i}{\text{Sales}} \tag{3}$$

where CR4_i is the sum of the share of sales for the top four firms in the industry i.

3 National Market Concentration

3.1 Industry-level Concentration

First, I show the trends of concentration in national markets at the industry level. I start with the HHI of sales within a 3-digit industry for the economy, including non-manufacturing sectors. I use the BSBSA data for this analysis. I restrict samples of industries to the ones surveyed throughout the periods since 1992. They are mining, manufacturing, wholesale and retail, and food service sectors.

Figure 1 shows the results. Figure 1a shows the trends of HHI of sales within a 3-digit industry for the economy. The figure shows that the HHI has been increasing since 2000. The HHI was around 0.05 between 1992 and 2000, but increased to around 0.1 in 2015, then decreased to 0.09 recently.

Previous literature for the US market concentration typically documented concentration measures in manufacturing sectors (Autor et al., 2020; De Loecker et al., 2020; Kwon et al., 2023). To compare the trend in Japan with these papers, I now restrict samples to manufacturing sectors in the BSBSA data and plot the HHI of sales within a 3-digit sector since 1992. Figure 1b shows the

[4] See Miyauchi (2023) for the details.

time series of HHI of sales within a 3-digit manufacturing sector in Japan. The figure shows that the HHI has been increasing since 2000, and the pattern is similar to the one reported in Figure 1a.

Figure 1c shows the CR4 for the entire economy. The sales CR4 for the entire economy was around 30% in the mid-1990s, increased to around 45% in 2010, then decreased to around 40% in 2020. and 1d shows the CR4 for the manufacturing sector. The CR4 was around 38% in the mid-1990s, increased to around 45% in 2010, and decreased to around 41% in 2020. The rising patterns until 2010 are similar while the decreasing patterns since then are present more clearly in these figures than in Figure 1a and 1b.

Since the BSBSA data only covers large firms, the increase in HHI may be driven by the increase in concentration among large firms. To check this, I use the CoM data, which covers all the establishments with more than three employees every year since 1980. Figure 1e shows the trends of HHI of shipment within a 3-digit industry for the manufacturing sector. The figure shows that the HHI has been increasing since the mid-1990s. The HHI was around 0.5 between 1980 and the mid-1990s, but it increased to around 0.85 in 2018. Note that this is the HHI based on the shares of shipment across establishments, not firms. The HHI based on the shipment shares across firms is likely to be higher than this. Figure 1f shows the CR4, and the pattern is quite similar. The shipment CR4 was below 15% in 1995 and increased to around 19% in 2015.

3.2 Industry-level Concentration and Markup

Another measure of market power studied in the literature is a markup (De Loecker et al., 2020). In this subsection, I examine the relationship between a concentration measure, namely HHI, and markups.

Markups I infer establishment-level markups from the CoM data. I follow Edmond et al. (2023) to estimate them. In particular, our estimated markups for establishment i in year t in sector s are as follows:

$$\hat{\mu}_{it}(s) = \frac{p_{it}(s)y_{it}(s)}{W_t l_{it}(s)} \times \hat{\alpha}_t^l(s), \tag{4}$$

where $p_{it}(s)y_{it}(s)$ is revenue, $W_t l_{it}(s)$ is payroll, and $\hat{\alpha}_t^l(s)$ is output elasticitis to labor in sector s. To be consistent across years, I only keep establishments with at least 30 employees.

Since revenue and payroll are observables, I only need to estimate $\hat{\alpha}_t^l(s)$. Several papers in the literature have estimated this by estimating sector-level production function. However, Bond et al. (2021) have shown that it is impossible to consistently estimate it when only revenue data are available in the presence of variable markups. Kasahara and Sugita (2020) have also demonstrated that these methods give biased estimates for markup if using revenue.

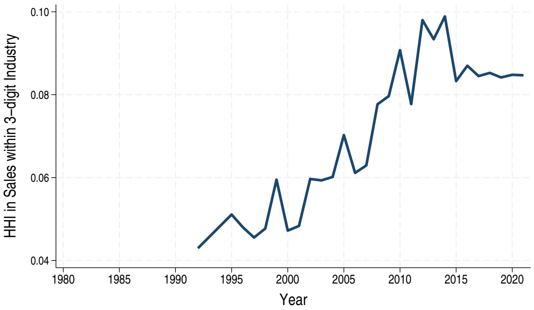
Thus, for the same reason to Edmond et al. (2023), I use the firm's cost-minimization conditions for each establishment i in time t to write

$$\alpha_t^l(s) = \frac{W_t l_{eit}(s)}{W_t l_{eit}(s) + R_t k_{eit}(s) + x_{eit}(s)} \times \text{ RTS} \tag{5}$$

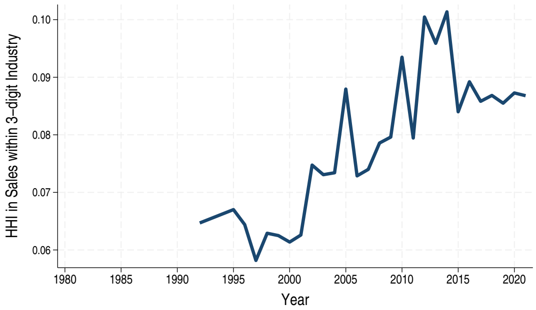
where $R_t k_{eit}(s)$ is capital cost, $x_{eit}(s)$ is material cost, and RTS is a return to scale, which I assume to be one following Edmond et al. (2023). Because of measurement error at the establishment level, I take the cost-weighted average of expenditure shares in labor input of establishments within each sector s to get $\hat{\alpha}_t^l(s)$ in each sector s.

Figure 1: HHI and CR4 for Sales and Shipment in Japan within 3-digit Industry

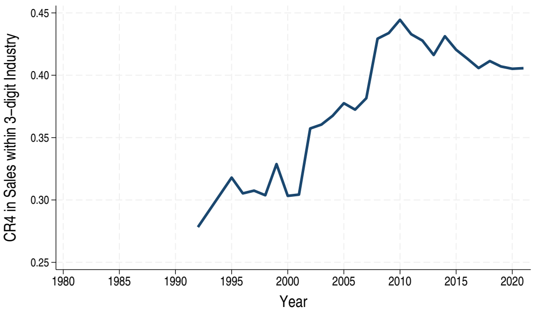
(a) HHI Sales, 3-digit, All Sectors, BSBSA



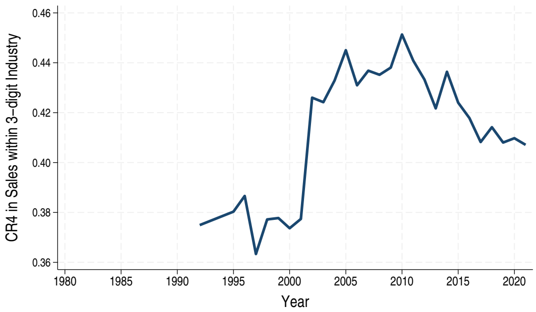
(b) HHI of Sales, 3-digit, Mfg., BSBSA



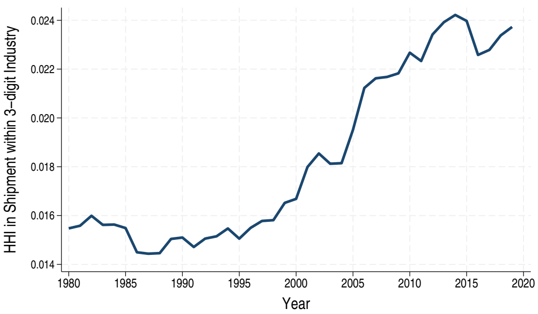
(c) CR4 of Sales, 3-digit, All Sectors, BSBSA



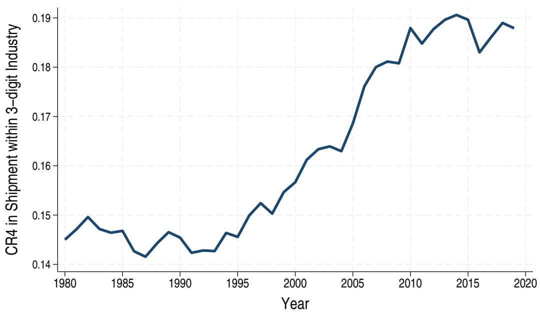
(d) CR4 of Sales, 3-digit, Mfg., BSBSA



(e) HHI of Shipment, 3-digit, Mfg., MFG Census



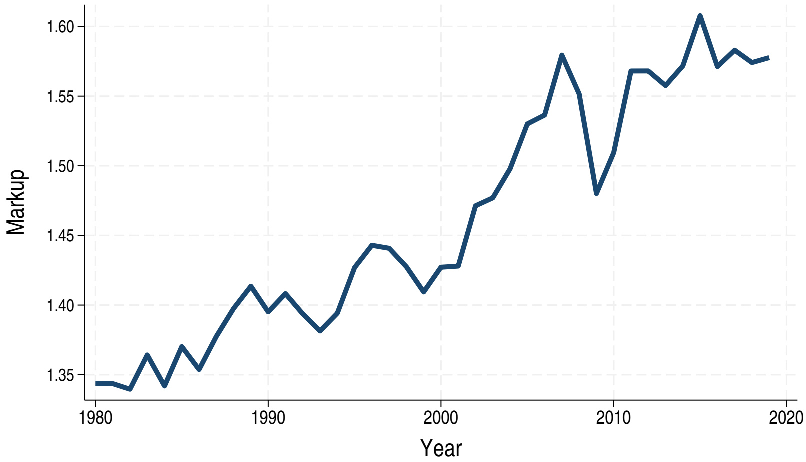
(f) CR4 of Shipment, 3-digit, Mfg., MFG Census



Note: The figures show a time series of concentration measures in the Japanese economy. Figure 1a shows the sales HHI for the entire economy. Figure 1b shows the sales HHI for the manufacturing sector. Figure 1c shows the sales CR4 for the entire economy. Figure 1d shows the sales CR4 for the manufacturing sector. Figures 1a, 1b, 1c, and 1d use the BSBSA data, and the original units of observation are firms. I first compute the HHI or CR4 of sales in each 3-digit industry in each year. I then take a weighted average using the total sales of each 3-digit industry as a weight. Figure 1e shows the shipment HHI for the manufacturing sector. Figure 1f shows the shipment CR4 for the manufacturing sector. Figure 1e and 1f use the CoM data, and the original units of observation are establishments. I restrict samples of establishments to the ones with at least four employees to be consistent across years. I first compute the HHI or CR4 of the value of shipment in each 3-digit industry in each year. I then take a weighted average using the total shipment of each 3-digit industry as a weight.

To get an economy-wide markup, I take a cost-weighted average of establishment-level markups each year. I drop the bottom 5% and the top 5% of the samples. Figure 2 shows the result. Before the mid-1990s, markups were around 1.4. Then, they increased to around 1.6 in 2015 and stayed between 1.55 and 1.6.

Figure 2: Markup in the Japanese Manufacturing Sector



Notes: The figure shows markups estimated following Edmond et al. (2023). The output elasticities are estimated within each 3-digit JSIC industry. The blue line is the economy-wide markup, which is a weighted average of industry-level markups, using total cost as a weight.

Relating Concentration and Markup The timing of this trend of increasing markups is consistent with the concentration measures shown in Figure 1e and 1f. This positive correlation is consistent with standard theories that suggest higher concentration leads to higher markups. However, this does not imply a causal relationship. The rise in markups could be due to other factors such as increasing productivity or increasing demand for high-quality goods. In a similar spirit to Albrecht and Decker (2024), I show a cross-sectional correlation across 3-digit industries.

Figure 3 and Table 1 show the cross-sectional relationship between HHI and markup across 3-digit manufacturing industries. Figure 3a shows the static relationship in 1980. Each blue dot represents a 3-digit manufacturing industry, and the size is proportional to the total cost in 1980. The red line is a fitted line using weighted linear regression using the total cost as a weight. Figure 3b shows the difference-in-difference relationship between HHI and markup from 1980 to 2019. Table 1 shows results in a table. Columns (1) and (2) use HHI in 1980, Columns (3) and (4) use HHI in 2019, and Columns (5) and (6) use changes in HHI between 1980 and 2019 as a dependent variable. Columns (1), (3), and (5) use a total cost as a weight. Robust standard errors are shown in parentheses.

First, comparing the levels in a given year, HHI and markup do not have a positive correlation in 1980 as seen in Figure 3a. The estimate of the coefficient reported in Column (1) of Table 1 is 0.000 with a standard error of 0.009. An unweighted regression (Column (2)) or regressions using 2019 (Column (3) and (4)) do not provide a positive association.

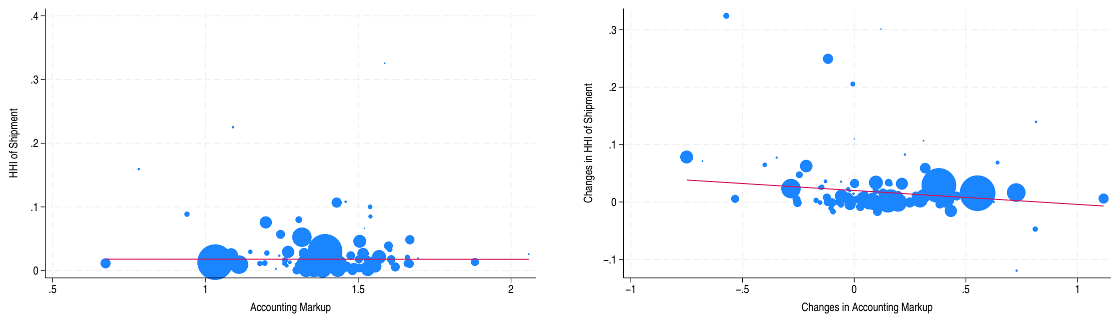
Second, comparing the changes between 1980 and 2019, HHI and markup again do not have a positive association as shown in Figure 3b. The estimate of the coefficient reported in Column (5) of Table 1 is now -0.024 with a standard error of 0.015, which is negative and significant at 10%. An unweighted version (Column (6)) also presents a negative estimate, which is significant at 10%.

In sum, I do not find a positive association between HHI and markup across manufacturing industries in Japan. There are several reasons why HHI and markups are uncorrelated across industries. First, a sign of the correlation between HHI and markups can be positive or negative, depending on the theoretical framework. On the one hand, higher HHI may allow firms to increase markups. On the other hand, higher markups may motivate entrants to enter more and decrease HHI. Thus, the simple correlation is not informative to support or reject any hypothesis. Second, domestic HHI may not be informative for the competitiveness of product markets for firms to consider when choosing prices. I am estimating markups and HHI in the manufacturing sectors, which are tradable. Thus, what may matter is an HHI at product markets, which include foreign firms. Finally, the estimate of markups can still not be a good proxy for market power. While the estimate based on Edmond et al. (2023) does not suffer from the critics on the method by De Loecker et al. (2020) and others raised by Bond et al. (2021), the method of Edmond et al. (2023) still assumes firm's cost minimization and others. Thus, using the method by Kasahara and Sugita (2020) and comparing it with HHI would be a fruitful direction for future research.

Figure 3: HHI and Markup: 3-digit Manufacturing Industries

(a) Static: 1980

(b) Difference in Difference: 1980-2019



Note: The figures show the cross-sectional relationship between HHI and markup across 3-digit manufacturing industries. Figure 3a shows the static relationship in 1980. Figure 3b shows the difference-in-difference relationship between HHI and markup from 1980 to 2019. In both panels, Each blue dot represents a 3-digit manufacturing industry, and the size is proportional to the total cost in 1980. The red line is a fitted line using weighted linear regression using the total cost as a weight.

3.3 Product-level Concentration

Finally, I leverage the CoM data to show the trends of concentration in product markets at the product level. Between 1980 and 2019, there were several re-classification of the product categories used in Japan in 1985, 1994, 1999, 2002, 2008, and 2014. I map all the classifications into the ones in 2002.

Figure 4a shows the trends of HHI of shipment at 6-digit product categories across establish-

Table 1: Association between HHI and Markup across Industries

	Static in 1980		Static in 2019		Changes: 1980-2019	
	(1)	(2)	(3)	(4)	(5)	(6)
Markup	-0.000	-0.027	-0.029	-0.097		
	(0.009)	(0.031)	(0.032)	(0.050)		
Chagnes in Markup					-0.024	-0.046
					(0.015)	(0.025)
Observations	122	122	120	120	120	120
Weighted	✓		✓		✓	

Notes: This table shows the relationship between HHI and markup across 3-digit manufacturing industries. Columns (1) and (2) use HHI in 1980, Columns (3) and (4) use HHI in 2019, and Columns (5) and (6) use changes in HHI between 1980 and 2019 as a dependent variable. Columns (1), (3), and (5) use a total cost as a weight. Robust standard errors are shown in parentheses.

ments within the manufacturing sector. Again, the figure shows that the HHI has been increasing since the late 1990s. The HHI was around 0.06 between 1980 and the mid-1990s, but it increased to around 0.09 in 2007 then has been constant until recently. Figure 4b shows CR4 of shipment at 6-digit product categories. The pattern is similar to the one of HHI in that concentration increased from 32% in the late 1990s to 40% in 2007 then has been constant until now.

These patterns do not depend on the granularity of the product categories. Figures 4c and 4e show the trends in HHI using 5-digit and 4-digit product categories, respectively. Figures 4d and 4f show the trends in CR4 using 5-digit and 4-digit product categories, respectively. These figures consistently show the rise in concentration between the late 1990s and 2007.

Figure 5 shows the histogram of the changes in HHI across 6-digit product categories between 1980 and 2019. The mean is 0.06, the median is 0.02, the p25 is 0.00, and the p75 is 0.06. It shows that not just economy-wide, but also most product categories experienced increases in concentration during this period.

4 Local Market Concentration

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 in 2015. 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.

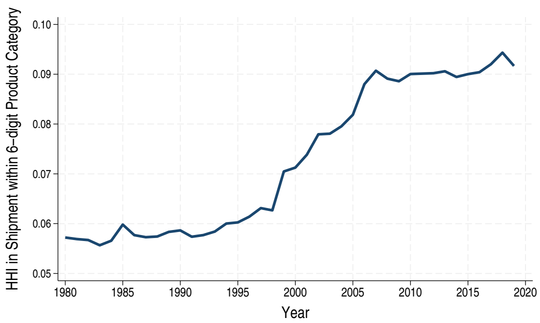
4.1 Trends in Local Market Concentration

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 a minimum of four employees to make the data time-consistent.

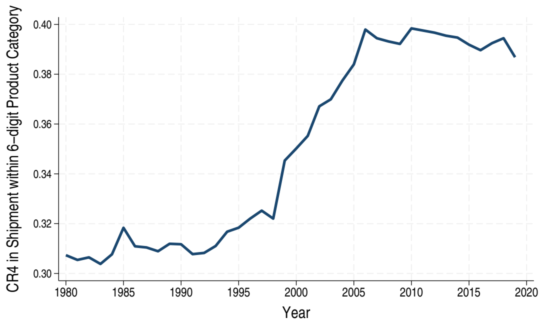
[5] Japan has 1,724 municipalities as of June 2023, including 6 municipalities in the Northern Territories. I drop these 6 municipalities as the CoM data does not cover them.

Figure 4: HHI and CR4 for Shipment in the Japanese Manufacturing Sector within Product Category

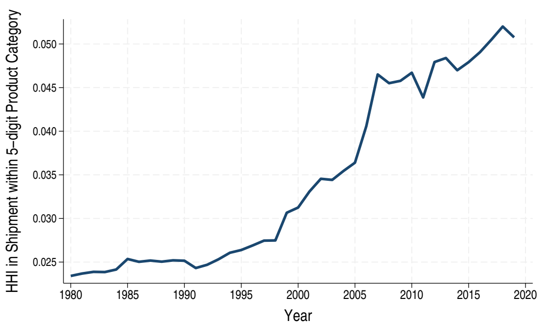
(a) HHI of Shipment, 6-digit Product



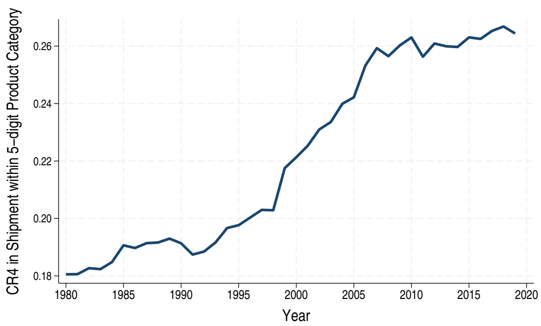
(b) CR4 of Shipment, 6-digit Product



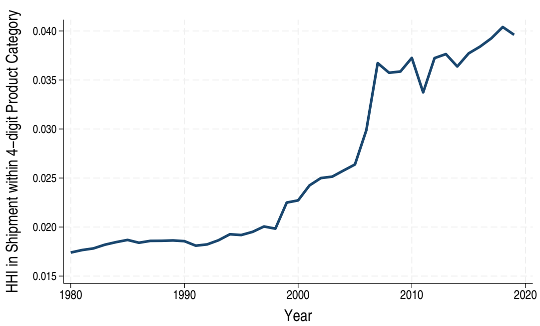
(c) HHI of Shipment, 5-digit Product



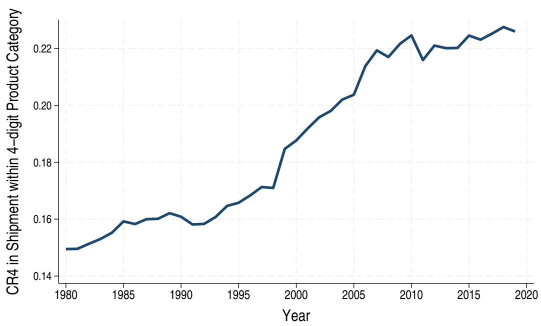
(d) CR4 of Shipment, 5-digit Product



(e) HHI of Shipment, 4-digit Product

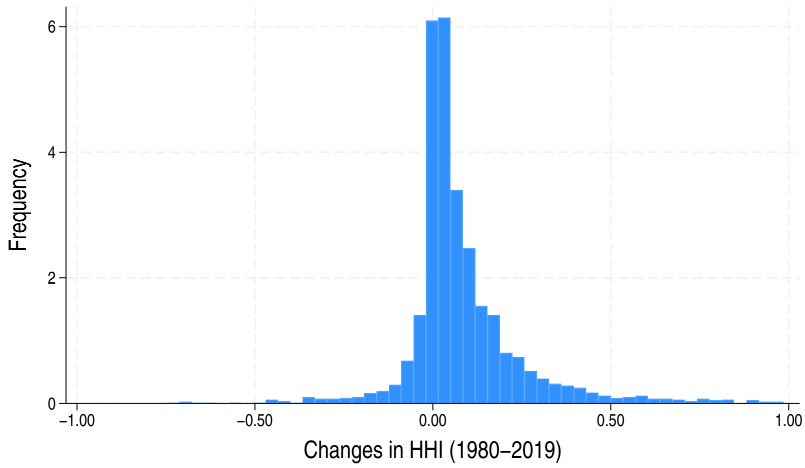


(f) CR4 of Shipment, 4-digit Product



Note: The figures show a time series of concentration measures in the Japanese economy. I restrict samples of establishments to the ones with at least four employees to be consistent across years. I first compute the HHI or CR4 of the value of shipment in each 3-digit industry in each year. I then take a weighted average using the total shipment of each 3-digit industry as a weight.

Figure 5: Changes in HHI for Shipment across 6-digit Product Categories



Notes: The figure shows the histogram of the changes in HHI of shipment across 6-digit product categories.

Figure 6a shows the HHI of payroll at the commuting zone level, and Figure 6b shows the HHI of payroll at the local labor market level, respectively. The timings of the trends are the same. The labor market concentration decreased between 1980 and the mid-1990s. Then, the time trend was reversed in the late 1990s, and the concentration has been increasing since then.

I can also observe the rising concentration since the late 1990s in shipment. Figure 6c shows the HHI of shipment at the commuting zone level, and Figure 6d shows the HHI of payroll at the local labor market level. Although there is no clear declining trend in the 1980s,

4.2 Local Market Concentration across Space

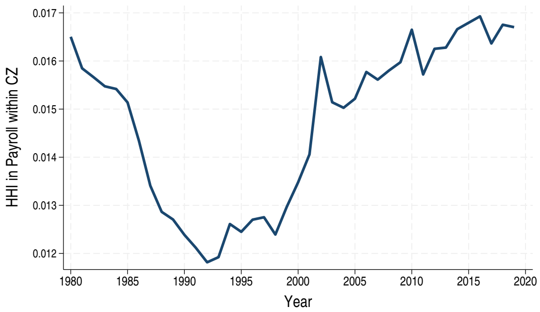
Changes in HHI across Space In the previous subsection, Figure 6c shows that HHI for shipment within commuting zones increased from 0.03 to around 0.05 over the 40 years. However, there are some differences in trends across spaces. Figure 7 shows the changes in HHI for shipment across commuting zones from 1980 to 2019. The darker areas show the commuting zones with larger increases in concentration. Large metropolitan areas with more establishments experienced modest increases in HHI. For instance, Tokyo areas increased HHI by 0.009, which is half of the aggregate increase, and Osaka areas increased HHI by 0.005, which is one-fourth of the aggregate increase.

HHI and Number of Establishments To document the spatial heterogeneity in HHI and its change across commuting zones in Japan, I examine the association between HHI and the number of establishments.

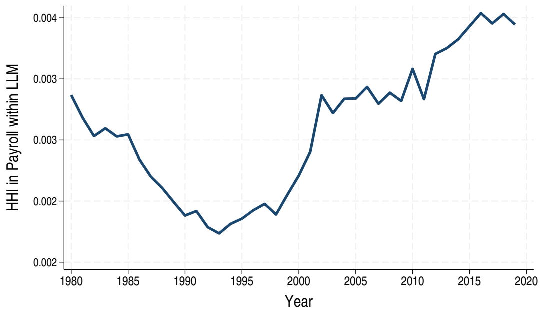
Table 2 shows the relationship between HHI and the number of establishments across commuting zones in Japan. Columns (1) and (2) use HHI in 1980, Columns (3) and (4) use HHI in 2019, and Columns (5) and (6) use changes in HHI between 1980 and 2019 as a dependent variable. Columns (1), (3), and (5) use an initial total employment as a weight. Robust standard errors

Figure 6: HHI for Shipment in the Japanese Manufacturing Sector: Local Market Concentration

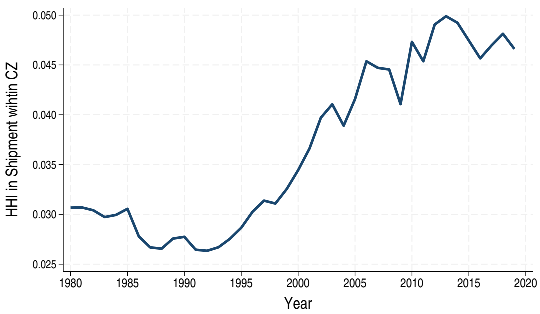
(a) HHI for Payroll within CZ



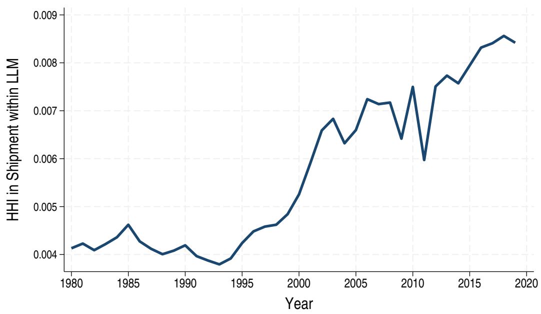
(b) HHI for Payroll within CZ x 3-digit Industry



(c) HHI for Shipment within CZ

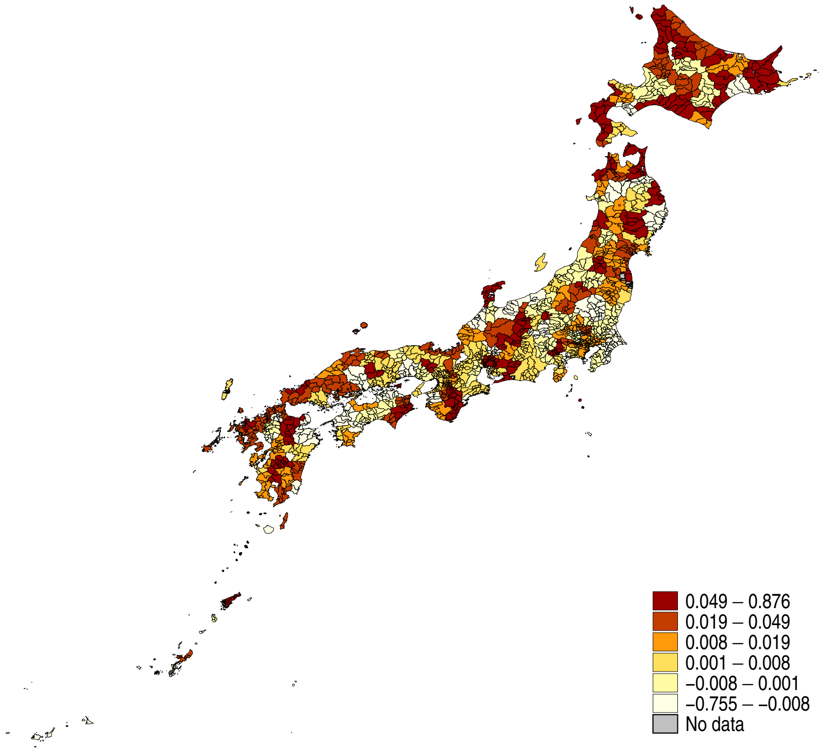


(d) HHI for Shipment within CZ x 3-digit Industry



Note: The figures show a time series of concentration measures in the Japanese economy. I restrict samples of establishments to the ones with at least four employees to be consistent across years. Figure 6a shows the HHI of payroll at the commuting zone level. Figure 6b shows the HHI of payroll at the local labor market level. Figure 6c shows the HHI of shipment at the commuting zone level. Figure 6d shows the HHI of payroll at the local labor market level. Local labor markets are defined as pairs of commuting zones and 3-digit industries.

Figure 7: Changes in HHI for Shipment across Commuting Zones in Japan



Notes: The figure shows the changes in HHI for shipment across commuting zones in Japan.

are shown in parentheses. In each column, I also report the means and the standard deviations of the dependent variables and the running variables.

Static correlations are strong both in 1980 and 2019, and the relationship is stronger if I do not weigh commuting zones by their sizes. For instance, Column (2) shows that commuting zones with 1% more numbers of establishments have higher HHI by 0.06, which is 60% of the mean and one-third of the standard deviation of HHI in 1980. The results are qualitatively and quantitatively similar in 2019 as shown in Column (4).

The difference-in-difference specification is strong without weighing commuting zones. Column (6) shows that a 1% decrease in the number of establishments leads to increases in HHI by 0.176, which is larger than the standard deviation of the changes in HHI across commuting zones (0.141).

Table 2: Association between HHI and Number of Establishments across Commuting Zones

	Static in 1980		Static in 2019		Changes: 1980-2019	
	(1)	(2)	(3)	(4)	(5)	(6)
Num. of Estab. (log)	-0.012	-0.061	-0.011	-0.082		
	(0.001)	(0.008)	(0.007)	(0.007)		
Chagnes in Num. of Estab. (log)					-0.006	-0.176
					(0.008)	(0.032)
Observations	257	257	263	263	256	256
Weighted	✓		✓		✓	
Mean of Dep. Var.	0.026	0.104	0.041	0.156	0.013	0.036
Std. Dev. of Dep. Var.	0.036	0.183	0.042	0.226	0.037	0.141
Mean of Run. Var.	8.576	5.891	7.532	5.026	-0.863	-0.758
Std. Dev. of Run. Var.	1.505	2.111	1.128	2.156	0.309	0.441

Notes: This table shows the relationship between HHI and the number of establishments across commuting zones. Columns (1) and (2) use HHI in 1980, Columns (3) and (4) use HHI in 2019, and Columns (5) and (6) use changes in HHI between 1980 and 2019 as a dependent variable. Columns (1), (3), and (5) use an initial total employment as a weight. Robust standard errors are shown in parentheses.

5 Conclusion

In this paper, I demonstrate that there has been a rise in market concentration in both national and local markets in Japan since the mid-1990s.

There are several next steps, which would be fruitful. First, one can estimate markups using the method developed in Kasahara and Sugita (2020). That would verify whether trends in markups align with the trends in concentration measures documented in this paper. Second, one can decompose the changes in the concentration measures into the changes in the number of firms and the changes in the size of firms. Third, one can study the productivity consequences of this rise in concentration. Is the rise in concentration due to the exit of less productive firms, or is it due to the rise of more productive firms? I am currently working on these questions.

References

Ackerberg, D. A., K. Caves, and G. Frazer (2015). Identification properties of recent production function estimators. *Econometrica 83*(6), 2411–2451.

Adachi, D., T. Fukai, D. Kawaguchi, and Y. U. Saito (2020). Commuting zones in Japan. Discussion papers 20-E-021, Research Institute of Economy, Trade and Industry (RIETI).

Albrecht, B. C. and R. A. Decker (2024). Rising markups and declining business dynamism: Evidence from the industry cross section. Technical report, Board of Governors of the Federal Reserve System (US).

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. Van Reenen (2020). The fall of the labor share and the rise of superstar firms. *The Quarterly Journal of Economics 135*(2), 645–709.

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

Bond, S., A. Hashemi, G. Kaplan, and P. Zoch (2021). Some unpleasant markup arithmetic: Production function elasticities and their estimation from production data. *Journal of Monetary Economics 121*, 1–14.

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.

Diez, M. F., M. D. Leigh, and S. Tambunlertchai (2018). *Global market power and its macroeconomic implications*. International Monetary Fund.

Edmond, C., V. Midrigan, and D. Y. Xu (2023). How costly are markups? *Journal of Political Economy 131*(7), 000–000.

Fukao, K., K. Ikeuchi, Y. Kim, and H. U. Kwon (2021). Business dynamism and productivity growth under abenomics: An empirical analysis based on micro data from japan's economic census for business activity. Discussion papers 21-J-015, Research Institute of Economy, Trade and Industry (RIETI). (in Japanese).

Hashimoto, M. and J. Raisian (1985). Employment tenure and earnings profiles in japan and the united states. *The American Economic Review 75*(4), 721–735.

Honda, J. and T. Igarashi (2021). Market concentration and competitive environment in japanese manufacturing. Discussion papers CPDP-91-J, Competition Policy Research Center (CPRC). (in Japanese).

Izumi, A., N. Kodama, and H. U. Kwon (2023). Labor market concentration and heterogeneous effects on wages: Evidence from japan. *Journal of the Japanese and International Economies 67*, 101242.

Jones, R. S. and H. Seitani (2019). Labour market reform in japan to cope with a shrinking and ageing population. Technical report.

Kasahara, H. and Y. Sugita (2020). Nonparametric identification of production function, total factor productivity, and markup from revenue data. Technical report, arXiv preprint arXiv:2011.00143.

Kawaguchi, D. (2018). Measurement of labor input in the productivity analysis: Insights from temporary help agency workers' labor market. *The economic review 69*(4), 328–345. (in Japanese).

Kondo, K. (2023). Municipality-level Panel Data and Municipal Mergers in Japan. Technical papers 23-T-001, Research Institute of Economy, Trade and Industry (RIETI).

Kwon, S. Y., Y. Ma, and K. Zimmermann (2023). 100 years of rising corporate concentration. Working papers 2023-20, University of Chicago, Becker Friedman Institute for Economics Working Paper.

Matsukawa, I. (2018). The effect of the use of it on markup in japanese manufacturing industry. Discussion papers 18-J-002, Research Institute of Economy, Trade and Industry (RIETI). (in Japanese).

Miyakawa, D. and M. Takizawa (2022). Productivity and business dynamism in japan: Comparison with the eu countries using firm-level data. Discussion papers 22-J-005, Research Institute of Economy, Trade and Industry (RIETI). (in Japanese).

Miyauchi, Y. (2023). Matching and agglomeration: Theory and evidence from japanese firm-to-firm trade. *Working Paper*.

Nakamura, T. (2018). A practical study about mark-up estimation based on production function. *The Journal of Tokyo Keizai University : Economics 299*, 139–165. (in Japanese).

Nakamura, T. and H. Ohashi (2019). Linkage of markups through transaction. Discussion papers 19-E-107, Research Institute of Economy, Trade and Industry (RIETI).

Rossi-Hansberg, E., P.-D. Sarte, and N. Trachter (2021). Diverging trends in national and local concentration. *NBER Macroeconomics Annual 35*(1), 115–150.

The Cabinet Office, Japan (2023). The annual report on the japanese economy and public finance. White paper, The Cabinet Office. (in Japanese).

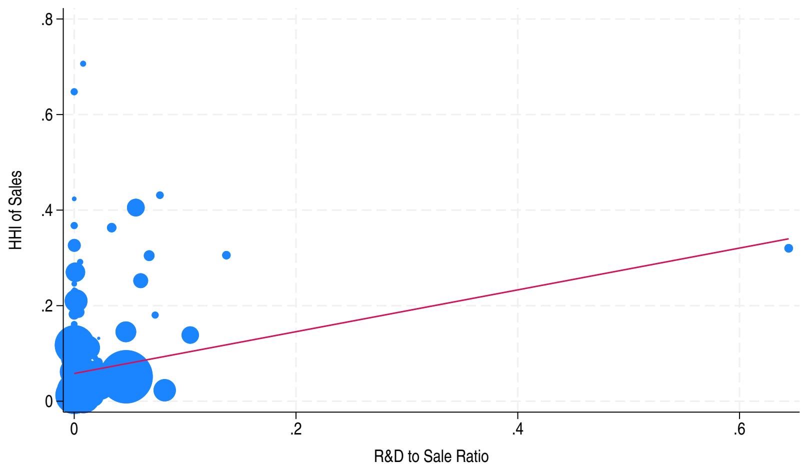
Yeh, C., C. Macaluso, and B. Hershbein (2022). Monopsony in the us labor market. *American Economic Review 112*(7), 2099–2138.

A Innovation and Concentration across Industries

Some papers, such as Autor et al. (2020), relate innovation to concentration. The logic is that the innovative activities have an increasing return to scale, which favors large firms so that the industries with more innovation have a higher concentration. While I leave causal analysis for future research, I show a simple correlation across industries.

Figure A.1 shows a scatter plot for the relationship between HHI of sales and R&D to sales ratio across 3-digit industries. The values are the median of industry-level variables over the years of 2015-2019. Each dot represents a 3-digit industry with the size showing the total sales in each industry. There is a positive association, which is consistent with the hypothesis that more innovative industries have higher concentration.

Figure A.1: R&D to Sales Ratio and HHI across Industries



Notes: The figure shows the relationship between HHI of sales and R&D to sales ratio across 3-digit industries in 2015-2019.

Table A.1 shows the results for the regressions with multiple robustness checks. Column (1) uses all industries. Column (2) drops industries with less than 10 firms, Column (3) drops industries with zero R&D ratio, and the outlier industry (Academic/development research institute with 64%). Column (4) drops both types of industries.

When I drop industries with only less than 10 firms (Columns (2) and (4)), there is a significant, positive correlation between R&D to sales ratio and HHI across 3-digit industries.

Table A.1: Association between HHI and R&D to Sales Ratio across Industries

	(1)	(2)	(3)	(4)
R&D Ratio	0.185	0.398	0.784	1.060
	(0.119)	(0.094)	(0.497)	(0.452)
Observations	168	151	144	139
Drop Industries with Less than 10 firms		✓		✓
Drop Industries with Zero R&D Ratio and the Outlier			✓	✓

Notes: This table shows the relationship between HHI and R&D to sales ratio across 3-digit industries. Robust standard errors are shown in parentheses.

B Spatial Decays in Firm-to-Firm Transaction

Local market concentration is closely related to geographical agglomeration. While there are several economic forces that cause agglomeration, I here provide evidence that firm-to-firm transactions may play a role in economic agglomeration across spaces.

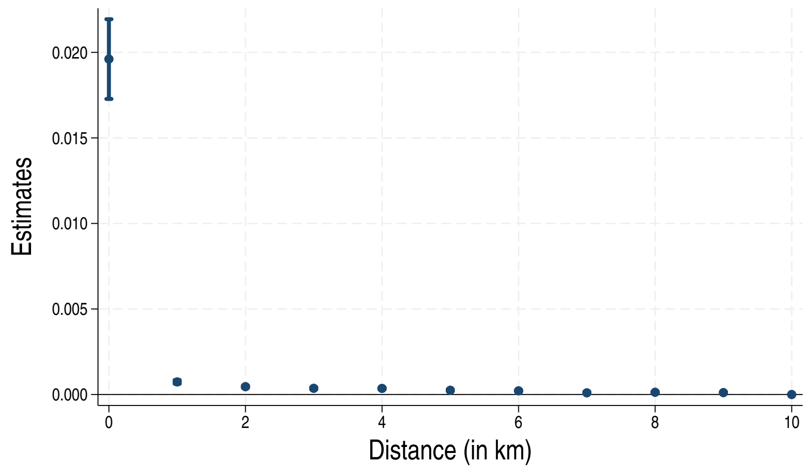
I use the TSR data to track the dynamic evolution of supplier-to-buyer linkages. In particular, I estimate the following equation

$$\text{Connected}_{i,j,t} = \sum_{b \in B} \beta^b \cdot \mathbb{1}\{\text{distance}_{i,j} \in b\} + \mu_{i,j} + \mu_t + \varepsilon_{i,j,t} \quad (6)$$

where $\text{Connected}_{i,j,t}$ is a dummy variable that takes one if firm i and j engage in a firm-to-firm transaction in year t and zero otherwise. $\mathbb{1}\{\text{distance}_{i,j} \in b\}$ is a dummy variable that takes one if the distance between firm i and j falls into 1km bins $b \in \{0.0km, 0.0km - 1.0km, ..., 9.0km - 10.0km, 10.0km+\}$, $\mu_{i,j}$ is a pair fixed effect, and μ_t is a year fixed effect. With the pair fixed effect $\mu_{i,j}$, I exploit the changes in distance of the pair. I restrict my sample to the firms in Tokyo with at least 200 workers.

Figure B.2 shows the result. The blue line shows estimates in each bin with 95% CI. This shows that the distance matters for firm-to-firm transactions and particularly so for the firm pairs in the same addresses (same buildings). While the estimates are statistically significant, they are quantitatively small. For example, the estimate for the first bin of 0.02 suggests that the firm pairs in the same buildings are 2% more likely to have firm-to-firm transactions compared to the firm pairs with a distance of more than 10 km.

Figure B.2: Decays in Firm-to-Firm Transaction by Distance



Notes: The figure shows the relationship between firm-to-firm transaction and distances between firms. The blue line estimates in each bin with the bar showing 95% CI for Equation (6).