New Technology Diffusion: Implications for Monopsony Power, Markups, and Labor Share*

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Abstract

This paper investigates the potential implications of ignoring heterogeneity in production technology at each plant on monopsony power and markups. We collect plant-level data where we directly observe the types of production technology during new technology diffusion. We demonstrate that estimating a common production function for all plants results in upward trends in both monopsony power, measured by the differences in growth rates of MRPL and wages, and markups, obtained by production approach. However, accounting for production technology in the analysis eliminates these upward trends, highlighting the importance of controlling for heterogeneity in production technology even within a narrowly-defined industry.

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Keywords: Technology adoption; Markups; Monopsony Power; Labor Share.

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1 Introduction

Production functions are one of the fundamental primitives in economics, and their estimates are key inputs for various economic analyses. One factor that complicates the estimation of production functions is that not all firms have access to the latest technology, resulting in heterogeneity in the production technologies owned by each firm. While there is heterogeneity in production technologies, many applied studies ignore such heterogeneity, assuming that firms within the same industry have the same production function. Recent research on markups and monopsony power has pointed out that incorrect markup estimates can be obtained when assuming firms in a broadly-defined industry have the same production technology (Foster, Haltiwanger and Tuttle, 2022) or when ignoring heterogeneity due to technical change (Demirer, 2022).

This paper precisely addresses this issue arising from ignoring such heterogeneity by collecting data where we directly observe the types of production technologies at each plant. Specifically, we exploit the plant-level data from the Japanese cement industry between 1970 and 2010, during which the evolution of new cement production technology occurred, from the suspension preheater (SP) kiln to the new suspension preheater (NSP) kiln. Moreover, cement is a homogeneous product, allowing us to assume away product differentiation and quality difference, and has a simple production process, which enables us to limit our attention to kiln technology. For these reasons, the cement industry provides an ideal environment to examine the possible implications of accounting for technological changes.

We first show that there is a plant-level heterogeneity in production technology due to the gradual adoption of new technology in the industry over time. To understand how to capture this diffusion of new technology as a change in the production function, we employ an event study design à la Callaway and Sant'Anna (2021). Using observed variation in the timing of technology adoption, we see the effect of the adoption on outcome variables such as the number of employees, wages, production capacity, output value, and capital-labor ratio. We find that, compared to the plants keeping the old technologies, the plants adopting the new technology exhibit (i) a decrease in the number of employees by approximately 20% over nine years, (ii) no significant changes in the growth rate of wages per person, (iii) an immediate increase in production capacity by 30%, and (iv) an increase in output value by approximately 30% one year after the new technology adoption. These findings suggest that the introduction of NSP kilns embodies the explicit technological change with a different shape of production functions across plants rather than a simple increase in total factor productivity (TFP). We confirm this by estimating the production function for each technology using the control function approach consolidated by Ackerberg, Caves and Frazer (2015). We estimate different output elasticities for different types of technologies and find that the new technology is indeed more capital-intensive.

We then use our production function estimates to examine implications for monopsony power and markups to illustrate that our conclusion would be qualitatively different if we lacked data on production technology. We estimate plant-level marginal revenue products of labor (MRPL) and find that *without* taking account of the differences in production technology, the growth rate of MRPL is higher than that of wages. In particular, this discrepancy occurs when new technology diffuses from the mid-1970s to the early 1980s. However, we find that this discrepancy vanishes once we control for plant-level technology, suggesting that the monopsony power of firms has not increased over time.

Next, we estimate plant-level markups using the methodology from De Loecker and Warzynski (2012) and find that *without* controlling for the differences in production technology, estimated markups exhibit an increasing trend over time. This finding is consistent with the recent studies by De Loecker, Eeckhout and Unger (2020) and Autor, Dorn, Katz, Patterson and Van Reenen (2020). However, when we control for the plant-level technology in our analysis, a large part of the markup increase disappears. Also, we show that with a single estimate of output elasticity imposing common production technology for all plants, an increase in the industry-level markup occurs when production shifts from plants with relatively labor-intensive technology to plants with relatively capital-intensive technology due to the fact that the output elasticity does not reflect different production technologies in the same industry.

We further relate our findings to the recent important debates in macroeconomics of why labor share declines in the modern economy. An enormous number of studies have investigated this issue, proposing hypotheses to explain the phenomenon, such as factor-biased technical changes, the increased exercise of product market power by large firms, declining worker power in labor relations, globalization and the rise of China, and changes in the composition of the workforce.[1] We show that "technology diffusion" is the primary driver of labor share decline by appropriately controlling for technology in our analysis. Without technology information, the decline of labor share coincides with the increase in markups and monopsony power. However, such a relationship vanishes once controlling for technology.

Our paper contributes to the recent literature on time-series changes in market power. There is a growing literature on market power from macroeconomics where the literature relies on the "production approach" (See Syverson, 2019). Drawing on De Loecker and Warzynski (2012) and production function estimation from the IO literature (e.g., Olley and Pakes, 1996; Levinsohn and Petrin, 2003; Ackerberg, Caves and Frazer, 2015), De Loecker, Eeckhout and Unger (2020) estimate markups during the period 1955-2016 for the U.S. economy and find that they have risen steadily. Similarly, Yeh et al. (2022) develop a new way to characterize aggregate markdowns from production function estimation and quantify the long-term trends of monopsony power in the US manufacturing sector. Our contribution to this literature is that we document the importance of estimation bias in market power due to the lack of production technology information. In this regard, Foster, Haltiwanger and Tuttle (2022) is the closest paper, where they find that the increase in markups is substantially dampened with more granular estimates of output elasticities obtained by estimating production function with six-digit industry code rather than two-digit level. Our results show that even in a narrowly-classified industry, different plants use different production technologies, and assuming the same technology across all plants would be problematic. Given the rise of the macroeconomics

[1] See Grossman and Oberfield (2022) for a more detailed summary of the literature.

approach, several studies, such as Grieco, Murry and Yurukoglu (2021) and Miller, Osborne, Sheu and Sileo (2023), re-examine findings using an IO-type demand estimation approach by focusing on specific industries as we do in this paper.

Our paper also relates to the burgeoning literature on technological change and production function estimation. A common approach to production function estimation assumes productivity as a Hicks-neutral shifter. Several authors, including Doraszelski and Jaumandreu (2018), Raval (2023), Zhang (2019), Jaumandreu (2022), and Demirer (2022), have recently considered departures from this standard assumption. These papers highlight the importance of labor-augmenting productivity and develop ways to estimate production functions with factor-augmenting productivity change. By contrast, our paper instead assumes that producers have an explicitly different production function according to their use of old or new types of kilns, aside from any productivity differences. The dataset, which is uncommon in that we can directly observe plant-level production technology, makes it possible, and there are only a few works with this approach. Examples are van Biesebroeck (2003), which models the choice between lean or mass production in the car industry, Rubens (2022), who features the introduction of mechanical coal cutters in the 19th-century coal mining industry, and Collard-Wexler and De Loecker (2015), who collect data on production technology directly as we do in this paper.

Finally, this paper also contributes to a large body of literature on labor share decline.[2] The decline of the labor share has been observed in many countries (Karabarbounis and Neiman, 2014) and in many industries (Kehrig and Vincent, 2021), and many researchers ascribe it to technological changes, in particular, introduction of computers and industrial robots, as in Acemoglu and Restrepo (2020), Autor et al. (2020), and Humlum (2021). Our focus on the advancement of kilns in the cement industry during the 1970s can ad-

[2]Grossman and Oberfield (2022) classify hypotheses for declining labor share into the following five categories: (i) technological changes, (e.g., Karabarbounis and Neiman, 2014; Acemoglu and Restrepo, 2020; Autor et al., 2020), (ii) increased exercise of product market power by large firms (e.g., Barkai, 2020; De Loecker et al., 2020), (iii) declining worker power in labor relations (e.g., Stansbury and Summers, 2020; Drautzburg et al., 2021), (iv) globalization and the rise of China (e.g., Abdih and Danninger, 2017; Sun, 2020), and (v) changes in the composition of the workforce (e.g., Glover and Short, 2020; Acemoglu and Restrepo, 2020).

dress the gap between the rise in automation and ICT in the 1990s and the labor share decline observed since the 1980s.

This paper is organized as follows. Section 2 describes the industry and provides the historical background of the Japanese cement industry as well as the data used in our empirical analysis. We conduct some reduced-form analysis to motivate how to translate new production technology into production functions and estimate them in Section 3. We then examine the implications for monopsony power and markups in Section 4. We also discuss the implications for the declining labor share in Section 5. Section 6 concludes.

2 Industry Background and Data

There are three important advantages to studying the cement industry: (i) the availability of production technology information at each plant, which is typically unobserved in the standard census data; (ii) the homogeneity of the product, which enables us to estimate markups accurately; and (iii) a simple production process, which enables us to estimate productivity easily through production function estimation.

In this section, we first explain the industry backgrounds, elaborate on the aforementioned features and advantages of the industry, and describe the two data sources that we use in this paper. We then show some key statistics.

2.1 Industry Background: Cement and Its Production Technology

Cement is one of the most important construction materials, as concrete and mortar are made from cement. There are several types of cement. For example, Portland cement is the most common type of cement, accounting for about 75% of cement products, according to the Japanese Cement Association.[3] They are defined by the Japanese Industrial Standards and thus can be treated as homogeneous products. To produce cement, crushed limestone, clay, and other minerals are mixed and put into a kiln to be heated at

[3]See https://www.jcassoc.or.jp/cement/1jpn/jc.html (Last accessed: November 25, 2022).

high temperatures. This process causes chemical reactions of raw materials inside a kiln and yields clinker. The final procedure of mixing ground clinker with gypsum produces cement. As demonstrated, the production process of cement is simple.

Cement kilns are the heart of this simple production process, and it is important for us to understand some technical aspects of cement kilns in Japan. Prior to our sample period, in the 1960s, the suspension preheater (SP) process was imported from Germany, and due to its high energy efficiency, SP kilns gained popularity and took a dominant position. Most of the newly built kilns in the 1960s were SP kilns, and in the 1970s, continuing improvements were made by Japanese engineering firms and cement firms, and new suspension preheater (hereinafter NSP) kilns were developed.[4] The main innovation of NSP kilns is attaching pre-calciner to the SP kilns, which breaks down CaCO3 in limestone into CaO and CO2 in an efficient way, and this feature enabled further mass production. In our data, after 1970, almost all newly built kilns were NSP kilns, and this homogeneity of investment also simplifies our analysis.

Note that the existing literature emphasizes the importance of spatial differentiation. For example, Miller and Osborne (2014) show that importance of import competition affects prices and Salvo (2010) shows that the potential threat of import competition restricts market power. However, as Japan is geographically isolated from other countries and cement is a bulky good, import and export were not so large in the period of our focus.[5] As for domestic spatial differentiation, as many plants are located near the ocean and shipping costs are low, the scope of spatial differentiation is limited.

2.2 Data Sources

For this study, we combine two complementary plant-level data sources: (i) *Cement Yearbook (Cement Nenkan)*, published by the Cement Press Co. Ltd. (Cement Shinbunsha), and (ii) Census of Manufacture, collected by the Japanese Ministry of Economy, Trade, and Industry. The yearbook mainly provides plant-level information on production out-

[4]For interested readers, Shimoda (2016) has a detailed discussion and explanation of the history of technology evolution in the cement industry.

[5]See Panel (a) of Figure 1 in Okazaki, Onishi and Wakamori (2022).

put (in tons), number of workers, and ownership and geographical location of the plants. In addition to these basic characteristics of the plants, the dataset also contains the types and the number of kilns that each plant owns, and their monthly production capacity (in tons), defined as how much clinker a plant can produce when operating for 600 hours per month. These variables on production technology at each plant make this dataset special. Although the technology each plant employs is typically unobserved in the census data, the Yearbook dataset provides such kiln-level information. By contrast, the Census of Manufacture provides a similar but slightly different set of information on the plants, i.e., the total shipment value (in JPY), material inputs (in JPY), number of employees, total wage (in JPY), investment (in JPY), and asset values (in JPY).

Note that the sample periods for these two data sources are slightly different. We obtain the former data from 1970 to 2010, whereas we obtain the latter data from 1980 to 2010 because the data from 1970 to 1979 are unavailable. We combine these two data sources via some common variables in both data sources. We impute the plant-level wage and material inputs before 1980 using the census data and variables that we observe throughout the entire sample period. See Appendix A for details.

2.3 Summary Statistics and Key Features

Summary statistics of our data are given in Table 1. Panel (A) presents plant-level summary statistics pooling all years, whereas Panels (B1), (B2), and (B3) present plant-level statistics for the years 1970, 1990, and 2010, respectively. Furthermore, Panels (C1) and (C2) present plant-level statistics for the plants with and without NSP kilns.

First, according to Panels (B1), (B2), and (B3), the number of observations in 1970 was 53, whereas it was 30 in 2010, implying that the number of plants decreased by about 40% over 40 years. By contrast, as there were four mergers and no entries occurred during this period, the number of firms in 1970 and 2010 was 22 and 18, respectively. These two facts imply that most firms concentrated their production on a single plant or a small number of plants in 2010. Although the number of plants decreased sharply, monthly capacity and annual clinker production per plant have increased over 40 years, so industry-level

Table 1: Summary Statistics

	Num. of Obs.	Mean	Std. Dev.	Min.	Max.
Panel (A): Plant-Level Statistics (All)					
Monthly Capacity (tons)	1,672	190,085	124,810	25,000	696,250
Annual Clinker Production (tons)	1,672	1,772,267	1,297,989	27,910	8,082,269
Average Cement Price (JPY/ton)	1,672	10,354	2,609	5,800	17,075
# of Workers (person)	1,672	193	141	16	1303
Average Wage per Worker (JPY)	1,672	4.38	1.44	.922	13.77
Share of NSP Kilns	1,672	.567	.427	0	1
Panel (B1): Plant-Level Statistics in 1970					
Monthly Capacity (tons)	53	128,396	80,840	25,000	350,000
Annual Clinker Production (tons)	53	1,025,507	621,417	48,000	2,684,197
Average Cement Price (JPY/ton)	53	5,965	202.0	5,800	6,900
# of Workers (person)	53	318	175	114	1,205
Average Wage per Worker (JPY)	53	2.32	.527	.928	3.62
Share of NSP Kilns	53	0	0	0	0
Panel (B2): Plant-Level Statistics in 1990					
Monthly Capacity (tons)	41	178,472	111,121	30,000	553,417
Annual Clinker Production (tons)	41	1,836,281	1,160,588	255,000	5,428,197
Average Cement Price (JPY/ton)	41	11,550	1,375	9,600	13,200
# of Workers (person)	41	169	94.4	57	560
Average Wage per Worker (JPY)	41	4.47	.571	2.83	5.41
Share of NSP Kilns	41	.750	.379	0	1
Panel (B3): Plant-Level Statistics in 2010					
Monthly Capacity (tons)	30	165,567	127,285	36,167	557,083
Annual Clinker Production (tons)	30	1,561,800	1,321,220	276,000	6,169,000
Average Cement Price (JPY/ton)	30	10,076	471.0	9,000	10,900
# of Workers (person)	30	104	65.5	34	371
Average Wage per Worker (JPY)	30	5.98	.842	4.32	7.91
Share of NSP Kilns	30	.861	.300	0	1
Panel (C1): Plants with NSP Kilns					
Monthly Capacity (tons)	1,234	212,440	130,193	31,667	696,250
Annual Clinker Production (tons)	1,234	2,025,289	1,365,910	131,550	8,082,269
Average Cement Price (JPY/ton)	1,234	10,889	2,265	5,883	17,075
# of Workers (person)	1,234	170	100.0	31	824
Average Wage per Worker (JPY)	1,234	4.74	1.38	1.40	13.77
Panel (C2): Plants without NSP Kilns					
Monthly Capacity (tons)	438	127,102	79,703	25,000	445,140
Annual Clinker Production (tons)	438	1,059,415	698,583	27,910	3,848,100
Average Cement Price (JPY/ton)	438	8,850	2,911	5,800	15,800
# of Workers (person)	438	259	205	16	1303
Average Wage per Worker (JPY)	438	3.38	1.13	0.92	6.96

Notes: This table reports summary statistics for the following variables: Monthly (Production) Capacity, measured in ton; Annual Clinker Production, measured in ton; Average Cement Price, measured in JPY per ton; Number of Workers, measured in number of people; Average Wage per Worker, measured in 1,000,000 JPY; and Share of NSP Kilns, defined as the fraction of NSP kilns out of total number of kilns in a given plant. Panel (A) shows summary statistics for all observations between 1970 and 2010. Panels (B1) to (B3) show summary statistics for some selected years to see the variation within a year and the changes in the variables over time. Panels (C1) and (C2) show summary statistics for the plants with and without NSP kilns.

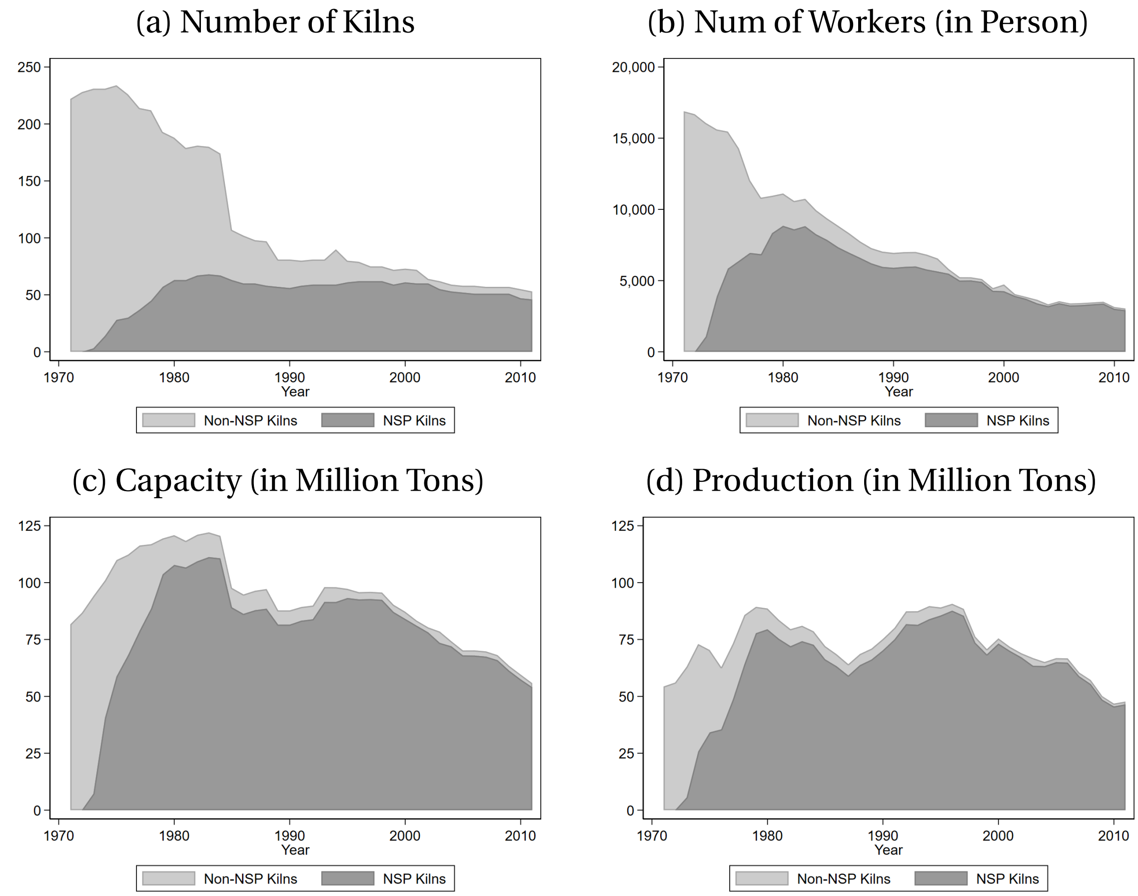
capacity and production have decreased only slightly. [6]

Second, the fraction of the number of NSP kilns at plant has increased considerably. There were no NSP kilns in 1970, whereas the old kilns were mostly replaced by NSP kilns over 40 years. To further see the change in cement production technology, Panel (a) of Figure 1 graphically shows the absolute number of kilns and share, by technology, i.e., types of kilns, over time. In 1970, the initial year of our sample period, there were about 220 kilns, the majority of which were kilns of old types. SP kilns accounted for less than 20%, and there were no NSP kilns. During the 1970s, however, NSP kilns dramatically increased their popularity, maintaining their dominant position after the 1980s. Based on Panels (C1) and (C2) of Table 1, we can clearly see that the plants with NSP kilns have larger production capacity, yielding more clinkers with fewer workers. We can clearly see that the plants with NSP kilns have larger production capacity, yeilding more clinkers with fewer workers in panels (b) to (d) of Figure 1. These observations can be also confirmed numerically in panels (C1) and (C2) of Table 1. In our main analysis, we explore monopsony power, the markups, and the labor share with and without controlling for this technology information.

Third, the number of workers has decreased sharply; the average number of workers per plant in 1970 was 318, whereas it was 104 in 2010. Figure 2 plots the plant-level number of employees over time. The solid line denotes the median, whereas the dotted lines denote the first and the third quantiles. This decrease in the number of workers means that the labor productivity—measured in output per worker—also increased over 40 years, as we see that the plant-level clinker production has increased. By contrast, though the average wage also increased over time, the change in the average wage is not as large as the change in labor productivity. These facts raise a couple of questions: whether this reduction in the number of workers was driven by the adoption of new tech-

[6] We might notice that there was a drop in the capacity of the industry in the early-mid 1980s without a significant change in employment. During the period, the industry experienced excess capacity problem after the two waves of the oil shock. Japanese government implemented the capacity coordination policy to let the cement firms to divest old kilns and reduce excess capacity. Since these divested old kilns were not utilized for production, we observe capacity reduction without declining employment. Okazaki et al. (2022) conducts the detailed welfare analysis of this policy.

Figure 1: Diffusion of Technology



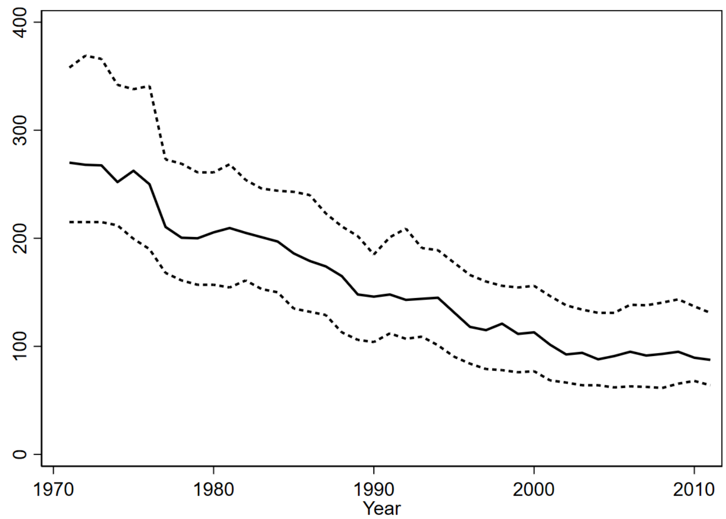
Note: Panel (a), (b), (c), and (d) graphically demonstrate the number of cement kilns, the number of workers, the production capacity, and the total production amount in the industry by types of kilns.

nology and whether the gap between growth in labor productivity and wages was due to increased monopsony power of firms in the labor market.

3 New Technology and Implications for Production Function

In this section, to investigate how to capture the diffusion of new technology as a change in the production function, we first examine the effects of the adoption on outcome variables such as the number of employees, wages, production capacity, output value, and capital-labor ratio, using an event study design à la Callaway and Sant'Anna (2021). We then show that new technology adoption comes with a change in the shape of produc-

Figure 2: Number of Workers per Plant Over Time



Note: This figure plots the plant-level number of employees over time. The solid line depicts the median, whereas the dotted lines depict the first and the third quantiles.

tion function by estimating the production function with information on plant technology. More specifically, we show that cement production becomes more capital-intensive when plants adopt new technology.

3.1 Evidence from Event Study Design

To assess the changes induced by new technology in the production function, we first examine what happened in the plants that have adopted new NSP kiln technology. To this end, we take advantage of the richness of our data, i.e., we can observe the timing of new technology adoption. Using the variation in the timing of technology adoption, we employ an event study design, i.e., difference-in-differences with leads and lags of treatment variable. The objective of this exercise is to descriptively quantify the change in variables of interest before and after the technology adoption, rather than claiming the causal impact of technology adoption. The difference-in-differences framework is convenient for such an objective as well. Formally, we adopt a method proposed by Callaway and Sant'Anna (2021). Here, the adoption of NSP kilns is the "treatment," and we estimate the average treatment effect on the treated (ATT) for each treatment cohort. ATT after τ

years from the treatment for the plants that adopted NSP kilns in year t is identified as:

$$\text{ATT}(t,\tau) = E\left[\left(\frac{G_{it}}{E[G_{it}]} - \frac{\frac{p_t(X_{i,t-1})C_{it}}{1-p_t(X_{i,t-1})}}{E\left[\frac{p_t(X_{i,t-1})C_{it}}{1-p_t(X_{i,t-1})}\right]}\right)(y_{i,t+\tau} - y_{i,t-1})\right], \tag{1}$$

where G_{it} is one if plant i adopts NSP kilns in year t and zero otherwise, C_{it} is one if firm i never adopts or has not yet adopted NSP kilns and zero otherwise, $p_t(X_{i,t-1})$ is the probability that plant i adopts NSP kilns in year t conditional on $G_{it} = 1$ or $C_{it} = 1$, and y_{iu} is the outcome variable of plant i in year u.[7] We define ATT τ years from the treatment as the weighted average of $\text{ATT}(t,\tau)$, that is,:

$$\text{ATT}(\tau) = \sum_t w_t \text{ATT}(t,\tau),$$

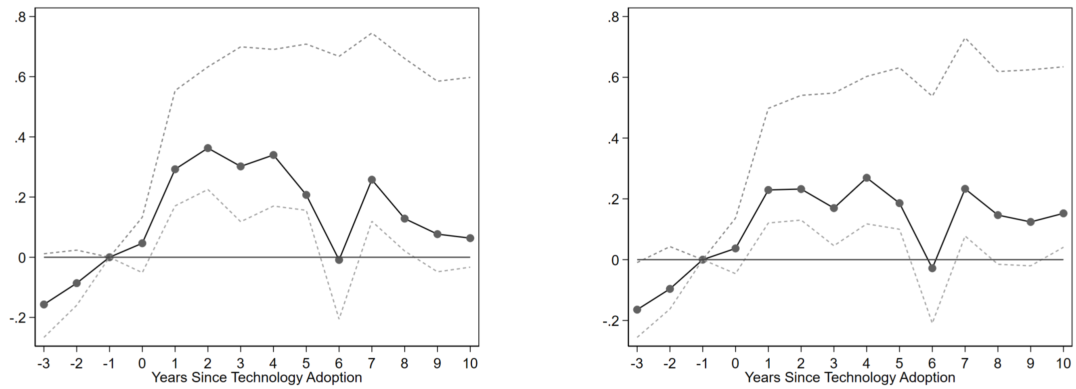
where w_t denotes the weight, which is the number of plants treated in year t divided by the total number of treated firms.

We estimate $\text{ATT}(t,\tau)$ by replacing the expectation with the empirical average, and $p_t(X_{i,t-1})$, the propensity score, by estimating a probit model. For $X_{i,t-1}$, we use the logarithm of plant i's total capacity and production quantity, the number of kilns at plant i, the vintage of the oldest kiln at plant i, and the logarithm of the number of plants in the region, and we estimate a separate probit model for each year. The estimated coefficient for the year before the adoption ($\tau = -1$) is normalized to be zero by construction. To fully utilize the data, we estimate $\text{ATT}(\tau)$ for $\tau = -3, -2, \ldots, 9, 10$, because the adoption of NSP kilns started in 1973 but the data is available only from 1970.

Figure 3 plots the evolution of plant-level revenue (PQ) and output quantity (Q) relative to the timing of the new technology adoption to examine whether output-level indeed increases by technology adoption. The x-axis shows the years relative to the year of NSP kiln adoption and the y-axis shows the estimated ATT. Here, the year of NSP kiln

[7] Callaway and Sant'Anna (2021) propose to use never treated individuals as the control group. However, it is not feasible in our context because the number of plants that never adopted NSP kilns is too small to derive any meaningful inference. In addition, they provide computer codes for Stata and R to implement the estimation and provide the option to use never-treated and not-yet-treated individuals as the control group.

Figure 3: The Effects of New Technology Adoption on Plant-level Revenue and Output Quantity



(a) Revenue (PQ) (b) Output Quantity (Q)

Note: This figure plots the estimated effect of new technology adoption from the event-study design, Equation (1). The year before the adoption is normalized to be zero.

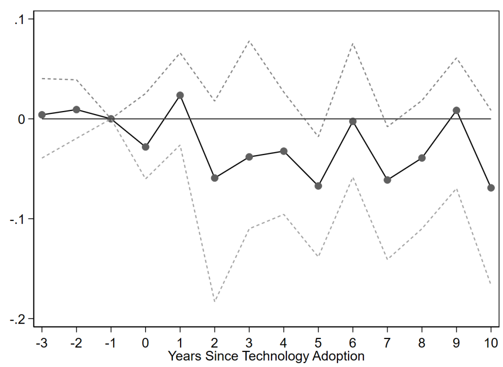
adoption is defined by the year the plant installed its first NSP kiln.[8] The solid line presents the estimated ATT, and the gray dotted lines represent a 90% confidence interval. The confidence interval is constructed by the bootstrap method with 200 replications. When we look at the solid line in Panel (a), revenue jumps after a year of the technology adoption and stays constant after two years. It takes two years for the production quantity to increase because it requires adjustment time to operate the new production facilities at full capacity. One may worry that the change is driven by the change in the cement price. This may be a valid concern if a new technology produces higher-quality output. However, in the cement industry, the output quality is homogeneous, and it is hard to believe the cement price varies based on the technology. To confirm that the change is attributed to output quantity rather than price, we estimate the same equation with output quantity itself in Panel (b). The estimates in Panels (a) and (b) are almost identical, suggesting that new technology adoption indeed increases the output level.

We next investigate the impacts of technology adoption on the input side. There is no clear difference between the treated group and the control group in terms of wage growth (per person) as in Panel (a) of Figure 4. Panel (b) of Figure 4 plots the evolution

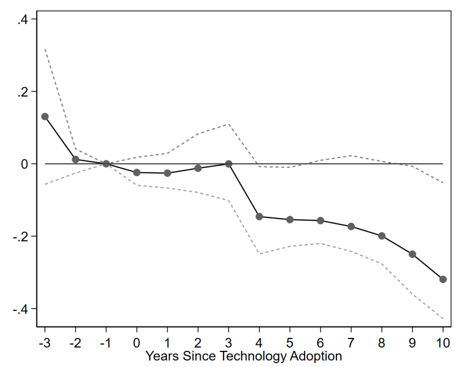
[8]A plant typically has multiple kilns, and the adoption of NSP kilns is typically gradual, i.e., each plant replaces one or two of its kilns first and then replaces the remaining kilns over time.

of plant-level (log) employment relative to the timing of new technology adoption. The number of employees decreases gradually and the estimated effect becomes statistically significant after 9 years of the new technology adoption. In the long run, the number of workers decreases by 20%. The growth of output, together with the decline in the number of workers, implies that labor productivity defined by output per worker has increased.

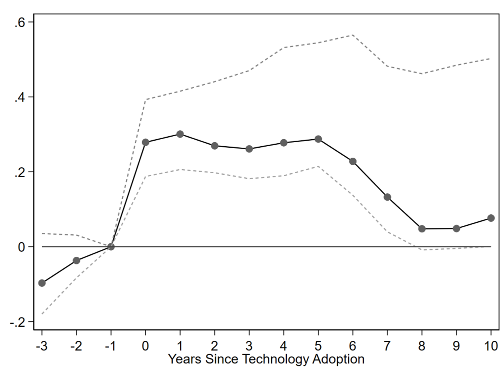
Figure 4: The Effects of Adoption of New Technology on Plant-Level Outcomes



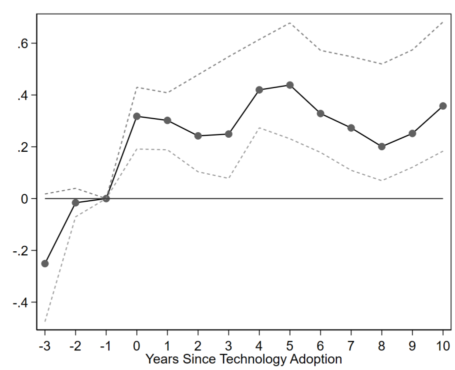
(a) Wage Growth (per Person)



(b) log(Num Workers)



(c) log(Capacity)



(d) Capital-Labor Ratio

Note: This figure plots the estimated effect of new technology adoption from the event-study design, Equation (1). The year before the adoption is normalized to be zero.

Why does labor productivity increase without any change in wage growth? To answer this question, we plot the evolution of plant-level (log) capacity relative to the timing of new technology adoption in Panel (c) of Figure 4. Capacity increases right after the adoption and stays at a higher level compared with the preadoption period. Similarly, Panel (d) of Figure 4 plots the evolution of plant-level capital-labor ratio relative to the timing of new technology adoption. As implied by the results in Panels (a) and (c), the capital-labor ratio increases, which suggests that the production technology and optimal capital-labor ratio are different between non-NSP kilns and NSP kilns.

3.2 Technology Adoption and the Shape of the Production Function

Our findings in the previous subsection—the increase of output quantity in tandem with the increase in capital-labor ratio after new technology adoption—are very difficult to rationalize if the new technology simply increases TFP. This is because if the new technology adoption simply increases TFP, what we should have seen is an increase in output quantity and labor input aswell as a constant capital-labor ratio. However, we observe an increase in the capital-labor ratio—a decrease in the number of workers together with an increase in capacity—after the new technology adoption, which should not happen if the new technology adoption just brings a change in TFP.

Then, what are the implications of these findings for production function? The recent literature on factor-augmenting technical changes, such as Doraszelski and Jaumandreu (2018), Zhang (2019), Raval (2023), and Demirer (2022), suggests that our findings may be explained by incorporating labor-augmenting technical changes. Although we could employ such an approach, we adopt a more straightforward one. Taking advantage of the data where we can directly observe technology for each plant, we estimate production functions separately by technology, because it is more natural to assume that the shape of production functions differs across technologies.

Here, we assume that the production function takes a Cobb-Douglas form:

$$Y_{it} = A_{it} K_{it}^{\beta_k^\tau} L_{it}^{\beta_l^\tau},$$

where Y_{it} is the quantity of the output, A_{it} is the TFP, K_{it} is the physical capacity, L_{it} is the total wage payment, and $(\beta_k^\tau, \beta_l^\tau)$ is a set of parameters to be estimated for technology τ, $\tau \in \{\text{old, new}\}$. Following De Loecker and Scott (2016), Ackerberg et al. (2015), and De Loecker et al. (2020), we estimate the structural value-added production function and take the material input into the production process as a fixed-proportion (Leontief) technology. Formally, we consider the following production technology:

$$Y_{it} = \min\{\beta_{mt} M_{it}, A_{it} K_{it}^{\beta_{kt}} L_{it}^{\beta_{lt}}\},$$

where $\beta_{mt} M_{it}$ captures the material contribution to the final output. We use this specification to follow De Loecker et al. (2020), and believe that this specification is reasonable for the cement industry, because the final output is constrained by the chemical reaction of intermediate inputs, e.g., limestone and cray, regardless of the production technology. With this specification, we can also avoid potential identification problems regarding intermediate inputs and gross output production function, pointed out by Gandhi et al. (2020).

The specification is written as

$$y_{it} = \beta_k^\tau k_{it} + \beta_l^\tau l_{it} + \omega_{it} + \varepsilon_{it},$$

where each lowercase variable is in the form of a logarithm, ω_{it} is an unobserved productivity shock, and ε_{it} is the unanticipated shock to output or measurement errors. We control the unobserved productivity shock with a control function with the value of investment i_{it} as in Olley and Pakes (1996) and Ackerberg et al. (2015):

$$\omega_{it} = h^\tau(k_{it}, i_{it}).$$

The estimation procedure consists of two stages. First, we nonparametrically estimate

$$y_{it} = \phi^\tau(k_{it}, l_{it}, i_{it}) + \epsilon_{it},$$

where $\phi^\tau(k_{it}, l_{it}, i_{it}) = \beta_k^\tau k_{it} + \beta_l^\tau l_{it} + h(k_{it}, i_{it})$. Given the productivity process $\omega_{it} = g(\omega_{it-1}) + \xi_{it}$ and $\omega_{it} = \phi^\tau(k_{it}, l_{it}, i_{it}) - \beta_k^\tau k_{it} - \beta_l^\tau l_{it}$ from the first stage, we estimate a set of parameters θ including β_k^τ and β_l^τ using the following moment condition:

$$E[\xi_{it}(\theta) | \mathcal{I}_{it-1}] = 0,$$

Table 2: Production Function Estimates With and Without Technology Information

	(i) Pooling Both Technologies	(ii) Separately Old Tech	(ii) Separately New Tech	(iii) Pooling Both Technologies
β_k	0.971	0.778	0.907	0.872
	(0.110)	(0.110)	(0.085)	(0.071)
β_l	0.184	0.259	0.099	0.237
	(0.140)	(0.103)	(0.096)	(0.094)
β_0 (TFP Gain)	-	-	0.106	0.060
	-	-	(0.710)	(0.103)
N	1,408	1,408		1,408

Notes: This table reports the production function estimates based on Ackerberg et al. (2015). Column (i) reports the estimates by pooling all data and estimating a single production function, column (ii) reports the estimates by allowing for technology specific productivity as well as technology specific coefficients on capital and labor, and column (iii) reports the estimates by allowing for technology specific productivity but common coefficients on capital and labor.

where $\mathcal{I}_{it-1}$ is plant i' information set at time $t-1$, which includes $(i_{it-1}, k_{it}, l_{it-1})$.

Table 2 summarizes the estimation results. Column (i) demonstrates the results when we estimate the labor and capital coefficients by pooling all plants regardless of their technology:

$$y_{it} = \beta_k k_{it} + \beta_l l_{it} + \omega_{it} + \varepsilon_{it},$$

whereas Column (ii) demonstrates the results when we estimate them separately for each technology via introducing kiln-type dummies and their interaction terms with other variables to obtain output elasticities by kiln types:

$$y_{it} = \beta_k^{old} k_{it} + \beta_l^{old} l_{it} + \mathbf{1}_{\{\text{NSP Kilns}_{it}\}}(\beta_0 + \beta_k^{new} k_{it} + \beta_l^{new} l_{it}) + \omega_{it} + \varepsilon_{it}. \tag{2}$$

Standard errors are calculated by the bootstrap method with 200 replications.

When we estimate the model by pooling all plants, β_k is close to 1, and β_l is about 0.18, implying that technology exhibits increasing returns to scale. By contrast, when we estimate the model separately for each technology, as in Column (ii), capital and labor coefficients are 0.778 and 0.259 for old technology and 0.907 and 0.099 for new technology, respectively, implying that both technologies no longer exhibit economies of scale.

One of the reasons for technology exhibiting economies of scale when estimating the model by pooling both technologies is omitted variable bias. As mentioned in Section 2, NSP kilns tend to be larger in size and have higher TFP (more efficient) than the older types of kilns. Thus, if we do not control for the TFP gain of new technology, $\mathbf{1}_{\{\text{NSP Kilns}_{it}\}}\beta_0$ in Equation (2), we would have an upward bias for capital and labor coefficients, as there are positive correlations between the TFP gain and labor input and between the TFP gain and capital input.

Coming back to the results in Column (ii), as we expect, the new technology is more capital intensive, whereas the old technology is more labor intensive. We indeed test a hypothesis that $H_0 : \beta^k_{old} = \beta^k_{new}$ and reject the null hypothesis at the 10% significance level. Therefore, profit-maximizing plants would need less labor, which results in a lower level of labor share. When more plants adopt new technology, the industry-level labor share falls consequently.

One natural concern is that we may reach the same conclusion by just including the technology dummy in the production function. To address this concern, we check how the estimated production function would change by including technology fixed effects, and the estimated results are presented in Column (iii). First, note that the scale parameter, i.e., $\beta_k + \beta_l$, is about 1.15 in Column (i), whereas the scale parameter is close to 1 in Column (ii) of Table 2 . Because new technology plants are more efficient (higher TFP) and have a larger capacity, ignoring the technology information creates an upward bias in the scale parameter as the plant size is seemingly correlated with efficiency. With technology fixed effects but with a single input elasticity for capital and labor (Column (iii)), the scale parameter is in between these, about 1.1, suggesting that the bias is at least partly mitigated. Interestingly, both the estimated capital coefficient and labor coefficient also fall between the estimated coefficients for old and new technology reported in Column (ii), suggesting that it is still different from our specification. These results indicate that technology fixed effects alone are not enough to capture the difference in technology.

So far, we have estimated the Cobb-Douglas production function. This functional

Table 3: Production Function Estimates (Translog)

		(i) Pooling	(ii) summary by technology	
			Old Tech	New Tech
β_k	mean	0.942	0.952	0.940
	median	0.942	0.955	0.940
	Std. dev.	0.022	0.026	0.020
β_l	mean	0.124	0.097	0.131
	median	0.127	0.097	0.132
	Std. dev.	0.034	0.040	0.028

Notes: This table summarizes the plant-level output elasticities of the translog production function based on Ackerberg et al. (2015). Column (i) reports the mean and median of output elasticities with respect to capital and labor. Column (ii) reports the mean, median, and standard deviation of output elasticities across plants without NSP kilns and across plants with NSP kilns.

form may not be able to flexibly capture the output elasticities, because they are constant across firms. The existing studies often estimate translog production function for allowing output elasticities to be more flexible, partly because its output elasticities can be varied across plants. For that reason, we also estimate translog production function, without using technology information, and examine whether this functional form actually captures the difference in production technology, i.e., whether plants with NSP kilns have lower output elasticity for labor and higher one for capital as is shown in Section 3.1 and in the Table 2.[9]

Table 3 summarizes the plant-level output elasticities of the translog production function without using the information on plant-level production technology. The mean output elasticity with respect to capital is 0.942, whereas the mean output elasticity with respect to labor is 0.124. These numbers are consistent with the estimates in Column (i) of Table 2. Column (ii) shows the mean, median, and standard deviation calculated by each technology type. The output elasticities for plants without NSP kilns are 0.952 and 0.097, on average, for capital and labor, while those for plants with NSP kilns are 0.940 and 0.131. As we can see in standard deviations, the translog production function allows

[9]Another functional form assumption used frequently in the literature is time-varying specification as in De Loecker, Eeckhout and Unger (2020) and Foster, Haltiwanger and Tuttle (2022). We also follow their approach when estimating markups in Section 4.2.

for heterogeneity in output elasticities across plants so that we can estimate output elasticity more flexibly than in the case of the Cobb-Douglas production function that imposes constant output elasticities. However, Column (ii) clearly shows that the translog specification of production function does not capture the heterogeneity in production technology across plants: whether plants have NSP kilns or not does not affect the output elasticities, and on average, plants *without NSP kilns* have lower output elasticity for labor and higher one for capital, which is not consistent with our findings in Section 3.1 and in Table 2. Contrary to one's expectation, the use of translog specification does not solve the issue, as it is just a second-order approximation of the underlying production function assuming common output elasticities across plants and does not capture technological changes in the production function.

4 Implications for Monopsony Power and Markups

Our analysis in the previous section reveals that new technology exhibits a different shape of production function compared with old technology. The gradual adoption of NSP kilns creates heterogeneity in production technology, even within the same industry. In this section, we investigate the issues arising from such heterogeneity in production technology in the context of monopsony power and markups.

In this section, to simplify the discussion, we consider two theoretical examples with either monopsony power, i.e., the market power in the labor market, or markups, i.e., the market power in the product market, separately. We present a model with both monopsony power and markups in Appendix B. Empirically, in the production function approach, the market power is measured as the difference between the marginal cost of production input and the marginal revenue of the same input, the estimated market power is the mixture of both the market power in the product market and the market power in the input market. Therefore, we cannot separately identify these two market power.

4.1 Does Firms' Monopsony Power Increase?

As documented in Stansbury and Summers (2018), several studies find that wedges between the growth rate of wages and the growth rate of the MRPL have been increasing. In many existing studies, however, we cannot observe plant-level technology information and estimates of production function would be biased, as we see in Table 2. This subsection, therefore, examines whether monopsony power increases over time in this industry in the presence of production technology information. More specifically, by using production functions estimated separately for new and old technologies, we calculate the growth rate of MRPL and compare it with the evolution of wage growth to see how the results would change if we did not have kiln information for the analysis.

4.1.1 A Simple Theoretical Model

As discussed in Section 3, production function estimates without technology information would be biased. Such a bias may further result in a qualitatively different conclusion on MRPL. To address such concerns, it is crucial to examine the relationship between MRPL and wages with and without technology information.

Formally, we consider the following production function;

$$Y_i = A_i K_i^{\beta_k} L_i^{\beta_l},$$

where Y_i is the physical unit of the output of firm i, A_i is the TFP, K_i is the physical capacity, L_i is the total number of employees, and β_k and β_l are the parameters to be estimated. Also, assume that the labor market competition is imperfect, i.e., firm i faces the following inverse labor supply function: $W_i(L_i) = \zeta L_i^{\epsilon_W}$. The profit-maximizing plant solves the following problem;

$$\max_{L_i} P_i Y_i - W_i(L_i) L_i,$$

where we assume that the labor input is the only variable input. The first-order condition of the problem induces

$$W_i = \frac{1}{1+\epsilon_W}\beta_l \frac{P_i Y_i}{L_i} = \frac{1}{1+\epsilon_W}\text{MRPL}_i,$$

which implies that the wage equals to the MRPL if the labor market is competitive, i.e., $\epsilon^W = 0$, but the wage is less than MRPL when market power exists. The industry-level MRPL is simply the weighted average of the firm-level MRPL as

$$\text{MRPL} = \sum_i \omega_i \text{MRPL}_i,$$

where ω is a weight, e.g., market shares or cost shares. In this environment, as long as the labor market is competitive or market power in the labor market is constant over time, the MRPL, both at the firm level and the industry level, and the wage should grow at the same rate. This is a testable implication of the model, and, in fact, many studies compare wage growth and MRPL growth. From the Data, researchers can estimate MRPL by substituting β_l with an estimate, $\hat{\beta}_l$.

In this environment, consider a case where there are two different types of firms. One type of firm has labor-intensive (old) production technology characterized by $Y_i = A_i K_i^{\beta_k^O} L_i^{\beta_l^O}$ and the other type of firm has capital-intensive (new) technology characterized by $Y_i = A_i K_i^{\beta_k^N} L_i^{\beta_l^N}$, where $\beta_k^N > \beta_k^O$ and $\beta_l^O > \beta_l^N$. At firm-level, the optimization problem takes the same form and we can derive the same wage-MRPL relationship as

$$W_i = \frac{1}{1+\epsilon_W}\beta_l^\tau \frac{P_i Y_i}{L_i} = \frac{1}{1+\epsilon_W}\text{MRPL}_i,$$

where τ denotes firm i's technology.

Suppose that the true environment is with two technologies, but researchers cannot distinguish the technologies and, therefore, estimate a single $\hat{\beta}_l$ by pooling all the data. A single estimate of β_l, $\hat{\beta}_l$, creates a discrepancy between the estimated MRPL and the wage, i.e., $\widehat{MRPL}_i - W_i = (\hat{\beta}_l - \beta_l^\tau)\frac{1}{1+\epsilon_W}\frac{P_i Y_i}{L_i}$. As a result, when a firm adopts the new technology in period t, the growth rate of the wage and the growth rate of MRPL seemingly become discrepant. Formally, the fraction of both growth rates is

$$\frac{\widehat{MRPL}_{it}/\widehat{MRPL}_{i,t-1}}{W_{it}/W_{i,t-1}} = \frac{\left(\hat{\beta}_l \frac{1}{1+\epsilon_W}\frac{P_{it}Y_{it}}{L_{it}}\right) / \left(\hat{\beta}_l \frac{1}{1+\epsilon_W}\frac{P_{i,t-1}Y_{i,t-1}}{L_{i,t-1}}\right)}{\left(\beta_l^N \frac{1}{1+\epsilon_W}\frac{P_{it}Y_{it}}{L_{it}}\right) / \left(\beta_l^O \frac{1}{1+\epsilon_W}\frac{P_{i,t-1}Y_{i,t-1}}{L_{i,t-1}}\right)} = \frac{\beta_l^O}{\beta_l^N} > 1,$$

whereas the growth rate of the wage and true MRPL would be the same.[10] This means that we observe a faster growth rate for MRPL compared to the wage when we do not have technology information at the firm level even though both grow at the same rate. As the industry level wage and MRPL are the weighted average of firm-level variables, these two variables show growing discrepancy when new technology is diffusing in the industry.

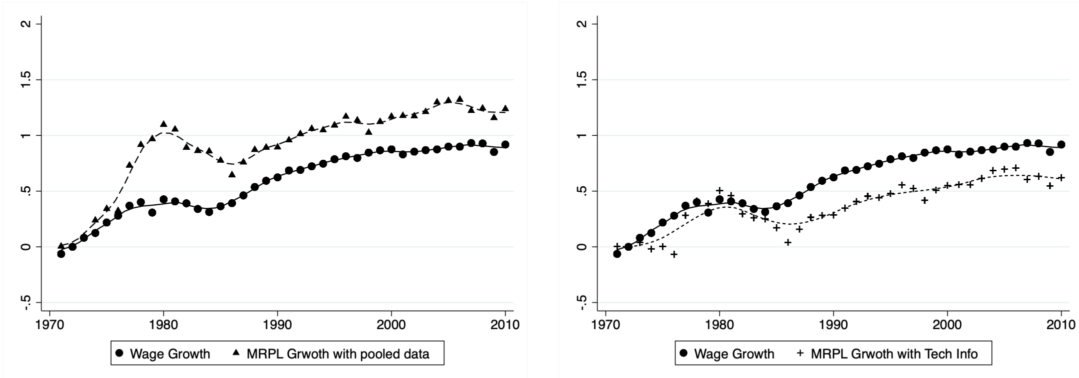
4.1.2 The Evolution of MRPL and Wage

Figure 5 plots the growth of industry-level real wage and MRPL. On the one hand, in Panel (a), we plot them using all the data pooled and not controlling for the technology at each plant. As is clear from the plot, the growth rate of the real wage and MRPL diverge during the period when the new technology diffuses in the industry. More specifically, the growth rate of real wage is lower than that of MRPL over time, implying that monopsony power increases during this period. In a typical dataset where we do not observe technology clearly, we would reach the same observation as in the literature—wage and MRPL diverge.

On the other hand, Panel (b) plots the same variables, but the production functions are separately estimated for new and old technologies. The plots differ from those of Panel (a). After controlling for plant-level technology, wage growth and MRPL growth are more closely aligned, suggesting that monopsony power does not increase over time or even decreases over time. When production shifts from labor-intensive plants to capital-intensive plants, if we do not control for the technology of the plants, the growth of MRPL is overestimated, which leads to a seemingly disconnected relationship. By contrast, in Panel (b), there is still some difference between the two variables, but these two vari-

[10] Here, we assume $\hat{\beta}_l$ to be time-invariant.

Figure 5: Growth of Real Wage and MRPL



(a) With Pooled Data (b) With Technology Controlled

Note: This figures plots the growth of the estimated MRPL together with the growth of real wage. The estimated MRPL in Panel (a) is based on production function estimation where we assume all plants have a common production function, whereas the estimated MRPL in Panel (b) is based on production function where we allow for technology-specific productivity as well as technology-specific coefficients on capital and labor.

ables grow together at a similar rate overall. These results highlight the importance of controlling for the technology to draw implications from data and the usefulness of our complementary approach.

When we use the estimates from the translog production function, this result does not change. Figure D1 in Appendix D plots the growth of industry-level real wage and MRPL with the translog specification. The gap between the two growth rates still increases over time. Although the translog production function is more flexible than the Cobb-Douglas case, it does not result in correctly capturing heterogeneity in production technology, and thus, it exhibits the seemingly increasing trend in monopsony power over time.

4.2 The Increase in Markups

There is a growing interest in how concentration affects macroeconomic conditions, and there are a number of studies that show that the increase in markups is paired with the decline of labor share. The literature follows the methods proposed by De Loecker and Warzynski (2012) and De Loecker et al. (2020) and estimates markups using a production function approach, assuming the optimality of variable inputs. Recently, a few studies (e.g., Raval, 2023; Doraszelski and Jaumandreu, 2019) have questioned whether the markup implied from cost minimization captures the actual product-level markups accurately. In this paper, we find another potential factor that may bias the estimated markups: the lack of information on plant- or firm-level technology. We find that, in the absence of technology information, the adoption of more capital-intensive technology at some plants would lead to an overestimation of their plant-level markups implied by cost minimization. Thus, as more and more plants switch to the new production technology, the industry-level markup would be overestimated, as if the labor share decline is caused by the increasing markups.

4.2.1 The Role of Technology Information

Let us first provide a similar example as in the previous section to highlight the mechanism by which the lack of information on the technology would lead to a bias in the industry-level markup.[11] Consider an environment where firm i has a production technology characterized by $Y_i = A_i K_i^{\beta_k} L_i^{\beta_l}$. In addition, suppose firm i faces a demand curve characterized by $P_i(Q_i) = \xi_i Q_i^{-\epsilon}$ where $\epsilon < 1$. The labor market is competitive with wage level w, and each firm maximizes its profit by choosing its optimal level of labor input. Firm i solves the following maximization problem:

$$\max_{L_i} P_i(Q_i)Q_i - wL_i \quad \text{subject to} \quad Q_i \leq A_i K_i^{\beta_k} L_i^{\beta_l}.$$

In this environment, we can analytically solve for the markup firm i charges. The corresponding cost minimization problem to the abovementioned profit maximization is

$$\min_{L_i} wL_i \quad \text{subject to} \quad Y_i \geq \overline{Q}.$$

The first-order condition of this problem gives us an analytical expression of the markup, which is given by

$$\text{Markup}_i = \beta_l \frac{P_i Y_i}{wL_i} = \frac{1}{1-\epsilon}.$$

Note that this markup is constant and solely depends on the demand elasticity ϵ. In this environment, researchers can easily estimate the markup when β_l is estimable. As P_i, Y_i,

[11] Again, to simplify the discussion, the model below assumes there is no monopsony power. In Appendix B, we present a model where both monopsony power and market power exist.

L_i, and w are in the data, firm i's markup can be estimated with an estimate of β_l, $\hat{\beta}_l$, by

$$\widehat{\text{Markup}}_i = \hat{\beta}_l \frac{P_i Y_i}{w L_i}.$$

The industry-level markup can be estimated by the weighted average of the firm-level markups by

$$\widehat{\text{Markup}} = \sum \omega_i \widehat{\text{Markup}}_i,$$

where ω_i is an appropriate weight (such as the share of sales).

Now, furthermore, consider again a case where there are two different types of firms. One type of firm has labor-intensive production technology characterized by $Y_i = A_i K_i^{\beta_k^O} L_i^{\beta_l^O}$ and the other type of firm has capital intensive technology characterized by $Y_i = A_i K_i^{\beta_k^N} L_i^{\beta_l^N}$, where $\beta_k^N > \beta_k^O$ and $\beta_l^O > \beta_l^N$. Even in this case of heterogeneous technologies, the markup is constant, $1/(1-\epsilon)$, regardless of production technology at each plant. Suppose the researchers do not have direct information on the production technology each firm uses and estimate a single production function, a single value for β_k and β_l, by pooling all the observations. Let $\tilde{\beta}_l$ be an estimate from such a misspecified model. When $\tilde{\beta}_l$ is used to estimate the firm-level markup, the estimated firm-level markups would be biased because

$$\widetilde{\text{Markup}}_i^t = \tilde{\beta}_l \frac{P_i Y_i}{w L_i} = \tilde{\beta}_l \frac{\beta_l^t}{\beta_l^t} \frac{P_i Y_i}{w L_i} = \frac{\tilde{\beta}_l}{\beta_l^t} \frac{1}{1-\epsilon},$$

where $t \in \{N, O\}$ denotes the type of firms. As $\beta_l^O > \beta_l^N$, the estimated markups for each technology under this misspecification would be different and have the relationship, $\widetilde{\text{Markup}}_i^O < \widetilde{\text{Markup}}_i^N$, even though the markups in this environment must be identical and only depend on the demand elasticity, ϵ. In addition, if $\tilde{\beta}_l \in (\beta_l^N, \beta_l^O)$, then the markup is downward biased for labor-intensive firms and upward biased for capital-intensive firms.

In an environment with heterogeneous technologies, as firm-level markups are constant across firms, the industry-level markup would also be constant. When production shifts from plants with labor-intensive technology to plants with capital-intensive technology, the misspecified model would lead to an increase in the estimated industry-level markup because the estimated industry-level markup is a weighted average of the estimated firm-level markups and $\widetilde{\text{Markup}}_i^O < \widetilde{\text{Markup}}_i^N$. If researchers had the firm- or plant-level technology information, such an issue would not arise, i.e., if the model is correctly specified and a production function is separately estimated for each technology, the estimated markups for both firm-level and industry-level would be constant.

This example matches the data pattern observed in the Japanese cement industry well; there are labor-intensive (old types of kilns) and capital-intensive (NSP kilns) technologies, and production has shifted to plants with NSP kilns because more and more plants adopt NSP kilns. Therefore, a natural concern arises that we would reach a qualitatively different conclusion as to whether a rise in markups is the main driver of labor share decline when we have or do not have plant-level technology information.

4.2.2 The Estimation of Markup

Given the aforementioned potential concern, we examine how the estimated markups change over time with and without controlling for the plant-level technology. For this purpose, we first hypothetically assume that we do not observe plant-level technology and follow De Loecker et al. (2020) to estimate the industry-level markups. Then, we use the estimation results in Section 3 and estimate markups taking into account the plant-level technology. The difference between these two tells us how the estimated markups are affected by the technology information.

For the case without technology information, again, we assume a Cobb-Douglas production function as

$$Y_{it} = A_{it} K_{it}^{\beta_{kt}} L_{it}^{\beta_{lt}}, \tag{3}$$

where we allow the shape of the production function to change over time as in De Loecker et al. (2020), i.e., β_k and β_l now depend on time t as well. The corresponding cost minimization problem is written as

$$\min_{K,L} r_t K_{it} + w_t L_{it} \text{ subject to } Y_{it} \geq \overline{Q},$$

and the implied markup is

$$\text{Markup}_{it} = \beta_{lt}\frac{P_t Y_{it}}{W_t L_{it}}. \tag{4}$$

In the estimation in Section 3, we consider a structural value-added production function where we took the material input into the production process as a fixed-proportion (Leontief) technology. Under this specification, the markup that takes into account the material input can be expressed as

$$\text{Markup}^M_{it} = \frac{1}{\text{Markup}^{-1}_{it} + \frac{P^M M_{it}}{P_t Y_{it}}}, \tag{5}$$

where Markup_{it} is the markup estimates from Equation (4) and $P^M M_{it}$ is total material spending. For the case with technology information, we follow the same steps and use the estimates in Table 2.[12]

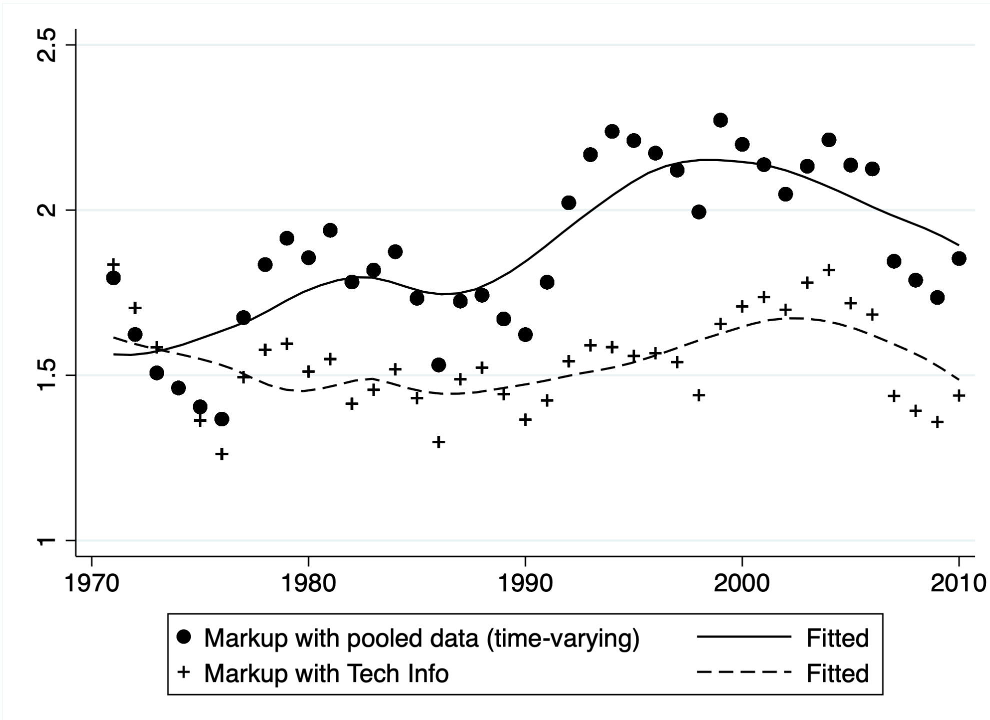
Figure 6 plots the industry-level markups with and without controlling for the plant-level technology; The dashed line plots the industry-level markups with controlling for technology, using the separate estimates for each technology as in Table 2, whereas the solid line plots the industry-level markups without controlling for technology but allowing the time-varying production function.[13] When we do not control for the technology as in the solid line, the estimated markup increases from mid-1970 to early 1980 when the new technology diffuses and production shifts to plants with new technology. By contrast, the estimated markup after controlling for the plant-level technology stays around 1.5 for the corresponding period. Until 1976, the estimated markups are almost identical for the both cases, whereas the discrepancy starts to appear as the new technology emerges. These contrasting plots, again, highlight that the availability of information on technology could change the result and its implications, qualitatively.[14]

[12]This procedure does not require us to estimate β_m, because we can directly estimate the input-adjusted markups from the markup in Equation (4) and the material share, $\frac{P^M M_{it}}{P_t Y_{it}}$.

[13]In the Japanese cement industry, there are about 30-50 plants per year. Given the small number of observations, we estimate the time-varying production function by smoothly approximating it via trigonometric polynomials. To check the robustness of the results, we also estimate the production function with a different approximation specification in Figure C1 in Appendix C, where we confirm qualitatively similar results.

[14]Interestingly, both markups with and without controlling for the plant-level technology seem to increase around the early 2000s. These increases may be due to the changes in market structure because

Figure 6: Markups With and Without Technology Information (Trigonometric Polynomials)



Note: This figure plots the aggregate markups over time, together with a linear polynomial fitted value. Markups are calculated using the estimates of production function controlling or without controlling plant-level technology information.

Our results are robust to (i) the functional form of the time-dependency of production function and (ii) the functional form of the production function itself. To address the first point, we allow the capital and labor coefficients to be arbitrarily different every five years, i.e., estimating different coefficients for years in 1971-1975, 1976-1980, 1981-1985, and so on. We plot the estimated markups together with the markups controlling for technology information in Figure C1 in Appendix C, where we observe qualitatively and quantitatively similar patterns; The markups are almost identical until mid-1970 with the discrepancy starting from late 1970s. For the second point, we estimate a translog production function and conduct the same exercise, where we plot the results in Figure C2. The results quantitatively differ from the results with Cobb-Douglas but the main

four mergers and one acquisition took place around this period, as studied by Nishiwaki (2016). To see this, Figure D2 in Appendix D plots the industry-level HHI, and the HHI indeed increased during this period. Having said that, our claim here highlights the importance of technology information and the mechanism of why the markups increase during this period is beyond the scope of our paper.

take-away remains the same; The markups seemingly increases from late 1970s when observations are pooled, whereas the markups stay constant when we explicitly control for the technology. See Appendix C for more detailed discussion of this robustness check exercise.

Our results are consistent with the recent findings of Demirer (2022), Raval (2023), and Jaumandreu (2022); Though they do not directly observe technology information, they account for technological differences across firms indirectly through labor-augmenting productivity and find relatively stable markups over time. In particular, we have similar quantitative results as those of Demirer (2022). Using the manufacturing industries in the US, he finds that the aggregate markup has risen from 1.3 in 1960 to 1.45 in 2012, though the aggregate markup has increased further without controlling for labor-augmenting productivity.

These studies and our study complement each other. Our results give support for their findings by highlighting the importance of technological changes in production, and their studies provide ways to reconcile these technological changes when we do not have access to technology information to derive implications on markups. An alternative way to take heterogeneity explicitly into account as a latent variable and incorporate it into a structural model is considered by Kasahara, Schrimpf and Suzuki (2022).

5 Implications of Technology Adoption for Labor Share

In the previous sections, we highlight the importance of technology information when quantifying the evolution of monopsony power and markups and correctly deriving implications for them; Without technology information, the estimated output elasticities are biased, which results in a qualitatively different conclusion on monopsony power and markups. In addition, our approach, collecting information on plant-level production technology and the timing of new technology adoption, complements existing macroeconomic debates on why labor share recently declined.

As discussed in the introduction, an enormous number of studies have investigated this issue, proposing many hypotheses to explain this phenomenon. Grossman and Oberfield (2022) classify these hypotheses into the following five categories: (i) technological changes (e.g., Karabarbounis and Neiman, 2014; Acemoglu and Restrepo, 2020; Autor et al., 2020), (ii) declining worker power in labor relations (e.g., Stansbury and Summers, 2020; Drautzburg et al., 2021), (iii) increased exercise of product market power by large firms (e.g., Barkai, 2020; De Loecker et al., 2020), (iv) globalization and the rise of China (e.g., Abdih and Danninger, 2017; Sun, 2020), and (v) changes in the composition of the workforce (e.g., Glover and Short, 2020; Acemoglu and Restrepo, 2020). Among these hypotheses, technology plays a key role; Not only some hypotheses related to technical changes but also other hypotheses—increasing monopsony power and product market power—hinge on technology, because estimation of marginal revenue products of labor and markups is often based on estimates of the production function, as demonstrated in the previous section. Therefore, the existing studies that do not control for technology may obscure the difference between technological changes and other factors.

We first show that the adoption of NSP kilns is the main driver for the decline of labor share in the industry by descriptive and event-study analysis. Then, using the estimates of production function in the previous section, we decompose the changes in the labor share into a technology-related component and a market-power-related component that includes monopsony power in the labor market and market power in the product market.

5.1 Descriptive and Reduced-form Evidence

To examine whether the labor share has been declining in this industry, we first plot the industry-level labor share, defining the labor share as the total wage payment divided by the monetary value of total output.[15] In Figure 7, each dot represents the labor share for each year and the gray line represents the smoothed nonparametric fit.

[15] As the Census data are available only after 1980, we compute the labor share using the data in the Cement Yearbook. More specifically, the total wage payment is computed as the number of employees multiplied by the average wage and the monetary value of total output is computed as the output multiplied by the average cement price in that region.

Figure 7: Industry-level Labor Share

Note: This figure plots the industry-level aggregate labor share over time, together with a local-polynomial fitted value.

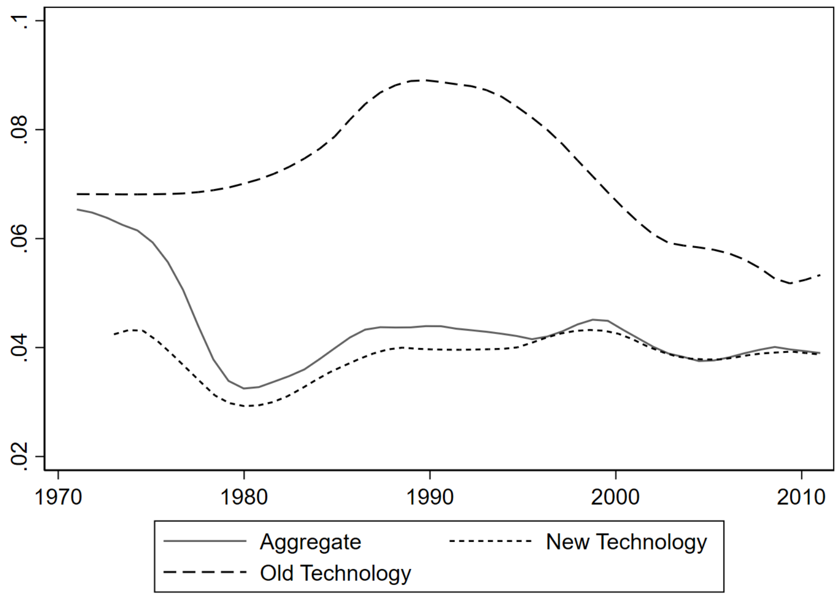
The industry-level labor share falls over our sample period with a sharper decline when the new technology diffuses between 1973 and the early 1980s, as we see in Figure 1. The presented labor share is very low. This is due to two factors. First, our definition of labor share is based on the total output value rather than the value added. We perform the same exercise with value-added as the denominator, and we confirm qualitatively the same results with a higher level of labor share, around 10%.[16] Second, the cement industry is a heavy equipment industry, and, by its nature, the labor share is lower compared with other industries.

The virtue of our approach is that we observe the exact technology used at each plant. To quantify how much the diffusion of new technology contributes to the decline of the labor share, we replicate the analysis in Figure 7 *conditional on* the plant-level technology. In Figure 8, we plot the average labor share within plants with new technology (the dotted line), the average labor share within plants with old technology (the dashed line), and the industry-level labor share (the solid line). The last line, the industry-level labor

[16]Here, value added is defined as the monetary value of total output minus the material expenditure. Since the material expenditure is only present in the census data, we use the imputed value for the 1970s.

share, corresponds to the solid line in Figure 7. Interestingly, the labor share does not fall within the same technology plants as the dashed and dotted lines stay relatively flat. However, the industry-level labor share, the solid line, falls rapidly as new technology diffuses because the new technology plants have a lower labor share. Figure 8 clearly shows that the decline of labor share is associated with the new technology diffusion.

Figure 8: Labor Share Conditional on Plant-level Technology



Note: This figure plots (1) the local-polynomial fitted value of the industry-level aggregate labor share over time (solid line), (2) the local-polynomial fitted value of the aggregate labor share of plants with old technology over time (dashed line), and (3) the local-polynomial fitted value of the aggregate labor share of plants with new technology over time (dotted line).

To assess the argument more quantitatively in a descriptive manner, we estimate the following equations using the plant-level labor share by ordinary least squares (OLS);

$$\text{LaborShare}_{it} = \beta_0 + \beta_1 t + \beta_2 \mathbf{1}_{\{\text{NSP Kilns}_{it}\}} + F_i + \varepsilon_{it},$$

where i is a plant index, t denotes year, $\mathbf{1}_{\{\text{NSP Kilns}_{it}\}}$ is a dummy variable taking one if a plant owns at least one NSP kiln in year t and zero otherwise, F_i is a plant fixed effects, βs are the parameters to be estimated, and ε_{it} is an independent error term. Here, we are interested in the estimated coefficient on t, i.e., β_1. We expect that β_1 would be es-

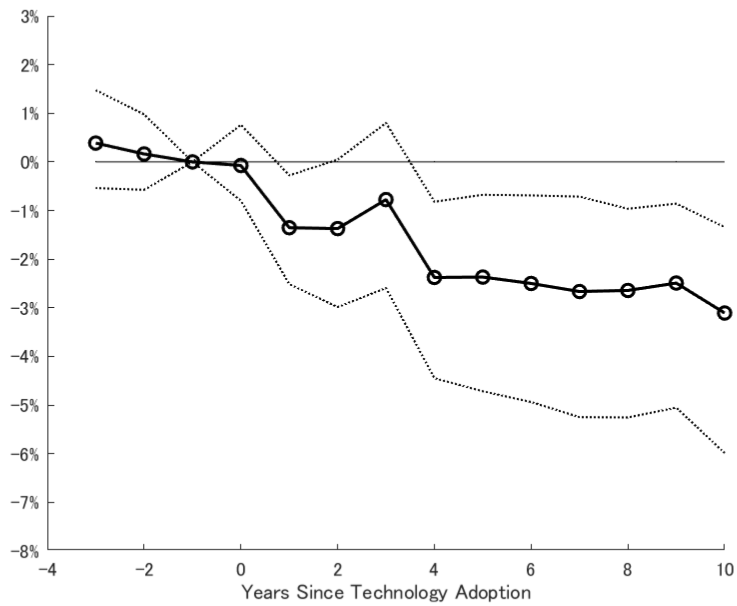
Table 4: Time Trend of Labor Share

Dependent Var.	(i) Labor Share	(ii) Labor Share	(iii) Labor Share	(iv) log(Labor Share)
Year (β_1)	-1.13$\times10^{-3}$ ***	-2.42$\times10^{-4}$	3.71$\times10^{-4}$ ***	0.006***
	(0.157$\times10^{-3}$)	(1.76$\times10^{-4}$)	(0.880$\times10^{-4}$)	(0.001)
NSP kiln dummy (β_2)		-0.0474***	-0.0244***	-0.389***
		(0.00469)	(0.00302)	(0.0301)
Constant	$\surd$	$\surd$	$\surd$	$\surd$
Plant fixed effects			$\surd$	$\surd$
N	1,673	1,673	1,673	1,673

Notes: Standard errors are reported in parentheses and significance levels are denoted by <0.1 (*), <0.05 (**), and <0.01 (***). The dependent variables for specifications (i) to (iii) are labor share, whereas the dependent variable for specification (iv) is logarithms of labor share.

timated as negative when we do not control for the plant-level technology because the industry-level labor share declines over time. By contrast, we expect that β_1 would be estimated near zero or positive when we control for the plant-level technology. Table 4 summarizes the estimation results and confirms our expectations. The first column presents the results without control for technology, and the coefficient on year is estimated as negative and statistically significant. In the second column, once we control for the technology, the significance of β_1 disappears. However, we now find that the coefficient on an NSP kiln dummy, β_2, is estimated as negative and statistically significant, implying that a plant introducing NSP kilns has a lower labor share. When we further control for the plant fixed effects, the estimates become positive and statistically significant. These results are consistent with Figure 8. To quantify the economic significance of the results in the third column, we replace the left-hand-side variable with the logarithm of labor share, which allows us to quantify the percentage change easily. The result is presented in the fourth column, suggesting that the labor share increases at the plant level by 0.6% every year. The magnitude is not very large but not negligibly small. Note that the labor share here is computed using the data from the Cement Yearbook. Even when we use the value-added variables in the census data, we obtain the same qualitative results.

Figure 9: The Effects of New Technology Adoption on Plant-level Labor Share



Note: This figure plots the estimated effect of new technology adoption from the event-study design, Equation (1). The year before the adoption is normalized to be zero.

We again employ event study design to further examine the plant-level changes in the labor share when adopting new technology. Figure 9 plots the evolution of plant-level labor share relative to the timing of the new technology adoption. When we look at the solid line, the labor share starts to decline after the technology adoption. However, the decline is not immediate. Rather, it takes several years. After four years of adoption, the labor share remains below the preadoption level with statistical significance.

5.2 Labor Share Decomposition

In Section 4, we examine the implications of monopsony power and product market power in the presence of technology information and we *cannot* conclude that monopsony power and product market power have increased in this industry. These results suggest that the labor share decline cannot be explained by monopsony power or product market power. To examine our hypothesis—the labor share decline is caused by technology diffusion— from a different angle, we now quantify the impact of technology adoption on the labor share by decomposing the change in the labor share into a technology-related component and a market-power-related component that includes market power in the product market and monopsony power (market power in labor markets).

The labor share can be expressed as

$$LS \equiv \frac{wL}{PQ} = \frac{wL}{wL + rK + \pi} = \frac{\frac{wL}{wL+rK}}{1 + \frac{\pi}{wL+rK}} = \frac{\beta_l}{1 + \frac{\pi}{wL+rK}},$$

where π is the total profit, defined as $\pi = PQ - (wL + rK)$, and β_l is a labor coefficient of production function, Then, the change in labor share is given as

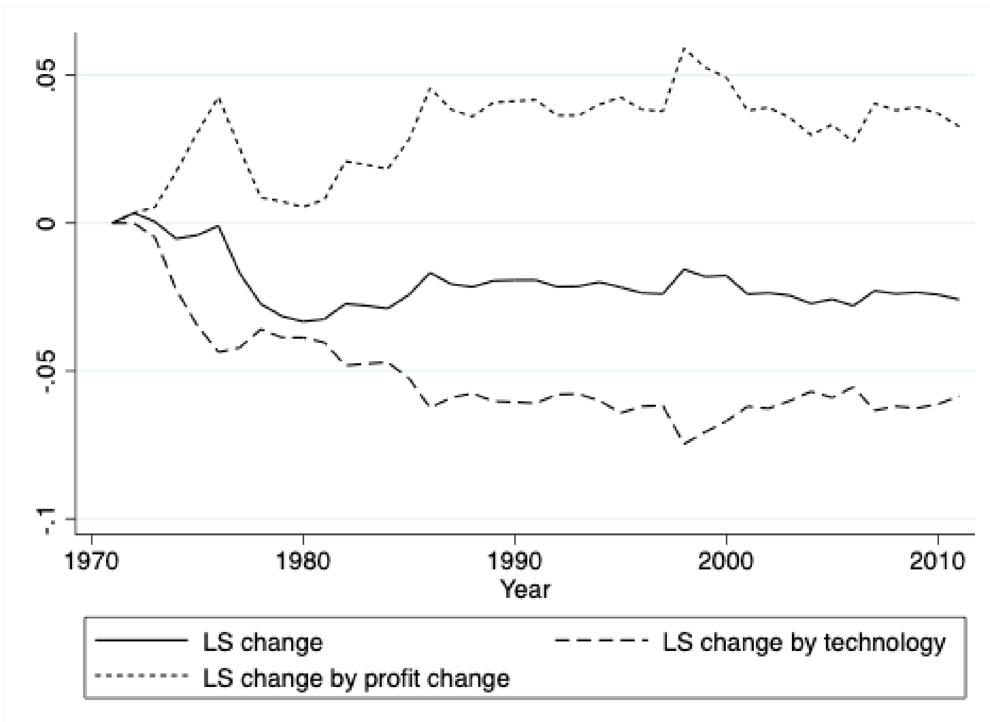
$$\begin{aligned}
LS' - LS &= \frac{(wL)'}{(wL)' + (rk)' + \pi'} - \frac{wL}{wL + rK + \pi}, \\
&= \frac{\frac{(wL)'}{(wL)'+(rk)'}}{1 + \frac{\pi'}{(wL)'+(rk)'}} - \frac{\frac{wL}{wL+rK}}{1 + \frac{\pi}{wL+rK}}, \\
&= \frac{\beta_l'}{1 + \frac{\pi'}{(wL)'+(rK)'}} - \frac{\beta_l}{1 + \frac{\pi}{wL+rK}}, \\
&= \left(\frac{\beta_l'}{1 + \frac{\pi'}{(wL)'+(rK)'}} - \frac{\beta_l}{1 + \frac{\pi'}{(wL)'+(rK)'}} \right) + \left(\frac{\beta_l}{1 + \frac{\pi'}{(wL)'+(rK)'}} - \frac{\beta_l}{1 + \frac{\pi}{wL+rK}} \right).
\end{aligned}$$

The first term corresponds to the change in labor share due to the change in technology (the change in labor coefficient in production function), whereas the second term corresponds to the change in labor share due to the change in market power. Moreover, β_l corresponds to the labor share for old technology in our production function estimation, whereas β_l' corresponds to the labor share for new technology.

Figure 10 demonstrates the result of labor share decomposition. The solid line plots the actual evolution of the labor share, which coincides with Figure 7. The dashed line plots the contribution of the technology adoption to the change in the labor share, whereas the dotted line plots the contribution of the change in profit. First, as discussed in Section 2 and demonstrated in Figure 10, the labor share was about 7% in the early 1970s and about 3% in the 2010s. This decomposition indicates that the labor share could have been even smaller if there were no other factors affecting the labor share. Second, we find that the other factors, including monopsony power or market power in the product market, contribute to an increase in the labor share.

These observations are also consistent with our descriptive analysis in Table 4 in two ways. First, the results in Columns (ii) and (iii) of Table 4 indicate that the labor share decreased by 2-4 percentage points due to technological adoption. This magnitude is identical to our findings in Figure 10. Second, when controlling for other factors through plant fixed effects in Table 4, we find a statistically significant time trend of labor share in Columns (iii) and (iv). The magnitude is again identical to our findings in Figure 10.

Figure 10: Labor Share Decomposition



Note: This figure plots the actual evolution of labor share and its changes caused by technology and profit margin, respectively.

5.3 Remaining Hypotheses: Worker Composition and Globalization

Among the hypotheses listed in the beginning of this section, we have not yet discussed the change in worker composition and globalization.

For the former point, we test whether the change in worker composition occured in the period of our focus, taking advantage of the census data that contain worker composition for some years. More specifically, the Japanese census collected the number of blue-collar and white-collar workers and the total payment bill for these workers for the years 1981, 1984, 1987, and 1990. We tabulate the employment share and payment share of blue-collar workers at non-NSP plants and NSP plants over time in Panels (a) and (b) of Table 5, respectively. These numbers immediately suggest that worker composition did not change over time, at least for these years, because both employment and payment shares at non-NSP and NSP plants are not statistically different from each other. Therefore, the changes in worker share composition cannot be a persuasive explanation for the labor share decline in our context.

Table 5: Employment and Payment Shares of Blue-collar Workers

	Non-NSP Plants		NSP Plants	
	Mean	Std. Dev.	Mean	Std. Dev.
Panel (a): Employment share of blue-collar workers				
1981	.714	.103	.681	.140
1984	.717	.100	.656	.128
1987	.697	.093	.683	.113
1990	.647	.107	.649	.121
Panel (b): Payment share of blue-collar workers				
1981	.731	.118	.666	.125
1984	.695	.082	.646	.137
1987	.671	.101	.677	.122
1990	.592	.170	.673	.113

Note: This table provides employment and payment share of blue-collar workers over 1981-1990. All statistics are based on Census data.

In terms of a globalization hypothesis, we believe it cannot explain the labor share decline in this specific industry, as the import and export of cement were not important in the period of our focus. Even though there are several papers that focus on the cement industry and emphasize the importance of international competition, including Miller and Osborne (2014) who show that import competition affects prices and Salvo (2010) who shows that the potential “threat” of import competition restricts market power, Japan is geographically isolated from other countries. Less than 10%, at maximum, of total cement production was exported to other Asian countries, and there is almost no import from other countries in the period of our focus, according to Okazaki et al. (2022). Therefore, globalization cannot be a major concern in the Japanese cement industry.

Overall, a series of our results suggest that the main driver of the labor share decline is the diffusion of new technology rather than other hypotheses proposed in the literature.

6 Conclusion

We investigate the potential implications of ignoring heterogeneity in production technology owned by each plant on monopsony power, markups, and labor share, using unusually detailed plant-level data of the cement industry in Japan. With information on plant-level technology, estimated monopsony power and markups would have increasing trends over time as more and more plants adopt new capital-intensive production technology. However, when appropriately controlling for the plant-level heterogeneity in production technology, such upward trends would disappear. In addition, we find that most of the labor share decline can be explained by the new technology diffusion; the labor share stays constant or even slightly increases over time within the same technology plants, whereas the aggregate labor share declines because production shifts to plants with new and more capital intensive technology.

References

Abdih, Yasser and Stephan Danninger, "What Explains the Decline of the U.S. Labor Share of Income? An Analysis of State and Industry Level Data," International Monetary Fund Working Papers 2017/167, 2017.

Acemoglu, Daron and Pascual Restrepo, "Robots and Jobs: Evidence from US Labor Markets," *Journal of Political Economy*, 2020, *128* (6), 2188–2244.

Ackerberg, Daniel A., Kevin Caves, and Garth Frazer, "Identification Properties of Recent Production Function Estimators," *Econometrica*, 2015, *83* (6), 2411–2451.

Autor, David, David Dorn, Lawrence F. Katz, Christina Patterson, and John Van Reenen, "The Fall of the Labor Share and the Rise of Superstar Firms," *The Quarterly Journal of Economics*, 2020, *135* (2), 645–709.

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

Callaway, Brantly and Pedro H. C. Sant'Anna, "Difference-in-Differences with Multiple Time Periods," *Journal of Econometrics*, 2021, *225(2)*, 200–230.

Collard-Wexler, Allan and Jan De Loecker, "Reallocation and Technology: Evidence from the US Steel Industry," *American Economic Review*, 2015, *105* (1), 131–171.

De Loecker, Jan and Frederic Warzynski, "Markups and Firm-Level Export Status," *American Economic Review*, 2012, *102* (6), 2437–2471.

_ and Paul T. Scott, "Estimating Market Power Evidence from the US Brewing Industry," NBER Working Paper No. 22957, 2016.

_ , Jan Eeckhout, and Gabriel Unger, "The Rise of Market Power and the Macroeconomic Implications," *The Quarterly Journal of Economics*, 2020, *135* (2), 561–644.

Demirer, Mert, "Production Function Estimation with Factor-Augmenting Technology: An Application to Markups," Unpublished Manuscript, 2022.

Doraszelski, Ulrich and Jordi Jaumandreu, "Measuring the Bias of Technological Change," *Journal of Political Economy*, 2018, *126* (3), 1027–1084.

_ and _ , "Using Cost Minimization to Estimate Markups," CEPR Press Discussion Paper No. 14114, 2019.

Drautzburg, Thorsten, Jesús Fernández-Villaverde, and Pablo Guerrón-Quintana, "Bargaining shocks and aggregate fluctuations," *Journal of Economic Dynamics and Control*, 2021, *127*, 104121.

Foster, Lucia S., John C. Haltiwanger, and Cody Tuttle, "Rising Markups or Changing Technology?," NBER Working Paper No. 30491, 2022.

Gandhi, Amit, Salvador Navarro, and David A. Rivers, "On the Identification of Gross Output Production Functions," *Journal of Political Economy*, 2020, *128* (8), 2973–3016.

Glover, Andrew and Jacob Short, "Can capital deepening explain the global decline in labor's share?," *Review of Economic Dynamics*, 2020, *35*, 35–53.

Grieco, Paul L. E, Charles Murry, and Ali Yurukoglu, "The Evolution of Market Power in the US Auto Industry," NBER Working Paper No. 29013, 2021.

Grossman, Gene M. and Ezra Oberfield, "The Elusive Explanation for the Declining Labor Share," *Annual Review of Economics*, 2022, *14* (1), 93–124.

Humlum, Anders, "Robot Adoption and Labor Market Dynamics," Unpublished Manuscript, 2021.

Jaumandreu, Jordi, "The Remarkable Stability of the US Manufacturing Markups," CEPR Press Discussion Paper No. 17490, 2022.

Karabarbounis, Loukas and Brent Neiman, "The Global Decline of the Labor Share," *The Quarterly Journal of Economics*, 2014, *129* (1), 61–103.

Kasahara, Hiroyuki, Paul Schrimpf, and Michio Suzuki, "Identification and Estimation of Production Functions with Unobserved Heterogeneity," ESRI Discussion Paper Series No. 368, 2022.

Kehrig, Matthias and Nicolas Vincent, "The Micro-Level Anatomy of the Labor Share Decline," *The Quarterly Journal of Economics*, 2021, *136* (2), 1031–1087.

Levinsohn, James and Amil Petrin, "Estimating Production Functions Using Inputs to Control for Unobserbables," *The Review of Economic Studies*, 2003, *70*, 317–341.

Miller, Nathan H. and Matthew Osborne, "Spatial Differentiation and Price Discrimination in the Cement Industry: Evidence from a Structural Model," *RAND Journal of Economics*, 2014, *45* (2), 221–247.

Miller, Nathan, Matthew Osborne, Gloria Sheu, and Gretchen Sileo, "Technology and Market Power: The United States Cement Industry, 1974-2019," Unpublished Manuscript, 2023.

Nishiwaki, Masato, "Horizontal Mergers and Divestment Dynamics in a Sunset Industry," *RAND Journal of Economics*, 2016, *47* (4), 961–997.

Okazaki, Tetsuji, Ken Onishi, and Naoki Wakamori, "Excess Capacity and Effectiveness of Policy Interventions: Evidence from the Cement Industry," *International Economic Review*, 2022, *63* (2), 883–915.

Olley, Steven G. and Ariel Pakes, "The Dynamics of Productivity in the Telecommunications Equipment Industry," *Econometrica*, 1996, *64*, 1263–1297.

Raval, Devesh, "Testing the Production Approach to Markup Estimation," *The Review of Economic Studies*, 2023, *90(5)*, 2592–2611.

Rubens, Michael, "Oligopsony Power and Factor-Biased Technology Adoption," NBER Working Paper No. 30586, 2022.

Salvo, Alberto, "Inferring market power under the threat of entry: the case of the Brazilian cement industry," *RAND Journal of Economics*, 2010, *41* (2), 326–350.

Shimoda, Takashi, "History of Cement Manufacturing Technology," in Center of the History of Japanese Industrial Technology, ed., *Survey Reports on the Systematization of Technologies*, Vol. 23, Tokyo: National Museum of Nature and Science, 2016, pp. 1–114.

Stansbury, Anna and Lawrence H. Summers, "Productivity and Pay: Is the link broken?," NBER Working Paper No. 24165, 2018.

_ and _ , "The Declining Worker Power Hypothesis: An explanation for the recent evolution of the American economy," *Brookings Papers on Economic Activity*, 2020, *2020(1)*, 1–96.

Sun, Chang, "Multinational Production with Non-neutral Technologies," *Journal of International Economics*, 2020, *123*, 103294.

Syverson, Chad, "Macroeconomics and Market Power: Context, Implications, and Open Questions," *Journal of Economic Perspectives*, 2019, *33* (3), 23–43.

van Biesebroeck, Johannes, "Productivity Dynamics with Technology Choice: An Application to Automobile Assembly," *The Review of Economic Studies*, 2003, *70* (1), 167–198.

Yeh, Chen, Claudia Macaluso, and Brad Hershbein, "Monopsony in the US Labor Market," *American Economic Review*, 2022, *112* (7), 2099–2138.

Zhang, Hongsong, "Non-neutral Technology, Firm Heterogeneity, and Labor Demand," *Journal of Development Economics*, 2019, *140*, 145–168.

Appendix A Imputing Missing Variables

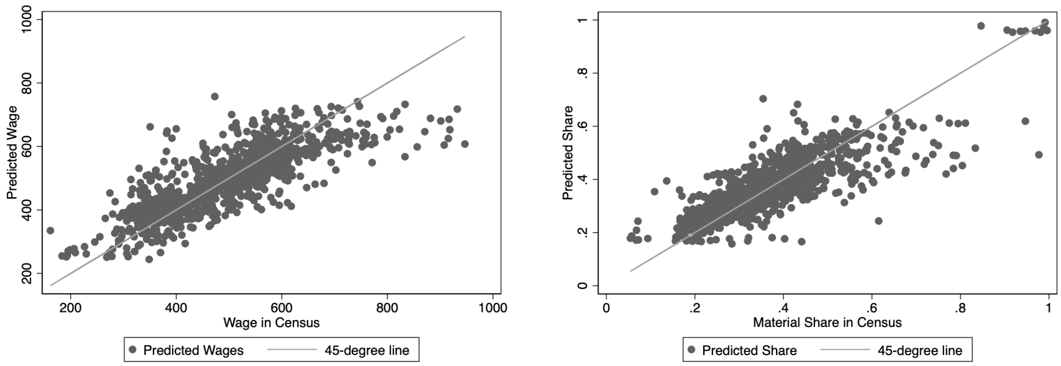
In our analyses, we combine two plant-level data sources: (i) Cement Yearbook(Cement Nenkan), published by the Cement Press Co. Ltd. (Cement Shinbunsha), and (ii) Census of Manufacture, collected by the Japanese Ministry of Economy, Trade, and Industry. The sample periods for these two data sources are slightly different. We obtain the former data from 1970 to 2010, whereas we obtain the latter data from 1980 to 2010 because the data from 1970 to 1979 are unavailable. We impute the plant-level wage and intermediate inputs before 1980 using the census data and variables that we observe throughout the entire sample period.

Plant-level wages from 1970 to 1979 are imputed using prefecture-level wages in the industry, which are available for 1970 to 2010, and plant fixed effects. We regress census wages on prefecture-level wage and plant fixed effects using the period between 1980 and 2010 and predict census wages from 1970 to 1979. We confirm that the prediction matches actual values for 1980-2010 well. The results of our main analysis do not change when we use prefecture-level wages for the entire sample period.

We imputed intermediate input expenditure between 1970 and 1979 as follows. First, we calculate the sales share of the expenditure of intermediate materials, including energy expenses. Then, we take the logit function of this share, $\log(\frac{s}{1-s})$. We regress it on the set of explanatory variables, plant fixed effects, the indicator function whether a plant uses NSP kilns, the number of kilns in the plant, the share of NSP kilns in all the kilns a plant uses, and oil prices. We also control time trends flexibly. After the regression, we predict $\log(\frac{s}{1-s})$ and recover the predicted material share $\hat{s}$ for 1970-1979. This procedure guarantees that the predicted material expenditure does not exceed the value of cement produced.

Figure A1 shows the fit of the prediction for wages and material shares. The x-axis of Panel (a) is wage levels in the census and that of Panel (b) is material shares in the census. The y-axis indicates the predicted value. For both two variables, the dots concentrate on the 45-degree line, which implies that the performance of imputation is good enough.

Figure A1: The Prediction of Imputed Variables



(a) Wages (b) Material Share

Appendix B An Example with Market Power in both the Product Market and the Labor Market

In this appendix, we extend the simple examples in the main text to derive the analytical solution to the relationship with MRPL and wage as well as the solution to the markup. Formally, we again consider the following production function;

$$Y_i = A_i K_i^{\beta_k} L_i^{\beta_l},$$

where Y_i is the physical unit of the output of firm i, A_i is the TFP, K_i is the physical capacity, L_i is the total number of employees, and β_k and β_l are the parameters to be estimated. Also, assume that the product market competition and the labor market competition are imperfect, i.e., firm i faces the following inverse demand function and labor supply function: $P_i(Q_i) = \xi_i Q_i^{-\epsilon_P}$ and $W_i(L_i) = \zeta_i L_i^{\epsilon_W}$. The profit-maximizing plant solves the following problem;

$$\max_{L_i} P_i(Y_i)Y_{it} - W_i(L_i)L_i,$$

where we assume the labor input is the only variable input. The first-order condition of the problem induces

$$W_i = \frac{1-\epsilon_P}{1+\epsilon_W}\beta_l \frac{P_i Y_i}{L_i} = \frac{1-\epsilon_P}{1+\epsilon_W}\text{MRPL}_i,$$

which implies that the wage equals to MRPL if both the product market and the labor market are competitive, i.e., $\epsilon^P = \epsilon^W = 0$, but the wage is less than MRPL when the firm has market power in either the product market or the labor market.

As in the main text, the solution to the markup can be derived by considering the dual problem, cost minimization.

$$\min_{L_i} wL_i \quad \text{subject to} \quad Y_i \geq \overline{Q}.$$

The first-order condition of this problem gives us the marginal cost as

$$\text{Marginal Cost} = \frac{(1+\epsilon_W)L_i W_i}{\beta_l Y}.$$

The FOC from the original profit maximization gives us

$$\frac{1}{1-\epsilon_P} = \frac{\beta_l P_i Y_i}{(1+\epsilon_W)L_i W_i},$$

and the markup is given by combining these two as

$$\text{Markup}_i = \beta_l \frac{P_i Y_i}{(1+\epsilon_W)W_i L_i} = \frac{1}{1-\epsilon_P}.$$

Appendix C Robustness

Figure C1: Markups With and Without Technology Information (Every Five Years)

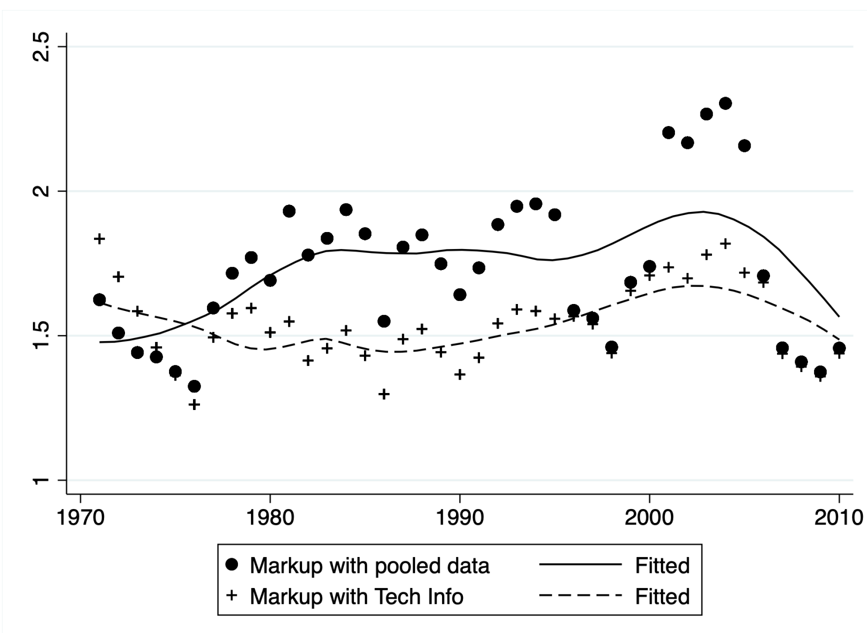
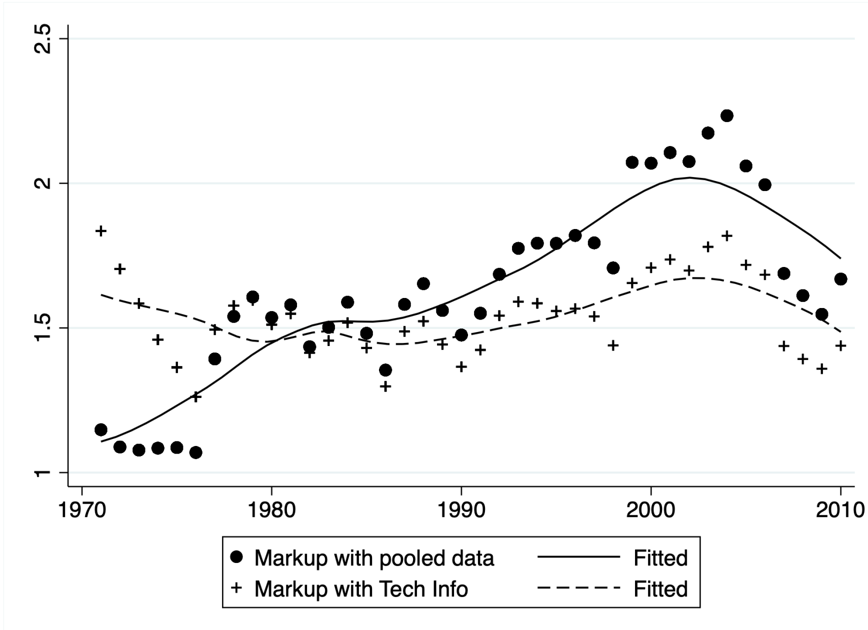


Figure C2: Markups With Translog Production Function



First, to check the robustness of our results to the specification of the technological changes over time, we use the same Cobb-Douglas production function as in Section 3.2 but estimate the production function with allowing the coefficients to change arbitrary every five years. Then, using these estimates, we obtain the markups over time. We plot them together with the markups controlling for technology information in Figure C1. Again, the dashed line plots the industry-level markups with controlling for technology, using the separate estimates for each technology as in Table 2, whereas the solid line plots the industry-level markups without controlling for technology but allowing the time-varying production function. We have qualitatively similar results as in Figure 6. The markups are almost identical until mid-1970 with the discrepancy starting from late 1970s, though the markups without controlling for technology fluctuate more over time, achieving higher markups around 2004.

Next, to address the robustness to the functional form assumption on production function, we also obtain the markups using the translog specification. Figure C2 compares the evolution of markups from translog specification without using technology information and the one in Table 6 with technology information. The initial level of markups in the early 1970s obtained from the translog production function is lower, and the aggregate markups jumped up in the late 1970s when more and more plants adopted NSP kilns. As a result, it has an increasing trend over time. Although the initial level of markups is lower compared with the Cobb-Douglas specification, the markups increased from 1.1 in 1973 to 2.2 in 2004. This result may lead to the conclusion that the markup increases over time. However, as discussed in Section 3.2, the translog specification fails to capture the difference in output elasticities between NSP kilns and old kilns. As a result, even with translog specification, if we do not have information on production technology, we obtain the same conclusion that markups would have an increasing trend over time when more and more plants adopt and produce with NSP kilns. However, as discussed in 3.2, the translog specification fails to capture output elasticities. We therefore conclude that, in the absence of technology information, regardless of the functional form assumptions,

Appendix D Additional Figures and Tables

Figure D1: Estimated MRPL with Translog Production Function

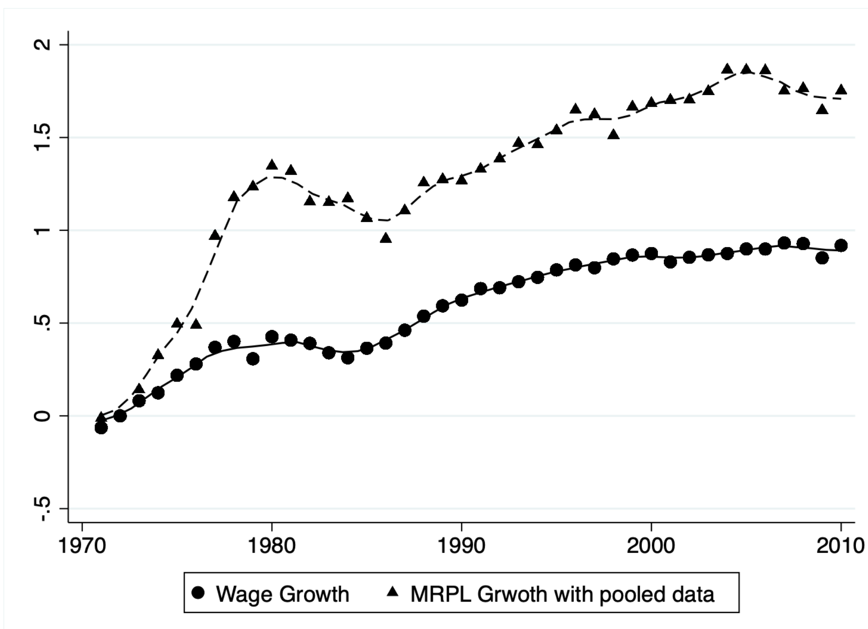


Figure D2: Evolution of the Industry-Level HHI