The Impact of Cartels on Productivity: A Concrete Example from Japan*

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Abstract

We study the impact of cartels on productivity using a novel plant-level dataset from the Japanese ready-mixed concrete industry, where cartels are legally permitted. After estimating plant-level productivity, we adopt a difference-in-differences design to show that cartel collapse increases plant-level and market-level productivity, while cartel formation has no effect. Furthermore, a triple-difference analysis reveals that productivity gains are more pronounced for initially less productive plants and those in high-density markets. These results, combined with decomposition analyses showing that market-level improvements are driven by within-plant changes rather than reallocation or exit, suggest that the treatment effect of competition drives productivity gains.

Keywords: Cartel, Collusion, Productivity, Reallocation
JEL Codes:L11, L41, L61

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1 Introduction

Cartels have long been central to industrial organization, and their effects on prices, quantities, and welfare have been studied extensively.[1] By contrast, much less is known about the supply-side impacts of cartels, despite recent work starting to shed light on misallocation (e.g., Asker, Collard-Wexler, and De Loecker, 2019). Although productivity is a primary determinant of supply-side efficiency, few studies have investigated the direct impact of cartels on productivity. Identifying this effect is empirically challenging because it requires observing variation in cartel activeness together with the rich microdata required to estimate production functions. This paper overcomes this challenge by constructing a novel dataset that links market-year cartel activeness to plant-level production data.

We study the impact of cartels on productivity using this dataset from the Japanese ready-mixed concrete industry, where cartels are legally permitted. We first link plant-level information on inputs and outputs to a dataset on the timing of cartel formation and collapse. After estimating plant-level productivity, we conduct a difference-in-differences analysis and show that cartel collapse increases both plant-level and market-level productivity, while cartel formation has no effect. Furthermore, a triple-difference analysis reveals that productivity gains are more pronounced for less productive plants and for those in markets with higher plant density. These results, combined with decomposition analyses showing that market-level improvements are driven by within-plant changes rather than reallocation or exit, suggest that the treatment effect of competition is the primary driver of productivity gains following cartel collapse.

The Japanese ready-mixed concrete industry is well suited to studying our research question. Ready-mixed concrete producers in Japan are legally permitted to form cartels under relatively relaxed conditions.[2] The market for ready-mixed concrete is clearly defined by a small group of municipalities, and each market has at most one cooperative that functions as a cartel. Although cartels are permitted, they do not enforce themselves, and there are many instances of collapse and formation. This institutional environment allows us to observe the presence of cartels and the timing of their transitions precisely.

We construct a dataset of cartels in Hokkaido, Japan's second-largest island, from an annual industry publication. The dataset includes membership information and the timing of collapse and formation over the period from 1993 to 2004 in 34 markets. We combine this cartel dataset with annual plant-level data from Japan's Census of Manufacture, which covers the universe of ready-mixed concrete plants and includes information on revenue, physical output, labor, and material input expenditure over the period from 1993 to 2020. We augment these data with information from other sources on plants' physical output capacity and market-level demand.

Our empirical approach proceeds in several steps. We start by estimating a production function

[1] See, e.g., the literature surveys by Asker and Nocke (2021) and Levenstein and Suslow (2006).

[2] Articles 22 and 23 of the Antimonopoly Act (Act No. 54 of 1947) provide exemptions for cooperatives that offer mutual support to small-scale enterprises, provided they are established under the Small and Medium-Sized Enterprise Cooperatives Act (Act No. 181 of 1949). See Section 2 for details.

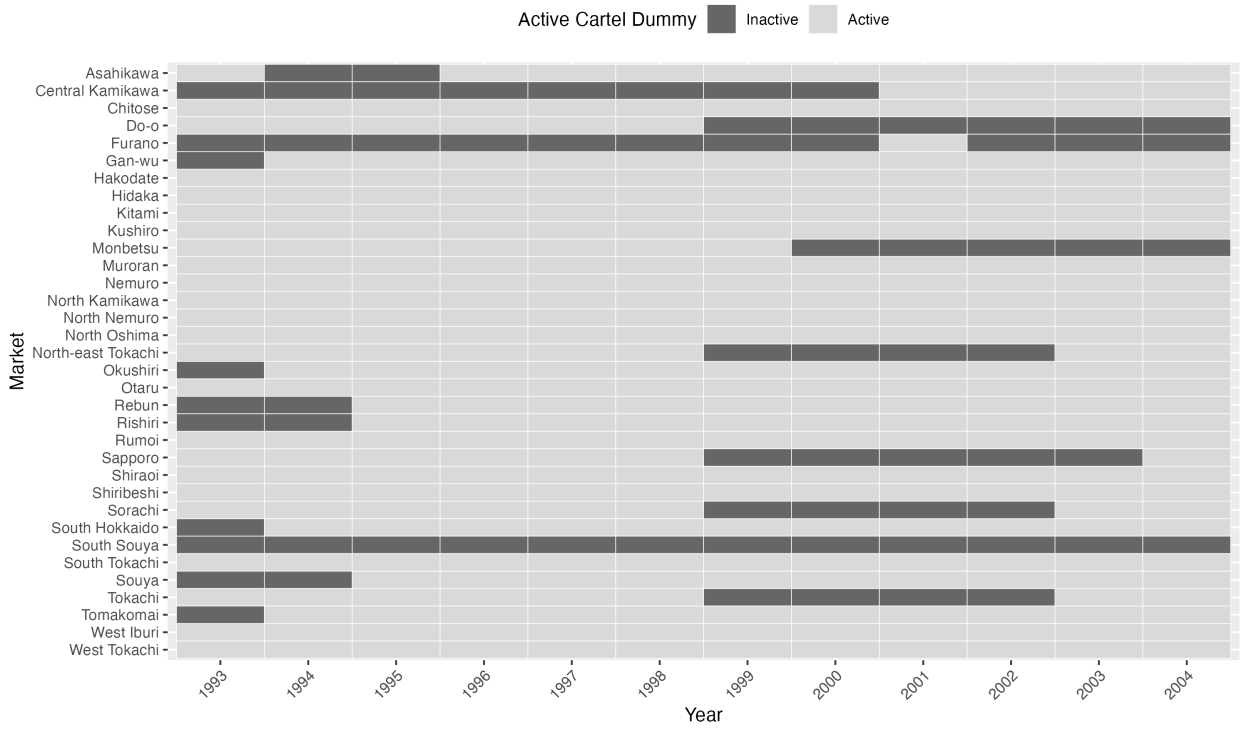


Figure 1: Cartel Activeness by Market

Notes: The figure shows cartel formation, operation, and collapse. Dark shading indicates periods when a cartel was absent; light shading indicates when there was an active cartel.

following Ackerberg, Caves, and Frazer (2015) and accounting for self-selection due to plant exit following Olley and Pakes (1996). We then use the estimated annual plant-level productivity as the dependent variable in our main analysis.

In the main analysis, we first study the plant-level impacts of cartel collapse and formation. We adopt staggered event study designs that are robust to heterogeneous treatment effects, following Callaway and Sant'Anna (2021) and Sun and Abraham (2021). We find that plant-level productivity increased by 14.3 to 19 percent on average following cartel collapse. In contrast, we find no statistically significant effect of cartel formation on productivity.

To address potential endogeneity in cartel collapse, we instrument the cartel collapse indicator with future market demand, given that cartels are more likely to collapse when they face lower future demand. We also address the selection of markets into treatment through propensity score matching. The estimates remain robust to these specifications.

To further understand the mechanism behind within-plant productivity improvements following cartel collapse, we adopt a triple-difference design to examine heterogeneity. Using the z-score of relative productivity within a market prior to treatment, we find that less productive plants improve their productivity more after cartel collapse. We also examine heterogeneity by plant density and find that plants in higher-density markets improve more. These results suggest a potential mechanism: plants that face heightened competitive pressure improve production efficiency more.

Furthermore, we find an employment decline among initially less productive plants and those in high-density markets. This pattern mirrors the heterogeneity in productivity gains and is consistent with the interpretation that these plants reduce labor slack more intensively in response to competitive pressure. This competitive pressure mechanism can partly explain the asymmetric response of productivity to cartel collapse and formation. While the restoration of intense competition acts as a sudden shock that forces rapid managerial improvements, the relaxation of competition following cartel formation is likely more gradual due to uncertainty about the cartel's stability.

We then study the market-level impact of cartel collapse and decompose its effects into within-plant improvement and reallocation to more productive plants. Decomposing aggregate productivity following Olley and Pakes (1996), we show that efficiency gains after cartel collapse are driven almost entirely by the within component, that is, improvements in average plant productivity rather than reallocation of market share toward more efficient plants.

To further disentangle the dynamic selection effects of entry and exit, we adopt the dynamic Olley-Pakes decomposition framework of Melitz and Polanec (2015). The results again show that the productivity gains are almost entirely driven by within-plant improvement. These findings are consistent with Backus (2020), who attributes productivity gains to the treatment effect of competition rather than the selection effect, a finding we complement by exploiting panel variation in cartel activeness to identify this channel.

Related Literature

How cartels and other forms of collusion affect productivity and economic performance is a central question in industrial organization. Most of the literature on the impact of cartels focuses on welfare losses arising from higher prices.[3] A smaller body of work examines how cartels influence industry productivity.[4] This research highlights three main channels: first, distortions in the allocation of production across firms, second, selection of firms resulting from the exit process, and third, effects on within-firm productivity through changes in incentives.

The misallocation channel, whereby cartel rules may distort the allocation of production toward less productive firms, can substantially reduce industry productivity.[5] Using historical cost data, Bridgman, Qi, and Schmitz (2015) show that the rigid quota system of the U.S. sugar cartel generated severe misallocation that eliminated nearly all cartel profits. Asker, Collard-Wexler, and De Loecker (2019) develop a method to quantify misallocation by comparing observed industry cost curves with counterfactual efficient allocations; applied to the global oil industry, they find that high-cost producers remain active while low-cost capacity is underutilized. At the macroeconomic level, Moreau and Panon (2023) calibrate a heterogeneous-firm model to French microdata

[3] See the survey by Asker and Nocke (2021) and Levenstein and Suslow (2006), and more recent studies include Igami and Sugaya (2022), Tiew (2024), Clark and Houde (2013), and Chaves, Clark, Duarte, and Houde (2025).

[4] Holmes and Schmitz Jr (2010) provides a short survey on the impact of cartel closure on productivity in the United States.

[5] The seminal work of Hsieh and Klenow (2009) demonstrates the impact of misallocation on aggregate productivity. See Hopenhayn (2014) for a survey of the broader literature.

and demonstrate that collusion amplifies misallocation. These studies highlight cartel-induced misallocation but treat firm-level productivity as exogenous. We extend this literature by allowing cartels to affect both the allocation of production across firms and productivity within firms, and by decomposing their total impact into these two distinct channels.

The second channel is the effect of selection resulting from firm exit and survival. While no paper explicitly investigates the impact of cartel on exit, there is a large literature studying the impact of selection on productivity.[6] The papers closest to ours are the ones studying this relationship using the U.S. ready-mixed concrete industry. Syverson (2004) considers how competition may affect productivity distribution, and Syverson (2008) decompose the product considers the importance of competition and survival on the market-level productivity. Backus (2020) further tries to decompose the productivity to this selection effect and the plant-level effect of competition. We add to this literature by exploiting a within-market variation in competition resulting from cartel collapse and formation to study the impact of selection on market-level productivity.

Changes in the incentives *within* firms is the third channel that a cartel may affect productivity. The lack of competition itself can reduce firms' incentives to operate efficiently, hence impacting productivity, which Backus (2020) calls *treatment* effect of competition. Using introduction of cartel law in UK, Symeonidis (2008) show cartel negatively affects labor productivity, while Burhop and Lübbers (2009) study the German coal mining cartel and find that cartel membership itself did not affect productive efficiency. Reed, Pereira López, Urrutia Arrieta, and Iacovone (2024) finds that Mexican antitrust sanctions increases productivity for all firms in the industry. Röller and Steen (2006) studies Norwegian cement industry and find that a specific cartel rule led firms to produce inefficiently. Our study complements this literature by combining detailed data on cartel formation and collapse with a plant-level annual panel, allowing us to isolate the treatment effect of competition.

2 Industry Background

Ready-mixed concrete is a fundamental construction material produced by mixing cement, water, sand, and gravel at manufacturing plants and transported to construction sites. As Syverson (2008) argues, the industry has three distinctive characteristics: the product is homogeneous due to standardized quality requirements, transportation barriers create geographically segmented markets, and demand is largely exogenous as concrete costs represent only a small fraction of total construction expenses. The Japanese Industrial Standards (JIS) mandate that concrete must be used within 90 minutes of production, and this time constraint combined with transportation costs creates naturally segmented geographic markets.

A distinctive feature of Japan's ready-mixed concrete industry is the legal status of regional cartels. Articles 22 and 23 of the Antimonopoly Act (Act No. 54 of 1947) exempt partnerships that provide mutual support to small-scale enterprises, provided they are established under the

[6] See, e.g., Foster, Haltiwanger, and Syverson (2008).

Small and Medium-Sized Enterprise Cooperative Act (Act No. 181 of 1949). Under this framework, ready-mixed concrete firms may form regional cooperatives that are permitted to engage in joint sales activities exempt from antitrust regulation. These joint sales arrangements function as cartels by setting common prices and allocating production quotas among member firms. However, coordination across cooperatives remains illegal, confining cartel activities to regional boundaries. Although cooperatives can legally coordinate prices and quantities among their members, they are prohibited from practices that unduly restrict competition, such as preventing construction companies from purchasing concrete from non-member plants.

The historical development of these legal cartels reflects both industry characteristics and policy objectives. The ready-mixed concrete industry consists predominantly of small and medium-sized enterprises with limited bargaining power against large construction companies. To foster industry development and stabilization, joint sales through cooperatives have been permitted since the 1960s, maintained by historical precedent and ongoing concerns about the viability of small producers.

The expansion and evolution of joint sales arrangements reflect changing industry dynamics. In the late 1970s, the Ministry of International Trade and Industry initiated structural improvement plans that promoted joint sales as a mechanism for industry rationalization after the industry was considered to have excessive capacity. Cement manufacturers, who operate in an oligopolistic market with ready-mixed concrete firms as their primary customers, actively promoted joint sales arrangements within cooperatives, leading to rapid spreading of these practices.

The cooperatives enforce joint sales arrangements by allocating orders to its members typically through their weekly or bi-weekly meetings. All member plants usually report their production volume to the cooperatives, often installing monitoring equipment to track member plants' shipment volumes and detect deviations from allocated quotas. Because formal penalties are not contractible, deviations from joint sales arrangements are usually resolved through negotiation.

This study focuses on Hokkaido, Japan's northernmost main island, which comprises 20% of Japan's land area and only 4% of its population.[7] Hokkaido's relatively low population density and sparse distribution of urban areas facilitate a clear definition of geographic markets, making it an ideal setting for analyzing cartel behavior.

Hokkaido's ready-mixed concrete industry experienced substantial restructuring of its cartel arrangements during the study period. Many cooperatives in Hokkaido experienced the collapse and subsequent reconstruction of joint sales arrangements during the 1990s and early 2000s, consistent with national trends. These changes in cartel participation and effectiveness allow for comparison of productivity outcomes under different market structures. Since the late 2000s, joint sales operations have stabilized across the region, providing further variation in the competitive environment faced by firms.

[7] According to official statistics from the Geospatial Information Authority of Japan and the Statistics Bureau of Japan, Hokkaido has a land area of approximately 83,424 km^2, accounting for about 22.1% of Japan's total land area, approximately 377,975 km^2, and a population of about 5.2 million, representing roughly 4.1% of Japan's total population of around 126 million in 2020.

3 Data and Descriptive Statistics

3.1 Data Sources

This study draws upon multiple administrative and industry datasets on Japan's Hokkaido region from 1993 to 2020. The primary data source is the Japanese Census of Manufacture, which covers all manufacturing industries, including the ready-mixed concrete industry. While this annual census typically includes all manufacturing plants with 4 or more employees, it encompasses all plants regardless of size in 1993, 1995, 1998, 2000, 2003, 2005, 2008, 2011, 2015, and 2020. The census provides plant-level annual information on physical output, revenue, employment, and material input expenditures.

The Yearbook of Ready-Mixed Concrete, published by the Concrete Press, serves as our second data source. This comprehensive industry publication provides detailed information on firms and cooperatives, including plant-level data on physical output capacity (number and capacity of mixers), employment, and dates of facility establishment and upgrade. At the cooperative level, the Yearbook documents business territories and the implementation of joint sales practices.

Importantly, from 1993 to 2004, the Yearbook reports cooperatives' self-assessed effectiveness of their joint sales programs at the market level, using five categories: "functioning," "mostly functioning," "not functioning well," "not functioning," and "joint sales not implemented/suspended." This unique feature allows us to observe variation in cartel activeness across markets and over time during this period.

Our third data source is the Hokkaido Ready-Mixed Concrete Engineering Association, which functions as an umbrella organization for regional concrete cooperatives in Hokkaido. This annual dataset provides cooperative membership information and plant-level characteristics including name, location, physical output capacity, and employment. Comparable nationwide data is available from the National Association of Ready-Mixed Concrete Cooperatives from 2001 onward.

The Construction Research Institute's monthly survey of construction material prices constitutes our fourth data source. This survey collects prices of ready-mixed concrete, cement, gravel, and sand across major Japanese cities, which are used as benchmarks for cost estimates of public construction projects. In Hokkaido, ready-mixed concrete and cement prices are monitored in 26 and 6 cities, respectively.

Finally, we use two complementary sources of municipal-level construction demand data from 1993 to 2020. The first is from Statistics on Building Construction Started, which reports total floor area of building projects, including both private and public building construction but excludes civil engineering projects. The second is municipal-level public construction expenditures obtained from Hokkaido Construction Surety Company, which encompasses both building and civil engineering projects.

3.2 Data Construction and Market Definition

We construct a comprehensive annual panel dataset at the plant level by combining the aforementioned data sources. Plant identification across years is achieved by tracking establishments by exact location information in the Census of Manufacture, which enables us to determine entry and exit years regardless of ownership changes.[8] To obtain real material expenditures, we construct a composite deflator using the Bank of Japan's Firm Price Index for normal portland cement, blast-furnace portland cement, and water. Physical production capacity data is compiled by combining information from the Yearbook and both concrete engineering associations. We calculate plant-level prices by dividing revenue by physical output using data from the Census of Manufacture. Our subsequent analysis uses these plant-level price measures as the primary price variable. We impute missing values for plant-level variables.

To measure cartel effectiveness, we construct a dummy variable using the self-assessed joint sales effectiveness reported in the Yearbook from 1993 to 2004. This variable takes the value of 1 when cooperatives report their joint sales as "functioning" or "mostly functioning," and 0 for the remaining categories ("not functioning well," "not functioning," or "joint sales not implemented/suspended").

Regarding the identification of cooperative members and non-members, we use the Hokkaido Ready-Mixed Concrete Engineering Association data to identify them annually.

Our market definition follows cooperative business territories, which serve as distinct geographical markets, typically covering several municipalities, as in Figure 2. These market boundaries are largely determined by geographical factors and have remained stable throughout the sample period, making them reasonably exogenous for our analysis. Overall, we delineate 34 geographical markets in Hokkaido, as illustrated in Figure 2. Despite a few cooperative separations,[9] we maintain the most granular market definitions consistently. We classify municipalities on isolated islands as separate markets, even though they are formally included in mainland Hokkaido cooperative territories.

We construct market-level variables by aggregating plant and municipal data to the market level. Using the Census of Manufacture combined with cooperative membership identification from the Hokkaido Ready-Mixed Concrete Engineering Association data, we calculate the numbers of total plants, cooperative member plants, and non-member plants for each market. We also aggregate municipal-level construction demand measures (total floor area of building projects and public construction expenditures) to the market level. Given the limited coverage of price monitoring locations for cement (the main ingredient in ready-mixed concrete), we assign each market the cement prices from the nearest surveyed city.

[8] During the study period, address formats in Japan underwent a major revision. When addresses did not match across years directly, or when two distinct plants shared the same address, we manually matched plants using auxiliary information such as telephone numbers, firm names, and plant names.

[9] There are three separation cases during the data period. We use the smallest area (i.e., the area corresponding to the area after separation) as the market boundary in such cases. This is because these three areas are all large areas and subdivision of cooperatives works as a regular cooperative before the separation based on our hearing. There was no merger of cooperatives throughout our sample period.

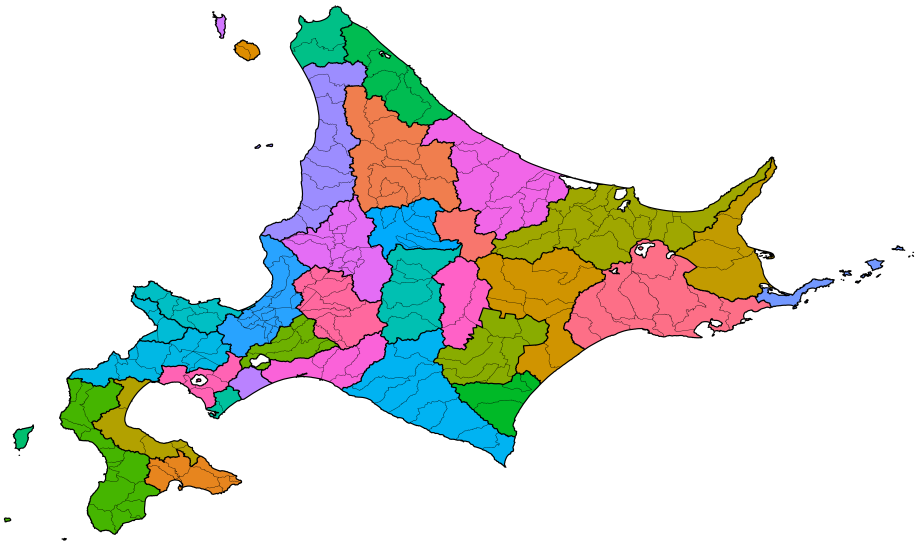


Figure 2: Market Definition in Hokkaido

Notes: This figure shows the 34 markets in Hokkaido. Each colored region bounded by thick lines represents a market. Thin lines within markets indicate municipal boundaries as of 2003.

3.3 Productivity

To analyze the impact of cartels on productivity in the ready-mixed concrete industry, we first need to recover plant-level productivity. We estimate a production function following the methodology of Ackerberg, Caves, and Frazer (2015). For our robustness check considering the possibility that capacity utilization may play a role, we further estimate productivity with capacity utilization as in Appendix B.

We assume that the production function follows a fixed-proportion (Leontief) technology that is appropriate in our context because raw materials such as cement, sand, and gravel cannot be easily substituted with labor or capital in the production of ready-mixed concrete. The production function of plant i at time t takes the following form:

$$Y_{it} = \min\{K_{it}^{\beta_k} L_{it}^{\beta_l} \exp(\omega_{it}), \beta_m M_{it}\} \exp(\varepsilon_{it})$$

where Y_{it} denotes physical output, K_{it}, L_{it}, and M_{it} represent capital, labor, and intermediate inputs, respectively, ω_{it} captures productivity, and ε_{it} is an idiosyncratic error term.

Given the first-order condition of the Leontief production function, the estimating equation in logarithmic form is written as:

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

where lowercase variables denote logarithms of their uppercase counterparts.

We estimate this production function using a control function approach in which intermediate input serves as a proxy for the unobserved productivity shock. The intermediate input demand

function is:

$$m_{it} = m(\omega_{it}, k_{it}, l_{it}, z_{it})$$

where z_{it} represents control variables. Assuming strict monotonicity of $m(\cdot)$ in ω_{it}, we can invert this function to obtain:

$$\omega_{it} = h(m_{it}, k_{it}, l_{it}, z_{it}).$$

Substituting this expression into our production function yields:

$$y_{it} = \beta_k k_{it} + \beta_l l_{it} + h(m_{it}, k_{it}, l_{it}, z_{it}) + \varepsilon_{it}.$$

Following Ackerberg, Caves, and Frazer (2015), we apply a two-stage estimation procedure. In the first stage, we estimate the following equation by OLS:

$$y_{it} = \phi(k_{it}, l_{it}, m_{it}, z_{it}) + \varepsilon_{it}$$

where $\phi(k_{it}, l_{it}, m_{it}, z_{it}) = \beta_k k_{it} + \beta_l l_{it} + h(m_{it}, k_{it}, l_{it}, z_{it})$. Here, k_{it} represents the log of mixer capacity, l_{it} is the log of the number of employees, and m_{it} is the log of total expenditure on material input deflated by the composite deflator described in Section 3.2. Additionally, $z_{it} = (z_{m(i),t},\, d_{it})$ is the vector of control variables, where $z_{m(i)t}$ includes market-level construction floor area of building projects (both private and public, excluding civil engineering), public construction expenditure (all project types), and cement prices (all of which are in logarithmic form) and d_{it} is a plant-level cooperative membership dummy. The function $\phi(\cdot)$ is specified as a third-degree polynomial in k_{it}, l_{it}, and m_{it}, with z_{it} entering linearly.

In the second stage, using the first-stage results, we express productivity as:

$$\omega_{it} = \hat{\phi}_{it} - \beta_k k_{it} - \beta_l l_{it}$$

To estimate the parameters β_k and β_l, we need to model the evolution of productivity over time. However, plants may exit the market when their productivity falls below a certain threshold, which can bias the estimation of productivity evolution if not properly addressed. Following Olley and Pakes (1996), we account for this self-selection due to plant exit by incorporating the exit probability into the productivity evolution equation.

We define the exit probability as:

$$\begin{aligned} p_{it+1} &\equiv \Pr(\text{exit}_{it+1} = 1 \mid \underline{\omega}_{t+1}(k_{it}, z_{it}), \omega_{it}) = \Pr(\text{exit}_{it+1} = 1 \mid \underline{\omega}_{t+1}(k_{it}, z_{it}), h(m_{it}, k_{it}, l_{it}, z_{it})) \\ &= \Pr(\text{exit}_{it+1} = 1 \mid k_{it}, m_{it}, l_{it}, z_{it}) \end{aligned}$$

where exit_{it+1} is the dummy variable that is equal to one if plant i exits the market in year $t+1$, and $\underline{\omega}_{t+1}(k_{it}, z_{it})$ denotes the threshold level of productivity below which a plant with k_{it} and z_{it} exits in year $t+1$. We estimate this probability using a probit model with a third-order polynomial in k_{it}, m_{it}, l_{it}, and z_{it}, yielding the predicted conditional exit probability $\hat{p}_{it+1}$ for each plant-year observation.

We then assume that productivity follows a first-order Markov process, conditional on survival:

$$\omega_{it} = g(\omega_{it-1}, p_{it}) + \xi_{it}$$

where $g(\cdot)$ is a nonparametric function that captures how productivity evolves, controlling for the exit probability p_{it}, and ξ_{it} represents an innovation to productivity. We specify $g(\cdot)$ as a third-degree polynomial in ω_{it-1} and $\hat{p}_{it}$.

The parameters β_k and β_l are identified through the following moment condition:

$$E[\xi_{it} W_{it}] = 0$$

where W_{it} is a vector of instrumental variables. We set $W_{it} = (k_{it}, k_{it-1}, l_{it-1})'$. The parameters β_k and β_l are estimated by GMM, with standard errors calculated using 500 bootstrap replications.

Table 1 presents the results from the production function estimation. When we test for constant returns to scale, we obtain $\chi^2 = 0.0049$ with a p-value of 0.94, which indicates that we cannot reject the null hypothesis of constant returns to scale. In the subsequent analysis, we treat the estimated productivity residuals $\hat{\omega}_{it}$ as given and use them as the primary variable of interest in examining the effects of cartels on productivity.

Table 1: Production Function Estimates

	Estimates
β_k	0.238
	(0.030)
β_l	0.746
	(0.239)
N	5985

Notes: This table reports the production function estimates based on Ackerberg, Caves, and Frazer (2015). The sample period is 1993-2020. Standard errors are calculated through 500 bootstrap iterations and reported in parentheses.

3.4 Descriptive Statistics

Table 2: Plant-Level Descriptive Statistics (1993-2004)

	N	Mean	SD	Median	P25	P75
Output (1000m^3)	3260	27	19	22	15	32
Revenue (M.JPY)	3260	328	188	295	207	403
Material Expenditure (M.JPY)	3260	256	170	220	150	312
Log TFPQ	3260	6.6	0.59	6.6	6.2	7
Concrete Price (JPY/m^3)	3260	13173	3192	13500	10854	15108
Mixer Size (L)	3260	1817	896	1500	1500	2000
Num of Employees	3260	11	10	8	6	13
Coop Member Dummy	3260	0.85	0.35	1	1	1

Table 2 presents summary statistics at the plant level from 1993 to 2004, the period we focus on in our empirical analysis in the next section.[10] On average, each plant produces 27,000 m^3 of output and earns annual revenue of JPY 328 million, equivalent to approximately USD 3.1 million.[11] The average price per cubic meter is JPY 13,173 (approximately USD 123.92). Average material expenditure is JPY 256 million (approximately USD 2.4 million), accounting for 78% of revenue. Regarding physical output, revenue, and material expenditure, the standard deviation is only two-thirds of the mean value, which reflects the fact that the industry does not benefit significantly from economies of scale.

Regarding labor and capital, the mean number of employees is 11, and the mean mixer capacity is 1,817 liters. Mixer sizes are relatively uniform across plants, with the majority having a single mixer with a capacity of 1,500 liters.

The last row of Table 2 is a dummy variable that equals one if the plant participates in a cooperative in its market. Although not all cooperatives conduct joint sales agreements in all years, plants need to be a member of a cooperative to participate in such agreements. Across all plant-year observations, 85% of plants participate in cooperatives.

Table 3: Market-Level Descriptive Statistics (1993-2004)

	N	Mean	SD	Median	P25	P75
Output (1000m^3)	340	217	296	150	83	252
Revenue (M.JPY)	340	2644	2583	1951	1294	3095
Log TFPQ	340	6.6	0.35	6.5	6.3	6.8
Concrete Price (JPY/m^3)	340	14034	3379	13989	12013	15288
Cement Price (JPY/m^3)	340	10428	1785	9500	9000	12300
Num of Plants	340	8	5.4	7	5	9
Num of Entry	340	0.12	0.38	0	0	0
Num of Exit	340	0.24	0.54	0	0	0
Cartel Active Dummy	340	0.83	0.37	1	1	1
Coop Member Ratio	340	0.86	0.21	0.89	0.8	1
Coop Member Production Share	340	0.87	0.22	0.94	0.84	1

Table 3 presents summary statistics at the market level. On average, a market includes 8 plants, with total production of 217,000 m^3 and revenue of JPY 2,644 million (approximately USD 24.8 million). The average market-level concrete price is JPY 14,034 (approximately USD 131.9) per m^3, while the cement price is about JPY 10,428 (approximately USD 98.1) per m^3. In a typical market, the number of entrants and exiting plants per year is 0.12 and 0.24, respectively.

From 1993 to 2004, effective cartels were in place in 83% of market-years. On average across

[10] Table C1 presents the logarithm version.

[11] Note that 1m^3 is equal to 35.314ft^3. The exchange rate of USD/JPY = 106.29 is the average of 2020, which is the base year of our deflator.

market-years, 86% of plants participate in cooperatives, and these members account for 87% of total physical output.

4 Empirical Analysis

4.1 Empirical Framework

We study the impact of cartels on productivity at both plant and market levels exploiting the annual frequency of the productivity and cartel activeness. To do so, we adopt a staggered event study design that uses cartel collapse and formation as treatment events. This approach identifies the impact using the variation in the timing of cartel status changes across different markets and the variation between markets that never experience cartel status changes and those that do.

Our baseline empirical specification follows the standard event study model:

$$y_{it} = \alpha_i + \delta_t + \sum_{j \in \{-4,\ldots,0,\ldots,3\}} \gamma_j D_{i,t-j} + \varepsilon_{it} \tag{1}$$

where y_{it} represents the outcome variable for unit i in year t. The variables α_i and δ_t are unit and year fixed effects respectively, and $D_{i,t-j}$ is an event dummy variable that equals one if period t is exactly j periods relative to unit i's event time. (where $j > 0$ indicates post-event periods and $j < 0$ indicates pre-event periods), and zero otherwise. Units can be both plants and markets. The coefficients γ_j capture the dynamic treatment effects relative to the event period.

We consider two distinct types of events in our analysis. Cartel collapse is defined as the transition event where a market's cartel status changes from active in the previous year to inactive in the current year. Cartel formation is defined as the opposite, that is transition from inactive to active status. Figure 1 illustrates that our sample includes markets with cartel collapses and formations occurring at different points in time, as well as markets in which cartels remain stable throughout. As shown in Figure C1, those events are associated with price changes in the market.

The control group consists of never-treated units and units that receive treatment at different times but have not yet been treated at the time of comparison. For cartel collapse events, this definition of the control group includes never-treated markets that maintain active cartel status and plants operating within such markets, as well as those that will experience collapse in later periods. For cartel formation events, the control group comprises never-treated markets that remain inactive and the plants in those markets, along with those markets and plants in those markets that experience formation in subsequent periods.

Given that treatment timing varies across units, OLS with two-way fixed effects may produce biased estimates due to heterogeneous treatment effects and negative weighting of certain treatment-control comparisons. To address these concerns, we implement the estimation approaches developed by Callaway and Sant'Anna (2021), and Sun and Abraham (2021), all of which provide robust inference for staggered adoption designs.

4.2 Sample Selection and Aggregation

Our plant-level data from the Census of Manufacture covers the period 1993-2020, and we use the full sample for production function estimation. However, since market-level cartel activeness can only be observed for the period 1993-2004, we restrict our event study analysis to this time frame.

Since markets may experience multiple transitions between active and inactive cartel status, we focus on single switching events for our staggered event study framework. When a market experiences additional status changes, we exclude the periods after the subsequent transition to isolate the effect of a single event. Additionally, some markets experience only a transition in the direction opposite to the event of interest (e.g., inactive to active in the cartel collapse analysis). In such cases, we exclude periods before the transition, as these periods represent an already-treated state that may result from an event occurring before our observation window. This sample selection ensures that our estimates capture the effects of isolated cartel transitions and that our control group consists only of observations not yet affected by the event of interest.[12]

As a result, for the cartel collapse analysis, our sample includes 8 treated markets (39 pre-treatment market-years and 38 post-treatment market-years) and 25 never-treated markets (282 market-years), yielding 2,937 plant-year observations in total. As a result of our sample selection criteria, the number of observed years varies across markets. Collapse events occur in 1994, 1999, 2000, and 2002, with 1, 5, 1, and 1 markets treated in each respective year. For the cartel formation analysis, the sample includes 14 treated markets (45 pre-treatment market-years and 96 post-treatment market-years) and 3 never-treated markets (23 market-years), with 1,090 plant-year observations. Formation events occur in 1994, 1995, 1996, 2001, 2003, and 2004, with 4, 3, 1, 2, 3, and 1 markets treated in each respective year.

For the event window, our baseline specification includes event time dummies from $j = -4$ to $j = 3$. In the OLS and Sun and Abraham (2021) estimations, observations outside this window are binned into the endpoint categories ($j = -4$ and $j = 3$, respectively). In the Callaway and Sant'Anna (2021) estimation, we instead exclude observations outside the event window from the sample. For aggregate average treatment effects, the OLS specification replaces the event time dummies with a single post-treatment dummy while retaining year and unit (plant or market) fixed effects. For Sun and Abraham (2021) and Callaway and Sant'Anna (2021), we compute weighted averages of the event study coefficients from their respective specifications described above.

[12]For example, the Sapporo market was active during 1993-1998, inactive during 1999-2003, and became active again in 2004. For cartel collapse analysis, we designate 1999 as the event year and restrict our sample to 1993-2003. For cartel formation analysis, we use 2004 as the event year with a sample period of 1999 onwards. Similarly, Central Kamikawa was inactive during 1993-2000 and became active in 2001. In the cartel collapse analysis, we retain only 2001-2004, treating this market as never-treated.

4.3 Plant-Level Analysis

4.3.1 Main Results

We examine the effect of cartel collapse and formation on plant-level productivity in this subsection, using individual plants as the unit of analysis. The left panel of Figure 3 reports event study estimates where the collapse of the cartel is treated as the event of interest. The figure reveals that plant-level productivity rises significantly by 10 to 15 percent immediately after the collapse. In subsequent years, productivity remains higher compared to the pre-collapse baseline, ranging from 10 to 24 percent depending on the year. The patterns are robust to the three estimation methods. Overall, the results indicate that the collapse of collusive arrangements had a substantial and persistent positive effect on plant productivity. As our estimates of productivity do not isolate the effects of capacity utilization, we also report results controlling for capacity utilization in the right panel of Figure 3. However, our capacity utilization measure is defined as the ratio of observed output to capacity, and because output mechanically depends on productivity, this control variable is not independent of the outcome variable. Consequently, these results should be interpreted with caution.[13]

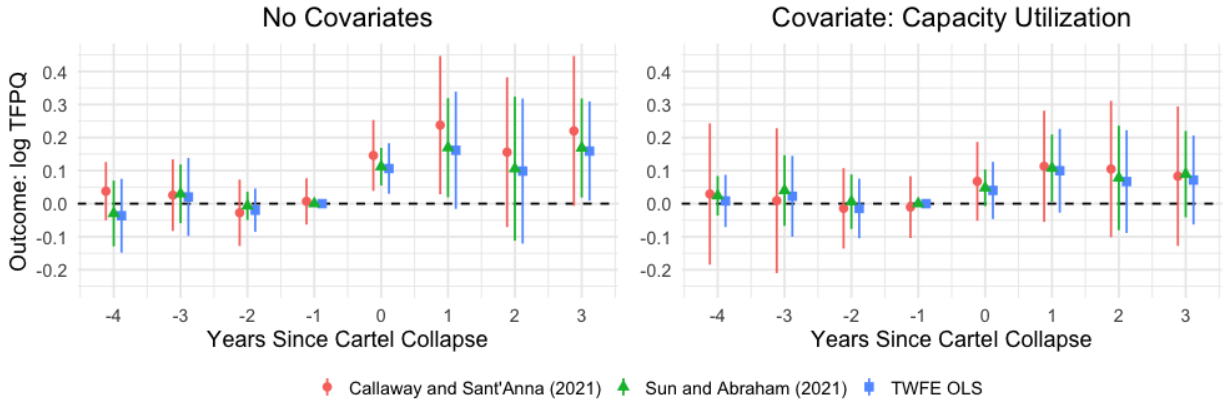


Figure 3: Event Study of Cartel Collapse (Plant Level)

Notes: The event-study plot shows the impact of cartel collapse on plant-level log TFPQ. The horizontal axis denotes years since the cartel collapse. The left panel reports the baseline results, and the right panel reports results that additionally control for capacity utilization. The figure presents estimates from three methods that account for staggered treatment timing: Callaway and Sant'Anna (2021) (orange circles), Sun and Abraham (2021) (green triangles), and TWFE OLS (blue squares). It displays point estimates and 95% confidence intervals; values in parentheses indicate standard errors. All specifications include year and market fixed effects. Standard errors are clustered at the market level.

Table 4 reports the aggregated average treatment effect in the post-collapse period. The esti-

[13] An alternative approach considers estimating productivity while accounting for capacity utilization by exploiting variation in a proxy variable correlated with utilization, such as electricity consumption (Dong, Ma, and Shen (2021)). In Appendix B, we use truck capacity as the utilization proxy, which is the best candidate for proxy among the available variables, and estimate utilization-adjusted productivity following this approach. Note, however, that truck capacity may not be as suitable as electricity, given its limited correlation with capacity utilization (correlation coefficient of 0.35).

mates indicate that productivity increased by 14.3 to 19.0 percent on average following the cartel collapse. This effect is statistically significant at the 10 percent level across all estimation methods adopted. The consistency of these findings across different specifications reinforces the conclusion that cartel dissolution led to meaningful productivity gains at the plant level. The magnitude of the effect is smaller when controlling for capacity utilization.

Table 4: Estimated ATT of Cartel Collapse on Log TFPQ (Plant Level)

	No Covariates			Covariate: Capacity Utilization		
	CS(2021)	SA(2021)	TWFE	CS(2021)	SA(2021)	TWFE
ATT	0.190***	0.143**	0.150*	0.092*	0.081	0.064
	(0.071)	(0.066)	(0.078)	(0.055)	(0.053)	(0.073)
N	2937	2937	2937	2937	2937	2937

Notes: The table reports difference-in-differences estimates of cartel collapse on plant-level log TFPQ. The estimates are from three methods that account for staggered treatment timing: Callaway and Sant'Anna (2021), Sun and Abraham (2021), and TWFE OLS. The three columns on the left-hand side show the estimates from each method. The three columns on the right-hand side additionally control for capacity utilization. Specifications control for plant and year fixed effects. The values in parentheses indicate standard errors. Standard errors are clustered at the market level and reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

In contrast, Figure 4 presents the event study results using cartel formation as the treatment event. The estimates vary considerably across estimation methods, with point estimates ranging from approximately negative 18 percent to positive 7 percent depending on the method and time horizon. The sign of the point estimates differs across methods, and the confidence intervals are notably wide, particularly for the Callaway and Sant'Anna estimator. None of the estimates are statistically significant at the 5 percent level. Similarly, Table 5 presents the average treatment effect for the post-formation period, but the results remain inconsistent across specifications and statistically insignificant. These findings indicate that cartel formation did not have a statistically significant effect on plant-level productivity.[14] Controlling for capacity utilization does not change these patterns.

[14]These results should be interpreted with caution, as limited sample variation may reduce statistical power. Because many markets maintained cartels throughout the sample period and are thus excluded from the analysis, the number of treated markets is small, and only 3 markets serve as a never-treated control.

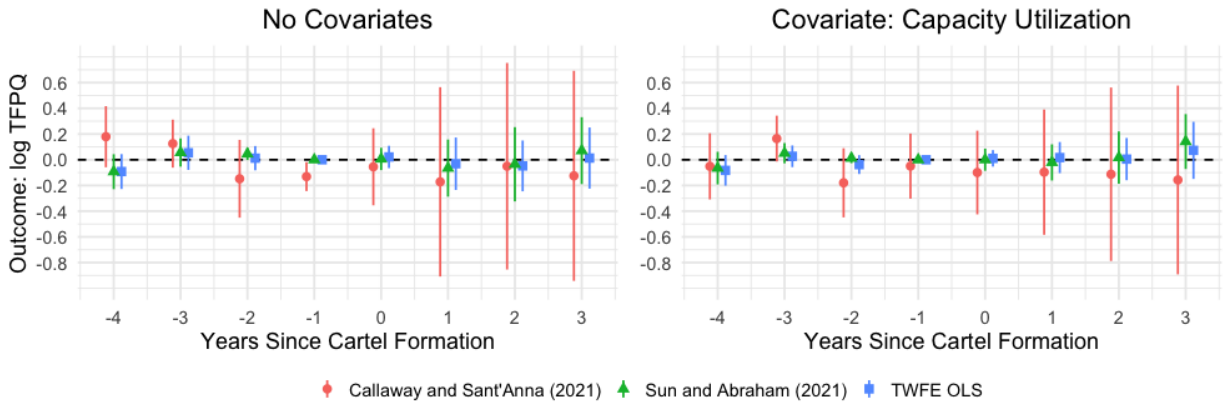


Figure 4: Event Study of Cartel Formation (Plant Level)

Notes: The event-study plot shows the impact of cartel formation on plant-level log TFPQ. The horizontal axis denotes years since the cartel formation. The left panel reports the baseline results, and the right panel reports results that additionally control for capacity utilization. The figure presents estimates from three methods that account for staggered treatment timing: Callaway and Sant'Anna (2021) (orange circles), Sun and Abraham (2021) (green triangles), and TWFE OLS (blue squares). It displays point estimates and 95% confidence intervals; values in parentheses indicate standard errors. All specifications include year and market fixed effects. Standard errors are clustered at the market level.

Table 5: Estimated ATT of Cartel Formation on Log TFPQ (Plant Level)

	No Covariates			Covariate: Capatity Utilization		
	CS(2021)	SA(2021)	TWFE	CS(2021)	SA(2021)	TWFE
ATT	-0.098	0.034	0.005	-0.112	0.086	0.028
	(0.296)	(0.103)	(0.055)	(0.259)	(0.082)	(0.041)
N	1090	1090	1090	1090	1090	1090

Notes: The table reports difference-in-differences estimates of cartel formation on plant-level log TFPQ. The estimates are from three methods that account for staggered treatment timing: Callaway and Sant'Anna (2021), Sun and Abraham (2021), and TWFE OLS. The three columns on the left-hand side show the estimates from each method. The three columns on the right-hand side additionally control for capacity utilization. Specifications control for plant and year fixed effects. The values in parentheses indicate standard errors. Standard errors are clustered at the market level and reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

The asymmetric response of productivity to cartel collapse and formation is notable. Plant-level productivity rises markedly after cartels collapse but shows no comparable decline when cartels form. One plausible mechanism behind this asymmetry is the effect of competition on productivity as discussed in Backus (2020). Plants face a sudden increase in competitive pressure after cartel collapse, potentially leading to improvements in management practices. In contrast, competitive pressure can only gradually decrease after cartel formation due to uncertainty about the stability

of the cartel.

4.3.2 Endogeneity Concerns

Potential concerns exist about the endogeneity of cartel collapse timing and the selection of markets where cartel collapse occurs. To address these issues, we adopt instrumental variables (IV) and propensity score matching (PSM) methods.[15]

First, to address the endogeneity of the collapse timing, we use future demand measures and their interactions with the treatment group indicator as instruments for $Treat_i \times Post_{i,t}$. Specifically, we use floor area of building projects and public construction expenditure one, two, and three years ahead as future demand measures at the market level. As Haltiwanger and Harrington (1991) suggest, cartels are more likely to collapse when they face lower future demand.[16] Consistent with this theoretical prediction, our first-stage regression indicates that cartel collapses are more likely to occur when future demand is lower. Regarding the exclusion restriction, we assume that future demand does not directly affect current productivity. While this assumption may not hold in industries where investment plays an important role, capital and production capacity remain unchanged over time in the vast majority of these plants.[17]

Second, to address the selection of markets into treatment, we conduct propensity score matching to construct a control group with similar characteristics to the treated group.[18] We match each treated market to its nearest neighbor based on the estimated propensity score. When a control market is the nearest neighbor for multiple treated markets, we assign it to only one treated market and match the remaining treated markets to their second nearest neighbors to avoid duplication in the control group.

Table 6 reports the results. All specifications adopt TWFE OLS estimation rather than the staggered treatment estimators. Given that the baseline results in Table 4 show similar estimates across TWFE and the staggered treatment estimators of Callaway and Sant'Anna (2021) and Sun and Abraham (2021), this simplification is unlikely to affect our conclusions. The OLS column replicates the baseline TWFE result, while the remaining columns present the IV, PSM, and combined IV and PSM specifications. Across all specifications, the impact of cartel collapse on plant-level productivity remains positive, with point estimates ranging from 14.6 to 17.8 percent. The estimates are statistically significant at the 10% level in across all specifications. The point estimates remain similar in magnitude, suggesting that the productivity improvement following cartel collapse is not

[15] We conduct analogous robustness checks for cartel formation in Appendix A. The results confirm that the effect of formation on productivity remains statistically insignificant across all specifications.

[16] Fabra (2006) suggest that this result reverses when firms face binding capacity constraints. In our setting, ready-mixed concrete plants possess sufficiently large production capacity, and hence the prediction of Haltiwanger and Harrington (1991) applies.

[17] In Table D1, we show that the correlation between future demand and capacity change is not statistically significant.

[18] The market-level variables used for propensity score estimation are as follows; floor area of building projects and public construction expenditure in the current year and one, two, and three years ahead, number of plants, area size, cement price, population, proportion of residents over 65 years old, number of marriages, average labor income, unemployment rate, and manufacturing sector sales.

entirely driven by the endogeneity of timing or the selection of treated markets.

Table 6: Alternative Identification Strategies for the Impact of Cartel Collapse

	OLS	IV	PSM	IV+PSM
ATT	0.150*	0.170*	0.146*	0.178*
	(0.078)	(0.098)	(0.072)	(0.093)
N	2937	2937	1466	1466
Year FE	Yes	Yes	Yes	Yes
Plant FE	Yes	Yes	Yes	Yes
First-stage F-stat	-	498.88	-	192.15

Notes: The table reports TWFE difference-in-differences estimates of the effect of cartel collapse on plant-level log TFPQ under alternative identification strategies. The OLS column replicates the baseline TWFE specification. The IV column instruments $Treat_i \times Post_{it}$ with market-level future demand measures and their interactions with $Treat_i$. The PSM column reports TWFE estimates on a matched sample constructed by nearest-neighbor propensity score matching at the market level. The IV+PSM column applies the IV specification on the matched sample. Standard errors are clustered at the market level. Standard errors are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

4.3.3 Heterogeneous Impacts of Cartel Collapse

To further investigate the mechanisms behind productivity improvement after cartel collapse, we estimate triple-difference (DDD) specifications built on a TWFE design. Specifically, we interact the treatment indicator ($Treat_i \times Post_{i,t}$) with variables capturing two dimensions of heterogeneity: pre-collapse productivity and competitive pressure. For productivity, we use the z-score based on the within-market pre-collapse productivity distribution.[19] For competitive pressure, we use pre-collapse plant density.[20]

Table 7 reports the estimates. In column 1, we interact the treatment indicator with the z-score. The results show that plants with lower pre-collapse within-market productivity experience larger productivity gains: a one-standard-deviation decrease in the z-score is associated with an additional 4.1 percentage point increase in productivity. This pattern suggest that cartel collapse disproportionately boosts lower-productivity plants and, in doing so, compresses the productivity distribution and reduces dispersion. In column 2, we interact the treatment indicator with plant density. The results show that plants in markets with higher pre-collapse plant density exhibit larger post-collapse productivity improvements, consistent with the hypothesis that stronger competitive pressure intensifies the response.

[19]The z-score is constructed as follows. We pool observations from the three years prior to cartel collapse and compute the mean and standard deviation of TFPQ for each market. We then calculate each plant's average TFPQ over the same three-year period and normalize it using the market mean and standard deviation.

[20]Plant density is defined as the number of plants per square kilometer in the year prior to collapse.

As shown in Table 7, productivity gains are concentrated among initially less productive plants and those in high-density markets. This result suggests a potential mechanism: plants that face heightened competitive pressure improve production efficiency more. This is consistent with the findings of Backus (2020) where productivity is driven by the treatment effects of competition, possibly due to channels such as managerial inputs.

Table 7: Heterogeneous Impacts of Cartel Collapse

	Log TFPQ		# Employees	
	(1)	(2)	(3)	(4)
Treat × Post	0.154*	-0.023	-0.316	1.048
	(0.080)	(0.095)	(0.646)	(0.662)
Treat × Post × Z score	-0.041*		0.317***	
	(0.021)		(0.099)	
Treat × Post × Plant density		0.012***		-0.089***
		(0.004)		(0.023)
N	2937	2937	2937	2937
Year FE	Yes	Yes	Yes	Yes
Plant FE	Yes	Yes	Yes	Yes

Notes: The table reports triple-difference estimates of the effect of cartel collapse on plant-level log TFPQ (column 1 and 2) and number of employees (column 3 and 4). The treatment indicator is $Treat_i \times Post_{it}$, where $Treat_i$ equals one for plants in treated markets and $Post_{it}$ equals one in the post-collapse period. Heterogeneity is captured by interacting $Treat_i \times Post_{it}$ with the z-score of pre-collapse within-market TFPQ (column 1 and 3), and pre-collapse plant density (column 2 and 4). Standard errors are clustered at the market level and reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

To investigate the mechanism behind the heterogeneous productivity response, we examine how labor adjusts after cartel collapse. If initially less productive plants reduce labor more than others, this would suggest that they improve managerial practices more intensively, such as reducing labor slack. Because capital is inflexible in the short run, such labor reductions would indicate productivity gains beyond mere increases in capacity utilization.

Column 3 and 4 in Table 7 reports heterogeneous effects of cartel collapse on employment. The signs of the coefficients mirror the productivity results: plants with lower pre-event productivity reduce employment more, and plants in markets with higher pre-collapse plant density exhibit larger employment declines. These results provide partial support for the hypothesis that heightened competition induces managerial improvements that reduce labor slack, although the evidence based on pre-collapse productivity is not conclusive.

We also examine whether the heterogeneous productivity response reflects within-plant improvements or selection through exit. If initially less productive plants are more likely to exit after cartel collapse, the observed heterogeneity could be driven by the changing composition of surviving plants rather than improvements within individual plants. To assess this, we examine heterogeneity in the impact of cartel collapse on exit probabilities. As shown in Table D2, although exit rates increase following the collapse, the change does not vary with pre-collapse productivity. This finding indicates that the heterogeneous productivity response is driven primarily by within-plant changes rather than differential exit rates across the productivity distribution.

4.4 Market-Level Analysis

This subsection moves the unit of analysis from individual plants to markets. The outcome variable is the output-share-weighted mean TFPQ, which allows us to examine whether productivity improvements occur at the market level following cartel collapses and formations.

4.4.1 Event Study Results

Figure 5 presents the event study results for both cartel collapse and cartel formation. The left panel shows that market-level productivity generally increased after the collapse, with point estimates ranging from approximately 0 to 14 percent depending on the method and time horizon, although some estimates are negative or not statistically significant. The right panel shows that the effects of cartel formation are not statistically significant, with point estimates varying in sign across methods and wide confidence intervals. Given this asymmetry, the remainder of this subsection focuses primarily on cartel collapse, where we observe positive effects that warrant further investigation into underlying mechanisms. Results for cartel formation are reported in Appendix A for completeness.

4.4.2 (Static) Olley-Pakes Decomposition

Changes in market-level productivity do not necessarily imply that individual plants improved their productivity. Since market-level productivity is defined as output-share-weighted mean TFPQ, changes can arise either from productivity improvements at individual plants or from differences in how production is allocated across plants within the market. To disentangle these two sources, we decompose market-level productivity changes using the Olley-Pakes framework.

We begin with the static Olley and Pakes (1996) decomposition, which separates aggregate productivity into average plant productivity and the covariance between productivity and output share within the market. This approach allows us to examine whether cartels distort efficiency by allocating production to less productive firms. The decomposition is expressed as:

$$\omega_t = \underbrace{\bar{\omega}_t}_{\text{within}} + \underbrace{\text{cov}_t}_{\text{reallocation}} \tag{2}$$

where ω_t is the output-share-weighted mean productivity in year t, $\bar{\omega}_t$ is the unweighted mean productivity in year t, and cov_t is the covariance between the plant-level market share s_{it} and

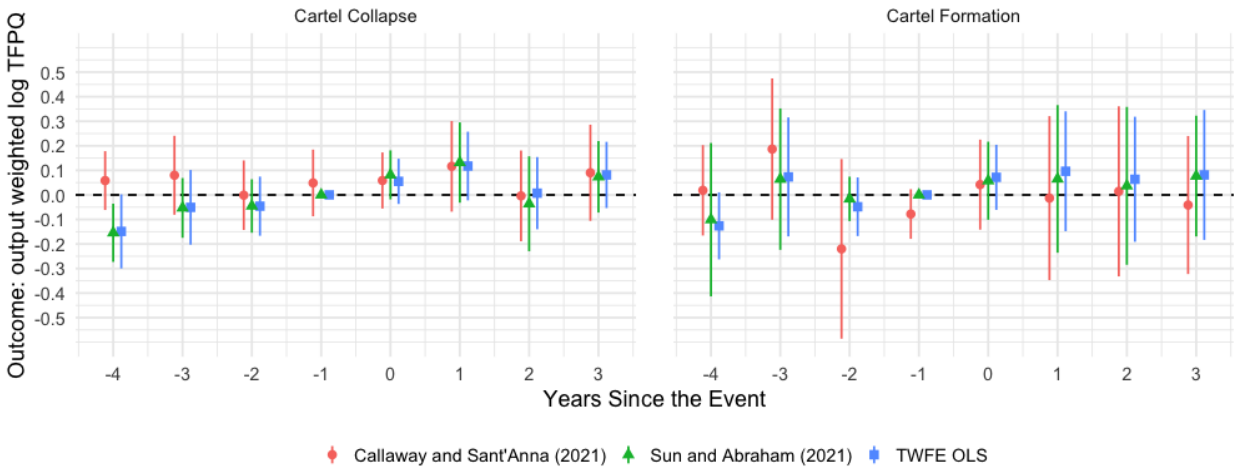


Figure 5: Event Study of Cartel Collapse and Cartel Formation (Market Level)

Notes: The event-study plot shows the impact of cartel collapse and formation on market-level log TFPQ, where the dependent variable is the quantity-weighted log TFPQ aggregated to the market level. The left panel reports the effects relative to the year of cartel collapse, and the right panel reports the effects relative to the year of cartel formation; the horizontal axis denotes years since the corresponding event. The figure presents results from three estimation methods that account for staggered treatment timing: Callaway and Sant'Anna (2021) (orange circles), Sun and Abraham (2021) (green triangles), and TWFE OLS (blue squares). It displays point estimates and 95% confidence intervals. All specifications include year and market fixed effects. Standard errors are clustered at the market level.

productivity ω_{it} within the market. We perform this decomposition separately for each market; the market subscript m is omitted for notational simplicity. The covariance term, called the OP residual, represents allocative efficiency within the market: it is positive when more productive plants have larger market shares.

Table 8 reports difference-in-differences estimates of cartel collapse on each component: the overall effect (output-share-weighted mean productivity), the within effect (unweighted mean productivity), and the reallocation effect (OP residual). The overall effect ranges from 6.4 to 14.8 percent, although it is statistically significant at the 5% level only for the TWFE estimator. The within effect ranges from 9.4 to 13.3 percent, with statistical significance again limited to the TWFE estimator. The reallocation effect shows mixed signs across estimators and is not statistically significant for any specification.

These results suggest that market-level productivity gains following cartel collapse are associated with increases in unweighted mean productivity rather than enhanced allocative efficiency. However, the static decomposition does not distinguish within-plant productivity improvements from composition effects: changes in unweighted mean productivity may reflect not only improvements at individual plants but also changes in the set of plants operating in the market due to entry and exit. To address this limitation, we turn to a dynamic decomposition in the next subsection.

Table 8: Estimated ATT of Cartel Collapse on OP Compoents of Market-Level Productivity

	CSA (2021)	SA (2021)	TWFE
Panel A: Overall			
ATT	0.064	0.065	0.148**
	(0.058)	(0.058)	(0.071)
Panel B: Within			
ATT	0.094	0.095	0.133**
	(0.079)	(0.085)	(0.065)
Panel C: Reallocation			
ATT	-0.031	-0.030	0.016
	(0.062)	(0.058)	(0.018)

Notes: The table reports difference-in-differences estimates of cartel collapse on the components of the Olley and Pakes (1996) decomposition at the market level. $N = 359$. Panel A reports effects on the output-share-weighted average log TFPQ (overall effect). Panel B reports effects on the unweighted mean log TFPQ (within effect). Panel C reports effects on the covariance term, the OP residual, which captures allocative efficiency within the market (reallocation effect). The estimates are from three methods that account for staggered treatment timing: Callaway and Sant'Anna (2021), Sun and Abraham (2021), and TWFE OLS. Specifications control for market and year fixed effects. Standard errors are clustered at the market level and reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

4.4.3 Dynamic Olley-Pakes Decomposition

To isolate within-plant productivity improvements from composition effects, we extend the analysis using the dynamic decomposition framework developed by Melitz and Polanec (2015). This framework explicitly accounts for plant entry and exit, which is particularly relevant for understanding cartel effects, as cartels may influence entry and exit decisions as well as productivity and market shares.

4.4.3.1 Decomposition Framework

The dynamic Olley-Pakes decomposition separates productivity growth between two periods into four components: (i) within-plant productivity improvements of surviving plants, (ii) reallocation of market shares among survivors, (iii) entry effects from new plants, and (iv) exit effects from departing plants. The within component captures productivity improvements at individual surviving plants. The reallocation component measures changes in allocative efficiency among survivors. The entry component is positive when entrants are more productive than the average survivor. The exit component is positive when less productive plants exit the market. The within and reallocation

components correspond to the unweighted mean and OP residual in the static decomposition, but are computed only for surviving plants.

We apply this decomposition to cumulative productivity growth from 1993 to each year $t \in \{1994, \ldots, 2004\}$. Unlike the previous analyses that use productivity levels as the outcome variable, we cannot decompose the level of productivity in each year into the four components. This is because the dynamic decomposition requires comparing two time periods to classify plants as survivors, exiters, or entrants, and these classifications depend on the choice of comparison years. We therefore use cumulative productivity growth from a fixed base year (1993) as our outcome variable. In our difference-in-differences framework, the estimated treatment effect on cumulative growth can be interpreted as the effect on the level of each component relative to the base year.

For each comparison year t, we classify plants into three groups based on their presence in 1993 and year t: survivors are plants operating in both years, exiters are plants operating in 1993 but not in year t, and entrants are plants operating in year t but not in 1993. Importantly, these classifications change with the comparison year. For example, a plant that operated from 1993 to 2000 is classified as a survivor when $t \leq 2000$ but as an exiter when $t > 2000$.

Formally, aggregate productivity in each period can be expressed as the weighted sum of productivity across plant groups. In the base year:

$$\omega_{1993} = \omega_{S,1993} + s_{X,1993}(\omega_{X,1993} - \omega_{S,1993}) \tag{3}$$

where $\omega_{S,1993}$ and $\omega_{X,1993}$ are the share-weighted mean productivity of survivors and exiters in 1993, respectively, and $s_{X,1993}$ is the aggregate output share of exiters in 1993. In the comparison year t:

$$\omega_t = \omega_{S,t} + s_{E,t}(\omega_{E,t} - \omega_{S,t}) \tag{4}$$

where $\omega_{S,t}$ and $\omega_{E,t}$ are the share-weighted mean productivity of survivors and entrants in year t, respectively, and $s_{E,t}$ is the aggregate output share of entrants in year t.

The aggregate productivity of survivors can be further decomposed following the static Olley-Pakes approach:

$$\omega_{S,t} = \bar{\omega}_{S,t} + \text{cov}_{S,t} \tag{5}$$

where $\bar{\omega}_{S,t}$ is the unweighted mean productivity of survivors and $\text{cov}_{S,t}$ is the covariance between the within-survivors share and productivity.

Combining these expressions, the cumulative productivity growth from 1993 to year t can be decomposed as:

$$\Delta\omega_t = \underbrace{\Delta\bar{\omega}_{S,t}}_{\text{within}} + \underbrace{\Delta\text{cov}_{S,t}}_{\text{reallocation}} + \underbrace{s_{E,t}(\omega_{E,t} - \omega_{S,t})}_{\text{entry}} + \underbrace{s_{X,1993}(\omega_{S,1993} - \omega_{X,1993})}_{\text{exit}} \tag{6}$$

4.4.3.2 Results

We compare cumulative productivity growth and its components between markets that experience cartel collapses and those that do not. For a market that experiences a cartel collapse in year τ, we

compare its cumulative growth from 1993 to year t with that of control markets. When $t < \tau$, both treated and control markets are in the pre-treatment period. When $t \geq \tau$, the difference captures the effect of cartel collapse on the level of each component in year t.

Table 9 presents the results. The within effect shows an increase of 9.9 to 14.0 percent following cartel collapset, although it is statistically significant at the 10% level only for the TWFE estimator In contrast, the reallocation, entry, and exit effects are all small in magnitude and not statistically significant for any specification. These results suggest that market-level productivity increases after cartel collapse are primarily associated with within-plant improvements at surviving plants rather than reallocation among survivors or selection effects through entry and exit.

Table 9: Estimated ATT of Cartel Collapse on Dynamic OP Components of TFPQ Cumulative Growth

	CSA (2021)	SA (2021)	TWFE
Panel A: Overall			
ATT	0.061	0.073	0.153**
	(0.060)	(0.056)	(0.073)
Panel B: Within			
ATT	0.099	0.121	0.140*
	(0.073)	(0.074)	(0.072)
Panel C: Reallocation			
ATT	-0.027	-0.040	0.018
	(0.060)	(0.060)	(0.016)
Panel D: Entry			
ATT	-0.008	-0.011	-0.001
	(0.016)	(0.019)	(0.017)
Panel E: Exit			
ATT	-0.002	0.003	-0.004
	(0.017)	(0.021)	(0.025)

Notes: The table reports difference-in-differences estimates of cartel collapse on the components of the dynamic OP decomposition at the market level. Details of the decomposition are provided in Section 4.4.3. $N = 354$. The table reports effects on the overall productivity growth, within, reallocation, entry, and exit components in Equation (6). Panels A, B, C, D, and E correspond to these components, respectively. The estimates are from three methods that account for staggered treatment timing: Callaway and Sant'Anna (2021), Sun and Abraham (2021), and TWFE OLS. Specifications control for market and year fixed effects. The values in parentheses indicate standard errors. Standard errors are clustered at the market level and reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

5 Conclusion

This paper examines the impact of cartels on productivity using a novel dataset from the Japanese ready-mixed concrete industry. The institutional setting, in which cartels are legally permitted, provides a unique opportunity to observe cartel activeness directly rather than relying on prosecuted cases. By linking market-level cartel status to plant-level production data from 1993 to 2004, we estimate the effects of cartel collapse and formation on productivity through an event study framework.

Our analysis produces several key findings. First, cartel collapse leads to substantial productivity gains at the plant level. Across multiple estimation methods that account for staggered treatment timing, we find that plant-level productivity increases by approximately 14 to 19 percent following cartel collapse. These effects are robust to alternative specifications using instrumental variables and propensity score matching to address potential endogeneity concerns. In contrast, cartel formation does not produce a statistically significant effect on productivity.

Second, heterogeneity analysis through a triple-difference design reveals that productivity gains are concentrated among plants that face stronger competitive pressure. Specifically, initially less productive plants and plants in markets with higher plant density show larger productivity improvements after cartel collapse. The parallel finding that these same plants reduce employment more substantially suggests that the productivity gains reflect genuine improvements in operational efficiency, possibly through the reduction of labor slack, rather than mere increases in capacity utilization.

Third, decomposition analysis at the market level indicates that aggregate productivity improvements are driven almost entirely by within-plant changes among surviving plants. Using the static Olley-Pakes decomposition and its dynamic extension by Melitz and Polanec (2015), we find no significant contribution from reallocation of market shares toward more productive plants or from selection effects through entry and exit. This finding suggests that the treatment effect of competition, rather than reallocation or selection, is the primary channel through which cartel collapse raises market-level productivity.

These results have important implications for understanding the costs of cartels. The existing literature has emphasized that cartels generate welfare losses through higher prices and that they may reduce industry efficiency by distorting the allocation of production across firms. Our findings highlight an additional channel: cartels diminish incentives for firms to improve their internal operations. The absence of competitive pressure allows inefficiencies to persist within plants, and the restoration of competition forces firms to address these inefficiencies.

Several limitations of our analysis warrant discussion. First, our cartel activeness measure is based on self-reported assessments by cooperatives, which may not perfectly capture the true degree of collusion. Second, the sample is limited to Hokkaido, and the findings may not generalize to other regions or industries with different characteristics. Third, while we document that productivity improves after cartel collapse, we cannot identify the specific internal mechanisms through which

this occurs. Possible channels include increased managerial effort, adoption of improved production practices, and elimination of organizational slack, but distinguishing among these explanations requires more detailed data on firm operations.

Future research could extend this work in several directions. Investigating the precise mechanisms behind within-plant productivity improvements would deepen our understanding of how competition affects firm behavior. Examining whether similar patterns hold in other industries or countries would help establish the external validity of our findings. Finally, studying the long-run dynamics of productivity following cartel transitions could reveal whether the effects we document persist or fade over time.

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Appendices

A Results on Cartel Formation

In this appendix, we present the results regarding cartel formation. We first consider potential endogeneity issues concerning treatment timing and selection, as in the main text. Regarding treatment timing of cartel formation, we were unable to identify instruments that satisfy both the relevance condition and the exclusion restriction. Turning to selection, Table A1 reports the results using propensity score matching (PSM). These estimates indicate no statistically significant impact.

Table A1: Alternative Identification Strategies for the Impact of Cartel Formation

	OLS	IV	PSM	IV+PSM
ATT	0.005	0.207	0.123	0.091
	(0.055)	(0.152)	(0.153)	(0.166)
N	1090	1090	240	240
Std.Errors	by: market	by: market	by: market	by: market
Year FE	Yes	Yes	Yes	Yes
Plant FE	Yes	Yes	Yes	Yes
First-stage F-stat	-	9.64	-	23.10

Notes: The table reports TWFE difference-in-differences estimates of the effect of cartel collapse on plant-level log TFPQ under alternative identification strategies. The OLS column replicates the baseline TWFE specification. The IV column instruments $Treat_i \times Post_{it}$ with market-level future demand measures and their interactions with $Treat_i$. The PSM column reports TWFE estimates on a matched sample constructed by nearest-neighbor propensity score matching at the market level. The IV+PSM column applies the IV specification on the matched sample. Standard errors are clustered at the market level. Standard errors are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Next, Table A2 presents the heterogeneous effects of cartel formation. The results in the first two columns suggest that low-productivity firms may be disproportionately affected, while the plant density has no effect. One possible interpretation for the first and third columns is that cartel formation increases the capacity utilization of less productive plants, although the decomposition analysis in Tables A3 and A4 shows no statistically significant evidence of such reallocation effect.

Table A2: Heterogeneous Impacts of Cartel Formation

	Log TFPQ		# Employees	
	(1)	(2)	(3)	(4)
Treat × Post	0.010	-0.012	0.538	1.146**
	(0.054)	(0.065)	(0.415)	(0.453)
Treat × Post × Z score	-0.123**		0.813	
	(0.049)		(0.495)	
Treat × Post × Plant density		0.001		-0.031*
		(0.001)		(0.016)
N	1090	1090	1090	1090
Year FE	Yes	Yes	Yes	Yes
Plant FE	Yes	Yes	Yes	Yes

Notes: The table reports triple-difference estimates of the effect of cartel formation on plant-level log TFPQ (column 1 and 2) and labor (column 3 and 4). The treatment indicator is $Treat_i \times Post_{it}$, where $Treat_i$ equals one for plants in treated markets and $Post_{it}$ equals one in the post-collapse period. Heterogeneity is captured by interacting $Treat_i \times Post_{it}$ with the z-score of pre-collapse within-market TFPQ (column 1 and 3), and pre-collapse plant density (column 2 and 4). Standard errors are clustered at the market level and reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A3 reports the effects of cartel formation on the market-level OP decomposition terms. We find no statistically significant impact on the within-plant component, the reallocation component, and overall market-level productivity.

Table A3: Estimated ATT of Cartel Formation on OP Compoents of Market-Level Productivity

	CSA (2021)	SA (2021)	TWFE
Panel A: Overall			
ATT	0.003	0.069	0.101
	(0.130)	(0.108)	(0.074)
Panel B: Within			
ATT	-0.006	0.073	0.088
	(0.152)	(0.122)	(0.084)
Panel C: Reallocation			
ATT	0.009	-0.004	0.013
	(0.023)	(0.029)	(0.024)

Notes: The table reports difference-in-differences estimates of cartel formation on the components of the Olley and Pakes (1996) decomposition at the market level. Panel A reports effects on the output-share-weighted average log TFPQ. Panel B reports effects on the unweighted mean log TFPQ. Panel C reports effects on the covariance term (the OP residual), which captures allocative efficiency within the market. The sample size is 164. The estimates are from three methods that account for staggered treatment timing: Callaway and Sant'Anna (2021), Sun and Abraham (2021), and TWFE OLS. Specifications control for market and year fixed effects. The values in parentheses indicate standard errors. Standard errors are clustered at the market level and reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Finally, Table A4 reports the effect of cartel formation on terms of dynamic OP decomposition. We find no significant effect of cartel formation on the within-plant, reallocation, and entry components, whereas the coefficient for the exit term is positive. This implies that cartel formation induces less productive firms to exit, thereby improving market-level productivity. This result may be attributed to better coordination among cartel members in scrapping excess capacity.

Table A4: Estimated ATT of Cartel Formation on Dynamic OP Compoents of TFPQ Cumulative Growth

	CSA (2021)	SA (2021)	TWFE
Panel A: Overall			
ATT	0.005	0.069	0.104
	(0.117)	(0.105)	(0.074)
Panel B: Within			
ATT	-0.032	0.054	0.098
	(0.144)	(0.120)	(0.078)
Panel C: Reallocation			
ATT	0.028	0.004	0.020
	(0.022)	(0.029)	(0.018)
Panel D: Entry			
ATT	-0.000	0.000	-0.017
	(0.005)	(0.006)	(0.012)
Panel E: Exit			
ATT	0.010*	0.011***	0.004
	(0.005)	(0.003)	(0.013)

Notes: The table reports difference-in-differences estimates of cartel formation on the components of the dynamic OP decomposition at the market level. Details of the decomposition are provided in Section 4.4.3. The table reports effects on the overall productivity growth, within, reallocation, entry, and exit components in Equation (6). Panels A, B, C, D, and E correspond to these components, respectively. The sample size is 163. The estimates are from three methods that account for staggered treatment timing: Callaway and Sant'Anna (2021), Sun and Abraham (2021), and TWFE OLS. Specifications control for market and year fixed effects. The values in parentheses indicate standard errors. Standard errors are clustered at the market level and reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

B Utilization-Adjusted Productivity

B.1 Utilization-Adjusted Production Function Estimation

In this appendix, we present the results based on an alternative approach that explicitly takes into account the capacity utilization (Dong, Ma, and Shen (2021)). This approach considers estimating productivity based on Ackerberg, Caves, and Frazer (2015) while accounting for capacity utilization by exploiting variation in a proxy variable correlated with utilization, such as electricity consumption.

We use truck capacity as the utilization proxy, which is the best candidate for proxy among the available variables, and estimate utilization-adjusted productivity following this approach. Note, however, that truck capacity may not be as suitable as electricity, given its limited correlation with capacity utilization (correlation coefficient of 0.29). Thus, the results presented in this appendix may be subject to this limitation, although they remain qualitatively unchanged from those presented in the main text.

While the basic structure of our production function remains the same as in the main text, we now distinguish between installed inputs and inputs actually used in production. Specifically, we define utilized capital as $K_{it}^{*} = U_{it}^{1-\gamma} K_{it}$ and utilized labor as $L_{it}^{*} = U_{it}^{\gamma} L_{it}$, where U_{it} represents the capacity utilization rate and $\gamma \in [0, 1]$ governs how utilization affects capital and labor intensity. Under this specification, the production function becomes:

$$Y_{it} = \min\{U_{it} K_{it}^{\beta_k} L_{it}^{\beta_l} \exp(\omega_{it}), \beta_m M_{it}\} \exp(\varepsilon_{it})$$

The key challenge is that utilization U_{it} is unobserved. We therefore need a proxy variable that reflects how intensively plants use their installed capacity. Unlike Dong, Ma, and Shen (2021), who use energy consumption data, we do not have access to plant-level energy usage.[21] Instead, we propose truck intensity as an alternative utilization proxy. We define truck intensity as:

$$E_{it} = \frac{T_{it}}{K_{it}}$$

where T_{it} is truck capacity and K_{it} is mixer capacity.

The rationale for this proxy is as follows. Trucks are essential for delivering ready-mixed concrete to construction sites, and firms must maintain sufficient truck capacity relative to their production volume. Crucially, trucks are more flexible than capital or labor. Firms can quickly lease additional trucks when demand is high or reduce their fleet when demand falls. This flexibility makes truck intensity responsive to short-term demand fluctuations. When a plant operates near full capacity, it requires more trucks per unit of mixer capacity to handle the delivery volume. Conversely, when

[21] Dong, Ma, and Shen (2021) propose using energy intensity (electricity consumption per unit of capital) as a utilization proxy. The underlying mechanism is that machines consume energy only when operating, so higher energy intensity indicates more intensive use of capital. When firms operate at full capacity, their energy consumption per unit of capital is high; when many machines sit idle, energy intensity falls.

many mixers sit idle, truck intensity declines. We assume that utilization can be expressed as a function of this proxy, that is, $U_{it} = U(E_{it})$.

Given the Leontief structure, the estimating equation in logarithmic form becomes:

$$y_{it} = \beta_k k_{it} + \beta_l l_{it} + \omega_{it} + u(e_{it}) + \varepsilon_{it}$$

where $u(e_{it})$ is a nonparametric function of the log utilization proxy. The estimation procedure closely follows the two-stage approach described in the main text. In the first stage, we now estimate:

$$y_{it} = \phi(k_{it}, l_{it}, m_{it}, z_{it}) + u(e_{it}) + \varepsilon_{it}$$

The function $u(e_{it})$ is specified as a third-degree polynomial in log truck intensity. We include year fixed effects in this specification to capture common utilization shocks that affect all plants in a given year. Because e_{it} does not enter the function $\phi(\cdot)$, the two functions $\phi(\cdot)$ and $u(\cdot)$ are separately identified. The second stage proceeds as before, with productivity expressed as:

$$\omega_{it} = \hat{\phi}_{it} - \beta_k k_{it} - \beta_l l_{it}$$

and the parameters β_k and β_l estimated by GMM using the moment condition $E[\xi_{it} W_{it}] = 0$.

The parameter estimates from this specification are $\hat{\beta}_k = 0.280$ (0.034) and $\hat{\beta}_l = 0.697$ (0.134). The test for constant returns to scale yields $\chi^2 = 0.0042$ with a p-value of 0.95, again failing to reject the null hypothesis. The similarity between these results and those in the main text indicates that omitting explicit utilization controls does not substantially bias our productivity estimates. This finding provides reassurance that our main analysis captures plant-level productivity variation appropriately. In subsequent analysis, we use the productivity residuals $\hat{\omega}_{it}$ from this specification as a robustness check for our main findings.

Table B1: Production Function Estimates with Utilization Adjustment

	Estimates
β_k	0.280
	(0.034)
β_l	0.697
	(0.134)
N	5985

Notes: This table reports the production function estimates based on Ackerberg, Caves, and Frazer (2015) and Dong, Ma, and Shen (2021). The sample period is 1993-2020. Standard errors are reported in the table. Standard errors are calculated through 500 bootstrap iterations and reported in parentheses.

B.2 Plant-Level Analysis

In this subsection, we present the results for plant-level analysis. The results do not qualitatively differ from those presented in the main text.

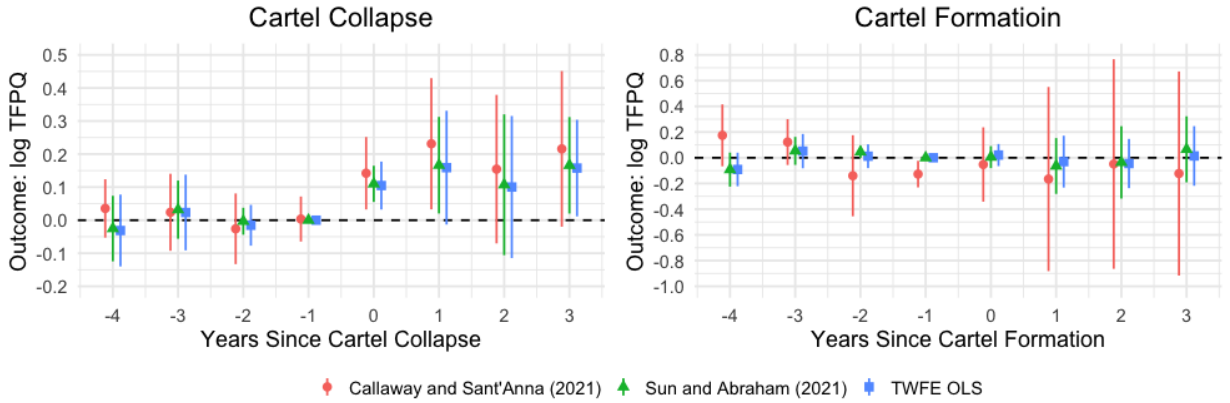


Figure B1: Event Study of Cartel Collapse and Cartel Formation (Plant Level)

Notes: The event-study plot shows the impact of cartel collapse and formation on plant-level utilization adjusted log TFPQ. The left panel reports the effects relative to the year of cartel collapse, and the right panel reports the effects relative to the year of cartel formation; the horizontal axis denotes years since the corresponding event. The figure presents estimates from three methods that account for staggered treatment timing: Callaway and Sant'Anna (2021) (orange circles), Sun and Abraham (2021) (green triangles), and TWFE OLS (blue squares). It displays point estimates and 95% confidence intervals; values in parentheses indicate standard errors. All specifications include year and market fixed effects. Standard errors are clustered at the market level.

Table B2: Estimated ATT of Cartel Changes on Log TFPQ (Plant Level)

	Cartel Collapse			Cartel Formation		
	CS(2021)	SA(2021)	TWFE	CS(2021)	SA(2021)	TWFE
ATT	0.186***	0.141**	0.146*	-0.095	0.030	0.005
	(0.072)	(0.064)	(0.074)	(0.284)	(0.102)	(0.055)
N	2937	2937	2937	1090	1090	1090

Notes: The table reports difference-in-differences estimates of cartel collapse and cartel formation on plant-level utilization adjusted log TFPQ. The estimates are from three methods that account for staggered treatment timing: Callaway and Sant'Anna (2021), Sun and Abraham (2021), and TWFE OLS. The three columns on the left-hand side show the estimates of cartel collapse. The three columns on the right-hand side show the estimates of cartel formation. Specifications control for plant and year fixed effects. The values in parentheses indicate standard errors. Standard errors are clustered at the market level and reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

B.2.1 Endogeneity Concerns

Table B3: Alternative Identification Strategies for the Impact of Cartel Collapse

	OLS	IV	PSM	IV+PSM
ATT	0.146*	0.165*	0.153**	0.187**
	(0.074)	(0.094)	(0.068)	(0.087)
N	2937	2937	1434	1434
Year FE	Yes	Yes	Yes	Yes
Plant FE	Yes	Yes	Yes	Yes
First-stage F-stat	-	498.88	-	179.46

Notes: The table reports TWFE difference-in-differences estimates of the effect of cartel collapse on plant-level utilization adjusted log TFPQ under alternative identification strategies. The OLS column replicates the baseline TWFE specification. The IV column instruments $Treat_i \times Post_{it}$ with market-level future demand measures interacted with $Treat_i$. The PSM column reports TWFE estimates on a matched sample constructed by nearest-neighbor propensity score matching at the market level. The IV+PSM column applies the IV specification on the matched sample. Standard errors are clustered at the market level. Standard errors are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

B.2.2 Heterogeneous Impacts of Cartel Collapse

Table B4: Heterogeneous Impacts of Cartel Collapse

	Log TFPQ		# Employees	
	(1)	(2)	(3)	(4)
Treat × Post	0.149*	-0.017	-0.314	1.048
	(0.076)	(0.092)	(0.644)	(0.662)
Treat × Post × Z score	-0.042**		0.293**	
	(0.020)		(0.107)	
Treat × Post × Plant density		0.011***		-0.089***
		(0.004)		(0.023)
N	2937	2937	2937	2937
Year FE	Yes	Yes	Yes	Yes
Plant FE	Yes	Yes	Yes	Yes

Notes: The table reports triple-difference estimates for plant-level utilization adjusted log TFPQ (column 1 and 2) and labor (column 3 and 4). The treatment indicator is $Treat_i \times Post_{it}$, where $Treat_i$ equals one

for plants in treated markets and $Post_{it}$ equals one in the post-collapse period. Heterogeneity is captured by interacting $Treat_i \times Post_{it}$ with the z-score of pre-collapse within-market TFPQ (column 1 and 3), and pre-collapse plant density (column 2 and 4). Standard errors are clustered at the market level and reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

B.3 Market-Level Analysis

We present the results of the market-level analysis. The results remain qualitatively unchanged from those presented in the main text.



Figure B2: Event Study of Cartel Collapse and Cartel Formation (Market Level)

Notes: The event-study plot shows the impact of cartel collapse and formation on market-level utilization adjusted log TFPQ, where the dependent variable is the quantity-weighted log TFPQ aggregated to the market level. The left panel reports the effects relative to the year of cartel collapse, and the right panel reports the effects relative to the year of cartel formation; the horizontal axis denotes years since the corresponding event. The figure presents results from three estimation methods that account for staggered treatment timing: Callaway and Sant'Anna (2021) (orange circles), Sun and Abraham (2021) (green triangles), and TWFE OLS (blue squares). It displays point estimates and 95% confidence intervals. All specifications include year and market fixed effects. Standard errors are clustered at the market level.

B.3.1 Decomposition

Table B5: Estimated ATT of Cartel Collapse on OP Compoents of Market-Level Productivity

	CSA (2021)	SA (2021)	TWFE
Panel A: Overall			
ATT	0.079	0.081	0.154**
	(0.059)	(0.056)	(0.068)
Panel B: Within			
ATT	0.113	0.115	0.139**
	(0.073)	(0.083)	(0.062)
Panel C: Reallocation			
ATT	-0.034	-0.034	0.015
	(0.060)	(0.058)	(0.017)

Notes: The table reports difference-in-differences estimates of the average effect of cartel collapse on the components of the Olley and Pakes (1996) decomposition at the market level. $N = 359$. We use utilization-adjusted log TFPQ as our productivity measure. Panel A reports effects on the output-share-weighted average log TFPQ. Panel B reports effects on the unweighted mean log TFPQ. Panel C reports effects on the covariance term (the OP residual), which captures allocative efficiency within the market. The estimates are from three methods that account for staggered treatment timing: Callaway and Sant'Anna (2021), Sun and Abraham (2021), and TWFE OLS. Specifications control for market and year fixed effects. The values in parentheses indicate standard errors. Standard errors are clustered at the market level and reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

B.4 Dynamic Olley-Pakes Decomposition

Table B6: Estimated ATT of Cartel Collapse on Dynamic OP Compoents of TFPQ Cumulative Growth

	CSA (2021)	SA (2021)	TWFE
Panel A: Overall			
ATT	0.075	0.088	0.158**
	(0.056)	(0.054)	(0.070)
Panel B: Within			
ATT	0.114	0.137*	0.144**
	(0.072)	(0.072)	(0.068)
Panel C: Reallocation			
ATT	-0.030	-0.042	0.016
	(0.063)	(0.060)	(0.015)
Panel D: Entry			
ATT	-0.008	-0.011	-0.003
	(0.015)	(0.017)	(0.015)
Panel E: Exit			
ATT	-0.002	0.004	0.000
	(0.017)	(0.019)	(0.023)

Notes: The table reports difference-in-differences estimates of cartel collapse on the components of the dynamic OP decomposition at the market level. Details of the decomposition are provided in Section 4.4.3. $N = 354$. We use utilization-adjusted log TFPQ as our productivity measure. The table reports effects on the overall productivity growth, within, reallocation, entry, and exit components in Equation (6). Panels A, B, C, D, and E correspond to these components, respectively. The estimates are from three methods that account for staggered treatment timing: Callaway and Sant'Anna (2021), Sun and Abraham (2021), and TWFE OLS. Specifications control for market and year fixed effects. The values in parentheses indicate standard errors. Standard errors are clustered at the market level and reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

C Descriptive Statistics

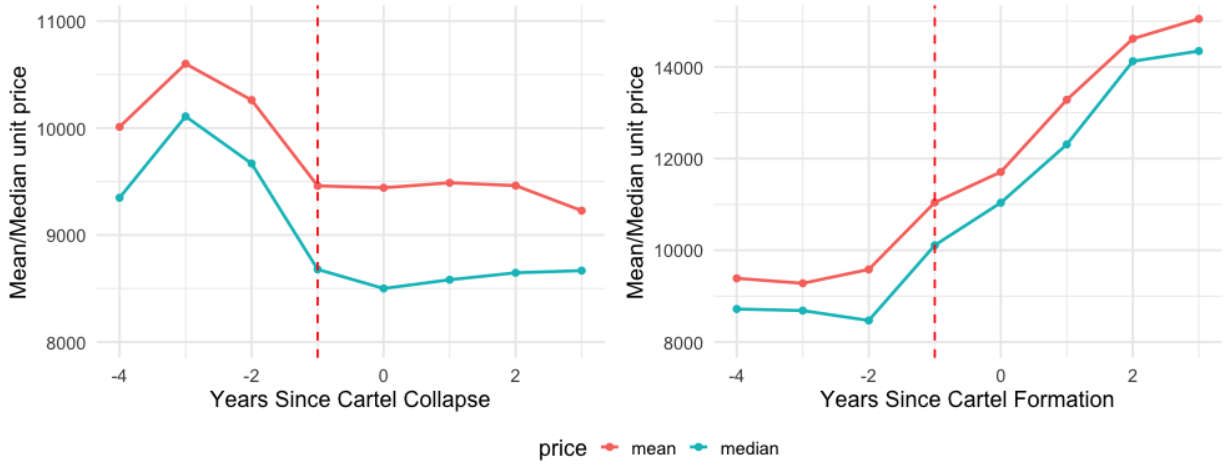


Figure C1: Time Series of Concrete Unit Prices Before and After Events

Notes: In the left panel, we plot the mean and median price in markets that experienced cartel collapse. In the right panel, we plot the mean and median price in markets that experienced cartel formation.

Table C1: Plant-Level Descriptive Statistics (1993-2004)

	N	Mean	SD	Median	P25	P75
Log Output	3260	10.01	0.6158	10	9.646	10.36
Log Revenue	3260	10.25	0.5601	10.29	9.938	10.6
Log TFPQ	3260	6.577	0.591	6.588	6.186	6.971
Log Material Expenditure	3260	9.957	0.6495	9.997	9.616	10.35
Log Mixer Size	3260	7.438	0.3448	7.313	7.313	7.601
Log Num of Employees	3260	2.222	0.5889	2.079	1.792	2.565

D Miscellaneous Results

Table D1: Log Capital Change and Future Demand

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
log private demand density at t+1	−0.004						−0.008
	(0.015)						(0.018)
log public demand density at t+1		−0.004					−0.007
		(0.024)					(0.043)
log private demand density at t+2			0.016				0.024
			(0.015)				(0.021)
log public demand density at t+2				0.011			−0.005
				(0.023)			(0.051)
log private demand density at t+3					−0.014		−0.021
					(0.013)		(0.017)
log public demand density at t+3						0.023	0.029
						(0.020)	(0.033)
N	2667	2667	2667	2667	2667	2667	2667
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Plant FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The table reports correlations between the changes in log capital of each plant from period t-1 to period t and future demand in period t+1, t+2, and t+3, respectively. Specifications control for plant and year fixed effects. Standard errors are clustered at the market level. Standard errors are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table D2: Heterogeneous Impacts of Cartel Collapse on Exit Probability

	(1)	(2)
Treat × Post	0.026***	0.019
	(0.009)	(0.013)
Treat × Post × Z score	0.002	
	(0.019)	
Treat × Post × Plant density		0.000
		(0.000)
N	2937	2937
Year FE	Yes	Yes
Plant FE	Yes	Yes

Notes: The table reports triple-difference estimates of the effect of cartel collapse on plant-level exit probability. The outcome variable is the dummy variable that takes one when the plant will exit next year and takes zero otherwise. The treatment indicator is $Treat_i \times Post_{it}$, where $Treat_i$ equals one for plants in treated markets and $Post_{it}$ equals one in the post-collapse period. Heterogeneity is captured by interacting $Treat_i \times Post_{it}$ with the z-score of within-market TFPQ (column 1) and pre-collapse plant density (column 2). Standard errors are clustered at the market level and reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.