Evaluating Cartel Impact in Electricity Procurement

Yuri Matsumura*

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Abstract

This paper examines the impact of a market allocation cartel in the Japanese electricity retail market, active from 2018 to 2020. During this period, four incumbents restricted competition by avoiding entry into each other's regions. Analyzing electricity procurement auctions from both competitive and cartel periods, I find that cartel members reduced their participation rates and submitted complementary bids in other regions while increasing bid levels within their own regions, leading to winning bids rising by up to 9% despite continued competition with non-cartel firms. Counterfactual simulations using a model of auctions with asymmetric, risk-averse bidders suggest that without the cartel, continued market entry by these firms could have lowered winning bids by up to 5.5% and reduced winning costs by 3.4%. While increased competition led to minor inefficiencies due to asymmetry among bidders, the cartel's exclusionary practices caused inefficiencies of up to 26%. Additionally, shifts toward nuclear energy generation were associated with lower procurement costs. These findings highlight the financial burden of cartel behavior and the benefits of fostering market competition for public institutions.

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1 Introduction

Cartels are a crucial area of research due to their destructive effects on markets and consumer welfare. While antitrust laws aim to prevent collusive behavior, understanding why firms engage in cartels, how to detect and deter such actions, and evaluating the resulting market distortions remain critical priorities for economists and competition authorities. The challenge is compounded by the covert nature of most cartel agreements, as only a fraction are uncovered by regulators, making it difficult to assess their broader impact on market dynamics.

This paper examines the impact of a cartel on electricity procurement. In December 2022, the Japanese Fair Trade Commission (JFTC) imposed fines on three major incumbents — Chugoku Electric Power Co., Inc. (Chugoku EPC), Kyushu EPC, and Chubu EPC—for violating competition laws by forming a cartel with Kansai EPC. This cartel targeted high and extra-high-voltage customers, including businesses, factories, and public facilities, while excluding low-voltage customers, such as households and small shops. The cartel comprised separate agreements between Kansai EPC and each of the other companies, effectively creating a market allocation scheme.

Each regional cartel agreement focused on different target markets: public buildings for Kyushu and Kansai EPC, private buildings for Chubu and Kansai EPC, and both types for Chugoku and Kansai EPC. While the companies did not fully exit each other's regions immediately, they refrained from aggressive competition. Given the broad impact across western Japan, the JFTC levied a record-breaking fine of 100 billion yen (approximately 670 million USD) on the cartel participants.

In this paper, I focus on procurement auctions for electricity supply to public institutions. I collected novel data from electricity procurement auctions between 2017 and 2023 held in Kansai, Kyushu, Chugoku, and Chubu.

The analysis yields several vital insights. First, I examine how the cartel influenced the participation behavior of the cartel members in public procurement auctions across the regions of Kansai, Kyushu, Chugoku, and Chubu. Before the cartel's formation in 2018, Kansai EPC expanded its participation in other regions, attending 50% in Kyushu and 25% in Chugoku. However, Kansai EPC's participation rate dropped sharply during the cartel period, even reaching zero in Kyushu and Chugoku after the cartel ended. Similarly, Kyushu EPC's participation in Kansai declined. This reduction in participation aligned with the market allocation scheme enforced by the cartel, minimizing competition among members in designated regions.

Second, the data reveal significant changes in bid levels submitted by cartel members during the cartel period. While fringe firms exhibited consistent bidding behavior, cartel members increased bid levels in their home markets and submitted complementary (phantom) bids in other regions. For instance, during the cartel period, Kansai EPC raised its bid levels by 25.5% in Kyushu and 24.5% in Chugoku. Kyushu EPC similarly increased its bids by 13% in Kansai. In their own regions, Kansai

EPC and Chugoku EPC raised bid levels by 20% and 11%, respectively. This pattern of behavior reduced competitive pressure and allowed for price coordination, benefiting cartel members at the expense of fair competition.

Finally, the analysis shows that winning bid levels increased across all regions during the cartel period. In Kyushu, winning bids rose by 9%, while in Chugoku, they increased by 8%. Kansai and Chubu experienced smaller increases of 4% and 3%, respectively, as Kansai EPC and Chubu EPC continued to compete in each other's markets without a cartel agreement. This increase in winning bid levels highlights the cartel's ability to inflate prices through reduced competition, ultimately driving up procurement costs for public institutions and negatively impacting market efficiency.

Given the reduced participation of incumbents from other regions and their complementary bids, I conduct a counterfactual analysis to examine the impact of adding an outside incumbent to auctions alongside existing home incumbents and fringe firms. To do this, I estimate a model of auctions with asymmetric risk-averse bidders.

The counterfactual simulation reveals that introducing an outside incumbent into auctions significantly affects competition and pricing outcomes. Specifically, adding one outside incumbent to an auction with one home incumbent and one fringe bidder reduces the winning bids by 5.5% and decreases the winner's cost by 3.4%. In auctions with one home incumbent and two fringe bidders, adding an outside incumbent results in a 3.7% reduction in winning bids and a 2.4% decrease in the winner's cost. This demonstrates the competitive pressure exerted by the entry of an outside incumbent, leading to more favorable procurement costs for public institutions.

During the cartel period, auctions in regions such as Kyushu, Kansai, and Chugoku were influenced by complementary bidding behavior. Adjusting for the presence of an outside incumbent during this period indicates potential reductions in winning bids ranging from 0.65 million yen to 7.07 million yen, with total reductions amounting to 242 million yen in Kyushu, 128 million yen in Kansai, and 230 million yen in Chugoku. This highlights the extent of cost savings that could be realized by fostering competitive market conditions.

While lower winning bids benefit public institutions by reducing procurement costs, considering the overall welfare impact is also important. Reducing the winner's cost contributes positively to social welfare, but inefficiencies may arise when the winning bidder is not the lowest-cost provider. In auctions with one home and one outside incumbent, the share of inefficient auctions is around 3.7%, with a minor efficiency loss relative to the overall bids. Conversely, the absence of outside incumbents due to cartel behavior significantly increases inefficiency rates, with inefficiency reaching 26% in auctions with one home and one fringe bidder configuration and 19% in auctions with one home and two fringe bidders. This underscores the importance of maintaining competitive pressures in procurement auctions to minimize welfare losses.

In the simulation, I investigate the effect of competition on market outcomes. However, changes in power plant composition also impact costs. For instance, a larger share of nuclear power generation tends to reduce procurement costs since nuclear power is cheaper than thermal. Using cost estimates adjusted by auction characteristics, the analysis shows that an increase in thermal power raises costs in regions like Kyushu, Kansai, and Chubu. At the same time, greater shares of nuclear and hydropower tend to lower costs in some cases. Shifts from nuclear to other energy sources can increase reliance on thermal power, driving up overall costs.

In conclusion, the descriptive and reduced-form analyses demonstrate that the cartel negatively impacted the market. The counterfactual analysis shows that competition has a positive effect by lowering winning bids and winning costs, with only minor impacts on efficiency.

The remainder of this paper is structured as follows. Section 1.1 reviews related literature. Section 2 details the institutional background and cartel context. Section 3 describes the data. Section 4 presents the reduced-form analysis of bids. Section 5 outlines the procedure for counterfactual analysis, including the structural estimation model, its results, and the counterfactual outcomes. Section 6 concludes the paper.

1.1 Literature review

Cartel is an important topic in the literature on industrial organization and has quite a large literature. (Asker and Nocke, 2021; Chassang and Ortner, 2023; Harrington, 2008; Levenstein and Suslow, 2006; Porter, 2005; Marshall and Marx, 2012; Whinston, 2006).

The empirical literature on cartels in auctions has two standards: detection of cartels and evaluation of cartel impact. The literature on detecting cartels has developed several statistical tests to detect cartels based on the difference in the relation between the observed bidder characteristics and the bids or the ranking of bids among the cartel members and the non-cartel members (Porter and Zona, 1993, 1999; Baldwin, Marshall and Richard, 1997), the variance of bids (Abrantes-Metz et al., 2006; Imhof, Karagok and Rutz, 2018), independence among bids and exchangeability of bidder characteristics (Bajari and Ye, 2003). Recent papers find that bidding rings generate a missing mass in the distribution of bids and develop detection tests (Chassang et al., 2022; Clark, Coviello and De Leverano, 2020; Kawai and Nakabayashi, 2022; Chen, 2023). Detection tests based on nonparametric identification results of auction models with cartel are also proposed (Aryal and Gabrielli, 2013; Guo, 2022; Schurter, 2020).

The literature on evaluating the impact of cartels uses the data with known cartel or bidding ring (Porter and Zona, 1993; Baldwin, Marshall and Richard, 1997; Porter and Zona, 1999; Pesendorfer, 2000; Kawai, Nakabayashi and Ortner, 2021; Seibel and Škoda, 2023). A few papers quantify the impact on auctions based on a structural model (Asker, 2010; Clark et al., 2018; Caoui, 2022; Gabrielli and Willington, 2023). Especially, Caoui (2022) and Gabrielli and Willington (2023) use the data of first-price sealed-bid auctions in school milk procurement auctions. However, the data in both papers has shortcomings. Gabrielli and Willington (2023) have only cartel period data, and the data in Caoui (2022) has cartel regions and competitive regions, but the cartel regions do not have competitive period. While both papers investigate known cartels, they do not know how the serious bidder from a bidding ring is chosen. Hence, both papers put additional assumptions on their estimations and counterfactual simulations.[1] Caoui (2022) also evaluates the impact on efficiency by comparing the competitive and cartel scenarios and finds that the cartel hurts efficiency. However, he assumes that while bidders are symmetric during the competitive period, asymmetric during the cartel period. In this case, efficiency loss never happens in the competitive scenario, so the negative impact is baked into the mode. This paper shows that efficiency is not guaranteed even in a competitive scenario.

2 Institutional detail and the cartel background

2.1 Japanese electricity market

The Japanese electricity market comprises generation, transmission and distribution, and retail. The generation and retail are liberalized, while the transmission and distribution remain regulated. Before the liberalization, ten regional private electricity companies called the General Electric Utilities (GEUs) had been providing a monopoly supply in their respective regions (See Figure 1).

The liberalization began with the generation segment in 1995, leading to the Independent Power Producers (IPPs) entry. The retail liberalization occurred gradually, starting with the extra-high voltage market (consumption above 2000 kWh) in 2000, followed by the high voltage market (50 kWh - 2000 kWh) in 2004 and 2005. The retail liberalization for the low voltage market (less than 50kWh) was completed in 2016. The GEUs now compete with new entrants, called Power Producer and Suppliers (PPSs). Therefore, all retail companies can sell electricity everywhere in Japan, and consumers can choose their electricity providers.

Figure 2 illustrates the market share of General Electricity Utilities (GEUs) and Power Producer and Suppliers (PPSs) in the retail market from 2016 to 2023 across the four regions affected by the cartel. These shares are based on the electricity supplied by each company in each region, with line styles distinguishing electricity types. GEUs consistently hold over 75% of the market share across all electricity types, while PPSs account for less than 25%. Given their historical role as regional monopolists, the dominant market share of GEUs is expected. The PPSs have gained a higher share within the high-voltage market segment than other electricity types. Since the liberalization of the market in 2016, the PPSs have also shown an increase in their share of the low-voltage market. In contrast, the GEUs dominate the most shares in the extra-high-voltage market across most regions.

[1] Because they do not know how the designated bidder is chosen, they consider two extreme scenarios. The designated bidder is the lowest-cost bidder in the bidding ring, and the designated bidder is randomly chosen.

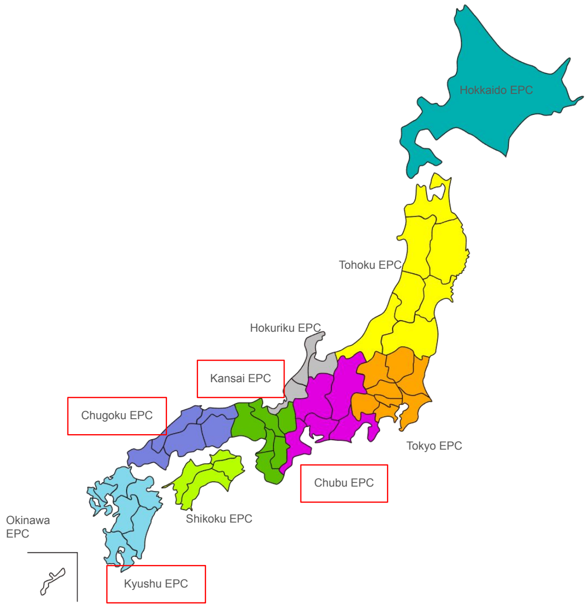


Figure 1: The map of Japan with the GEUs' territories before the liberalization

Note: The ten regions are Hokkaido, Tohoku, Tokyo, Hokuriku, Chubu, Kansai, Chugoku, Shikoku, Kyushu, and Okinawa. The corresponding GEUs in these regions are Hokkaido Electric Power Co., Inc. (in short, EPC), Tohoku EPC, Tokyo EPC, Hokuriku EPC, Chubu EPC, Kansai EPC, Chugoku EPC, Shikoku EPC, Kyushu EPC, and Okinawa EPC, respectively. The GEU's name with a red square is the GEUs involved in the cartel agreement. (Source: Electric power statistics by the Agency for Natural Resource and Energy)

Here, I introduce some factors that lead to differences in the cost structure among the electricity companies. Figure 3 shows the number of power plants owned by the GEUs and the PPSs.[2] The GEUs typically own around 100 power plants, whereas most PPSs own none or very few. The maximum output of power plants also has a large difference.

Ownership of power plants significantly impacts retail prices. Around 40% of retail electricity prices come from electricity purchase costs. The ownership of power plants significantly influences retail electricity prices, as around 40% of these prices stem from electricity purchase costs. Retail companies that lack their own power plants must procure electricity from plants owned by the GEUs, the IPPs, or through the Japan Electric Power Exchange (JEPX).[3] The JEPX has become a crucial electricity source for the PPSs, fulfilling 40% of their electricity demand in 2017 and growing to 93% by 2021.[4]

Since electricity purchase costs often include markups by power plant owners, the PPSs face higher expenses than companies that produce electricity directly, potentially resulting in increased

[2]Appendix B provide detailed summaries statistics of power plant maximum output and numbers.

[3]Founded in 2003 and operational since 2005, the JEPX includes all GEUs and some PPSs among its members. The JEPX operates an intraday market (with one-hour and four-hour-ahead trading), a day-ahead market, and a forward market.

[4]For more details on the JEPX, see https://www.emsc.meti.go.jp/activity/emsc_system/pdf/068_08_00.pdf. The share is calculated by dividing the total JEPX transactions for the PPSs by their overall electricity demand.

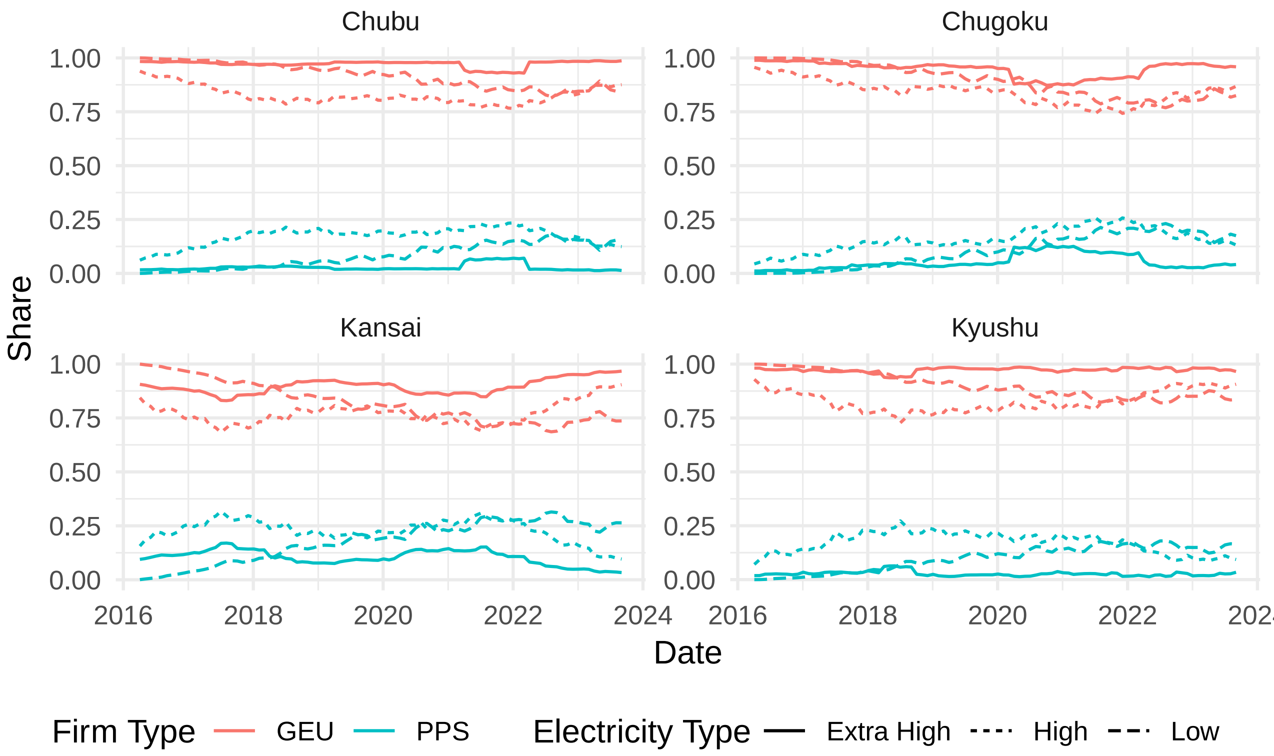


Figure 2: The market share of electricity suppliers

Note: The figure shows the market share of the GEUs and the PPSs in the retail market in regions that the cartel covered. The share is based on the electricity usage (mkw). The red lines are the share of the GEUs (incumbents), and the green lines are the share of the PPSs (fringes). The style of lines represents the electricity type.

retail prices. However, when the JEPX prices drop, the PPSs can pass on lower costs to consumers compared to the standard GEU contracts. Still, the volatility of the JEPX prices means the PPSs and their customers also bear the risk of sudden price surges.[5]

Regional differences exist among the GEUs in terms of electricity generation configurations. Figure 4 illustrates each region's electricity generation share by fuel type, primarily reflecting plants owned by the GEUs since the PPSs typically do not own power plants. The generation composition varies among the GEUs: thermal power accounts for over 75% of electricity generation in each region. While the share is stable at around 80% in Chugoku, it fluctuates in other areas. Hydropower ranks as the second-largest source in Chubu, while nuclear power holds that position in Kyushu and Kansai. The nuclear share in Kansai was zero until mid-2017, as all nuclear plants were suspended following the Fukushima Nuclear Accident. Thermal power generation is generally the most expensive source, while hydropower and nuclear power have much lower marginal costs, suggesting potential cost differences among incumbents.

[5]After fuel prices rose sharply in 2020, many PPSs faced severe financial strain or bankruptcy. See `https://www.tdb.co.jp/report/watching/press/p230613.html`.

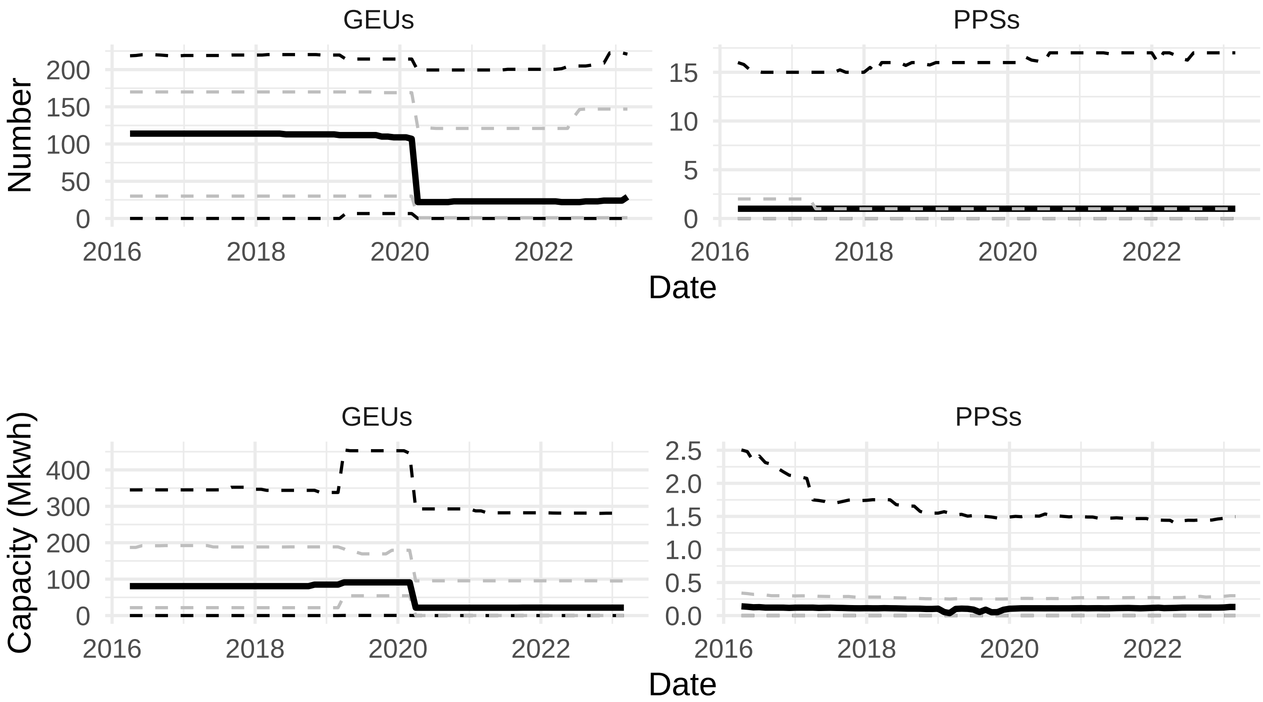


Figure 3: The number of power plants

Note: The figure shows the number of power plants owned by the GEUs (incumbents) and the PPSs (fringes) and their capacity (the maximum amount of electricity generated). The solid line is the median, and the dotted lines are the 5th, 25th, 75th, and 95th percentiles.

2.2 Cartels among electricity companies

In December 2022, the Japanese Fair Trade Commission (JFTC) ordered three incumbents - Chugoku Electric Power Co., Inc. (in short, EPC), Kyushu EPC, and Chubu EPC - to pay a fine for violating competition laws and forming a cartel. These three incumbents and Kansai EPC formed the cartel and targeted customers using extreme-high voltage and high voltage, including businesses, factories, and public facilities.[6] The JFTC provided detailed information about the cartel agreement. The summary is provided in Table 1, and the details of each case are found in Appendix A.

The cartel consists of three cartels between Kansai EPC and each of the other companies. As the extra-high and high-voltage markets were liberalized in the early 2000s, retail companies could enter any area in Japan. While the incumbents could potentially enter the other areas, they did not actively expand their sales areas even after the liberalization.

The situation changed in western Japan because, in late 2017, Kansai EPC announced it would start its sales activities in Kyushu, Chugoku, and Chubu in 2018. In response, Kyushu EPC, Chugoku

[6]The cartel did not cover low-voltage customers, such as households and small shops.

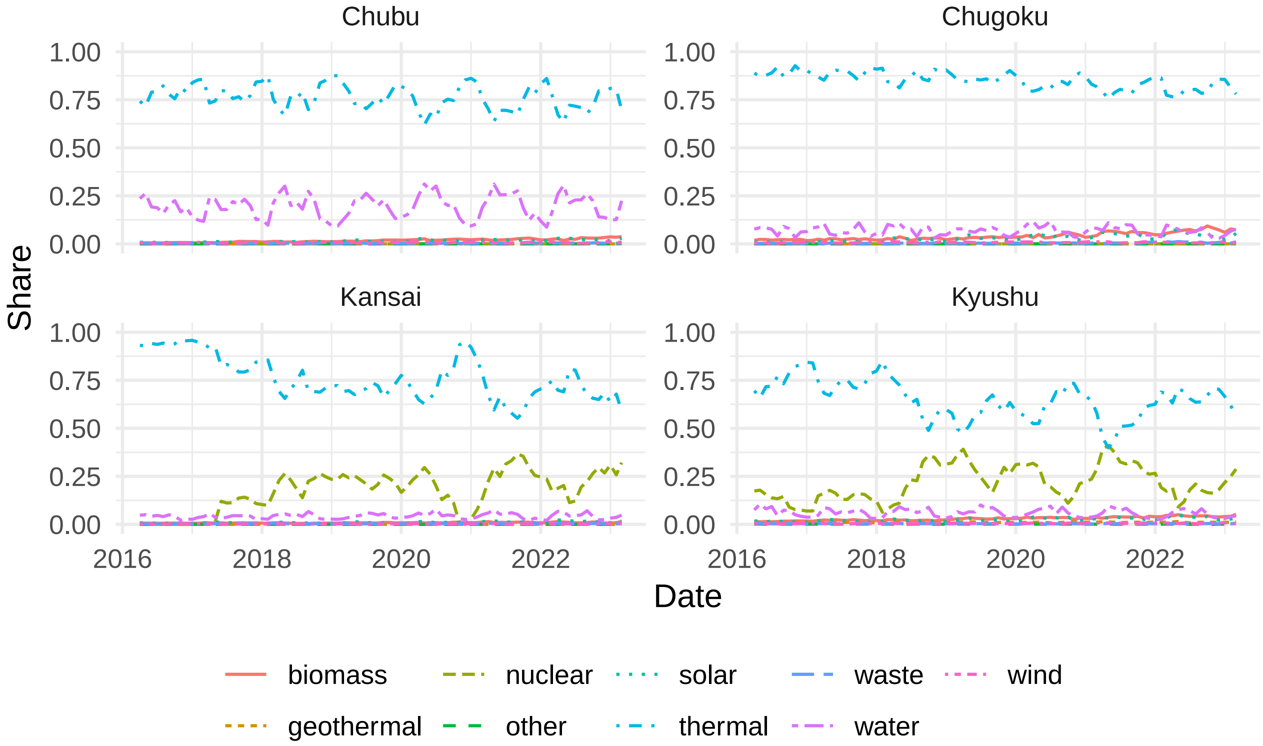


Figure 4: The share of electricity power generation by fuel type

EPC, and Chubu EPC also started their sales activities in the Kansai region. Thus, a competitive period started in 2018.

However, Kansai EPC and other companies had several meetings in 2018 and formed cartel agreements. The cartel started in late 2018 and ended in late 2020 because Kansai EPC applied for the leniency program. For the later analysis, I define October 2018 as the beginning of the cartels and October 2020 as the end of the cartels.

The cartel implemented a market-allocation scheme, avoiding entering each other's area. The target buildings are different among the cases. Kyushu EPC and Kansai EPC focused only on public buildings, Chubu ECP and Kansai EPC focused only on private buildings, and Chugoku EPC and Kansai EPC covered both types. Even after starting the cartel, they did not wholly exit from other areas immediately and refrained from submitting competitive prices and bids in each other's area.

As the cartels affected half of Japan, the JFTC imposed the historically highest total fine on the cartel, which amounted to 100 billion yen (about 670 million dollars).[7] As Kansai EPC applied to the leniency program, The JFTC did not impose a fine on Kansai EPC.[8]

[7]The fine to Chubu EPC is 27.5 billion yen, to Chugoku ECP is 70.7 billion yen, and to Kyushu EPC is 2.7 billion yen.

[8]By the deadline for the fine payments in October 2023, Kyushu EPC, Chugoku EPC, and Chubu EPC each filed lawsuits to overturn the Japan Fair Trade Commission's order requiring them to pay the fine.

Table 1: The summary of the cartel cases

Kansai EPC + Kyushu EPC	
Target	Public buildings
Pricing	Kansai EPC submitted complementary bids in procurement auctions, and Kyushu EPC increased the level of bids
Entry	Kansai EPC was absent from many procurement auctions in Kyushu. Kyushu EPC also exits from Kansai.
Kansai EPC + Chugoku EPC	
Target	Public buildings and private buildings
Pricing	For the contract of private buildings, both companies increased the level of electricity prices in its own area
Entry	Both companies restricted their sales activity in the other areas. Kansai EPC does not join procurement auctions whose expected usage is less than 300,000 kWh
Kansai EPC + Chubu EPC	
Target	Private buildings
Pricing	Increase the level of electricity price in Kansai and Chubu
Entry	Both companies restricted their sales activity in the other areas and increased the level of electricity prices in own area

3 Electricity Procurement Data

While the cartel affected public and private buildings, this study focuses on public buildings. Public institutions manage various buildings and facilities such as city halls, schools, and water utilities. Public institutions typically have several options when selecting an electricity provider for these facilities. This study focus on procurement auctions.

The dataset includes electricity procurement auctions held from 2016 to 2023, covering both the competitive period and the cartel period. It contains four regions: Kansai, Kyushu, Chugoku, and Chubu. The procurement auctions in Kansai, Kyushu, and Chugoku were directly affected by the cartel agreement. The data was collected from public institutions' websites and through information disclosure requests. The institutions include prefectures, cities, towns, and local branches of ministries. The dataset contains details such as the bidder's name, bid amounts, a winner indicator, total expected usage, total contract power (maximum demand capacity of all buildings), contract length, and the number of buildings included in the contract.

Table 2 summarizes the characteristics of the auctions, excluding those with only one bidder. Additional summaries based on regions are provided in Table 10 in Appendix B.

The timeline of an electricity procurement auction proceeds as follows: prior to the auction, a pub-

Variable	Min	25-th	Median	75-th	Max	SD	Obs
Number of Bidders	2.0	3.0	4.0	6.0	13	2.2	2,761
Expected Usage (mWh)	180.0	2,430.0	6,716.2	29,300.0	1,683,270	67,772.2	2,761
Contract Power (kW)	11.0	125.0	328.0	1,279.0	37,866	2,266.3	2,761
Number Building	1.0	1.0	1.0	3.0	432	22.6	2,761
Contract Length (days)	121.0	364.0	364.0	365.0	1,825	188.4	2,761
Bid ($)	1,830.8	25,852.8	66,627.8	297,155.1	18,716,145	593,198.8	12,534
Winning Bid ($)	1,830.8	25,163.1	72,311.3	301,739.9	17,925,624	669,034.1	2,761

Table 2: Summary of auction characteristics

Note: 1 USD = 140 JPY

lic institution announces the buildings included and provides relevant details. Electricity companies, based on this information, calculate their total expected payments for the contract period and submit these as bids. The bidder offering the lowest total payment wins the auction.

Although bidders submit total expected payments, the public institution does not pay this amount directly, as actual electricity usage often deviates from estimates. Instead, bids are structured with a two-part tariff comprising a monthly lump-sum fee and a per-unit price. [9] The winning bidder operates under the agreed lump-sum fee and per-unit price and receives monthly payments based on actual usage.[10]

Most public institutions set a secret reserve price for the auctions. Sometimes, these reserve prices are disclosed alongside auction results. However, in electricity procurement auctions, the reserve price seldom binds, with only a few instances in the data where bids exceeded these prices. As a result, the auction format for electricity procurement is typically a single-unit, first-price, sealed-bid auction.

4 The Impact of the Cartel

Based on the cartel description in Section 2.2, the cartel members restricted their sales activity in other sales areas and weakened their competition. This section shows some evidence of the cartel members' non-competitive behavior and the cartel's impact on market outcomes.

Figure 5 shows the participation rate of the GEUs in auctions in Chubu, Chugoku, Kansai, and Kyushu from 2017 to 2021. The shaded region represents the years after the cartel. To compute the rate, I count the number of auctions of a bidder attended in a year and divide the count by the total number of auctions in the year.

[9] The total expected price is typically calculated using the formula: Total expected price = (lump-sum fee × contract power) + (per-unit price × expected usage)

[10] While the lump-sum fee and per-unit price are used during the contract, they do not determine the auction winner. See Athey and Levin (2001), Luo and Takahashi (2019), and Bolotnyy and Vasserman (2023) for studies on auctions where bidders submit baseline and unit prices, with total prices determining the winner.

First, the incumbents started to enter other areas in 2018. In particular, Kansai EPC participated in 75% of auctions in Chubu, 25% in Chugoku, and 50% in Kyushu. However, after starting the cartel, the participation rate changed dramatically for some incumbents. First, the participation rate of Kansai ECP decreased sharply from the competitive year in Kyushu and Chugoku and reached zero after ending the cartel. Second, the participation rate of Kyushu EPC in Kansai also decreased after starting the cartel. In contrast, the participation rate of Chubu EPC in Kansai increased from 2018 to 2021, and the participation rate of Kansai EPC in Chubu did not show a sharp decrease after starting the cartel. Recall that the JFTC does not acknowledge the cartel case on procurement auctions between Kansai EPC and Chubu EPC. Therefore, Kansai EPC actively joined the auctions held in Chubu, and Chubu EPC also joined the auctions in Kansai.

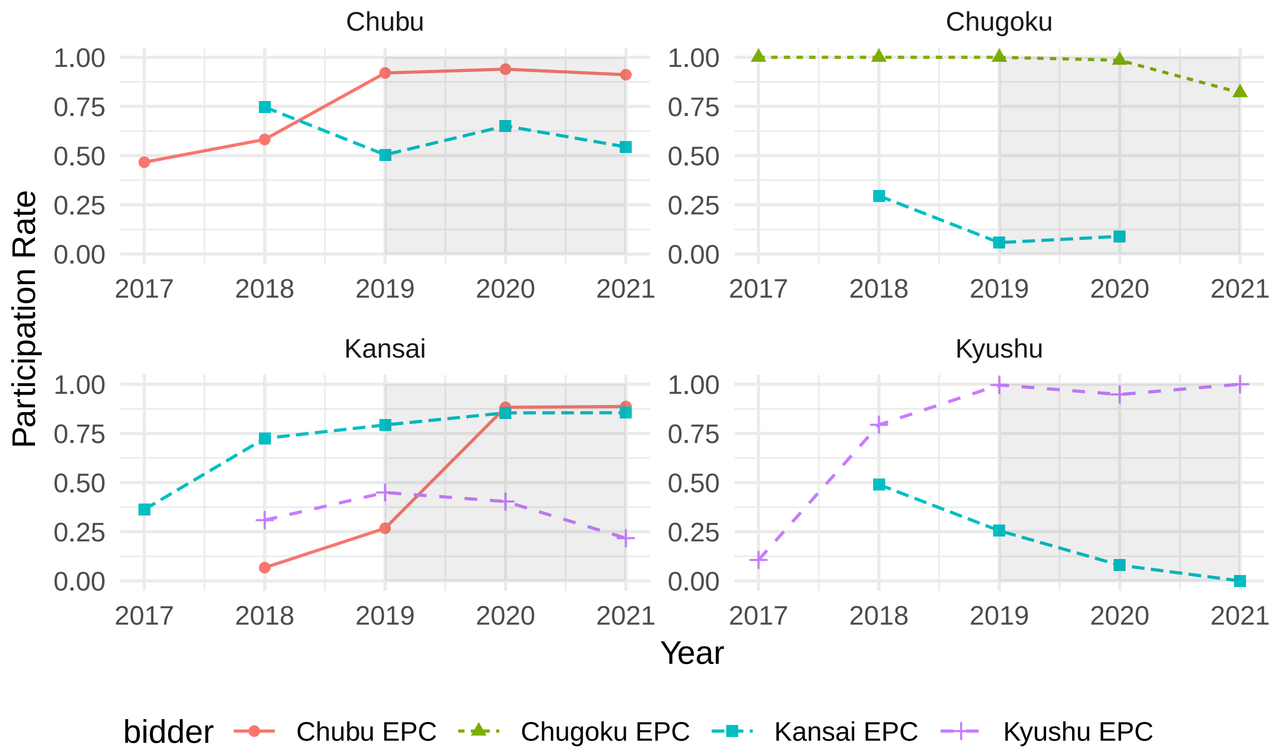


Figure 5: The participation rate of the incumbent in each region.

Note: The participation rate is the ratio of the number of auctions in which the incumbent participated to the total number of auctions in each region. The shaded region represents the years after the cartel.

Next, I check the change in bids. I conduct a reduced-form analysis to extract the change in the bids during the cartel period. Assume that the cartel agreement affects the bids of the cartel members during the cartel period but not the bids of other firms. For each region, I compare the bids of the incumbents and the fringe firms during the cartel and competitive periods. Therefore, I use a difference-in-differences strategy to estimate the effect. The treated group is the incumbents and the control group is the fringe firms. Given a region, I refer to an incumbent who was a natural monopolist in the region as a home incumbent and to incumbents from other areas as outside incumbents. Furthermore, given a region, I refer to a cartel member who is also the home incumbent as the home cartel member and to a cartel member who is also an outside incumbent as an outside cartel member. Therefore, in the following analysis, Chubu EPC is not regarded as a cartel member because Kansai EPC and Chubu EPC did not have any cartel agreement on procurement auctions. In contrast, Kyushu EPC is an outside cartel member in Kansai because Kyushu EPC and Kansai EPC had a cartel agreement.

The regression model is as follows: for each bidder i in auction l,

$$\log(\text{Bid}_{il}) = \alpha_1 \text{Cartel}_l + \sum_{k=1}^{4} \alpha_{2k} \text{Incumbent } k_{il} + \sum_{k=1}^{4} \alpha_{3k} \text{Incumbent } k_{il} \times \text{Cartel}_l$$
$$+ \beta X_{il} + F_{year} + F_{month} + F_{institution} + \varepsilon_{il}. \tag{1}$$

X_{il} is the vector of control variables and includes expected usage, contract power, number of bidders, number of buildings, contract length, thermal-plant cost, and distance between the headquarters of the bidders and the public institution. Thermal generation cost is an estimated cost for running thermal power plants. This variable reflects the change in fuel prices. As for the continuous variables, I take the logarithm. The fixed effects are for year, month, and public institution. Cartel_l is a dummy variable that takes the value one if the auction is held in the cartel period and zero otherwise. $\text{Incumbent}k_{il}$ is a dummy variable that takes the value one if the bidder is incumbent k and zero otherwise. Recall that four incumbents are included in the data, and incumbent k is one of Kansai EPC, Chugoku EPC, Chubu EPC, and Kyushu EPC. Therefore, I assume that the cartel period effect can differ between the incumbents. I run the regression of (1) for four regions separately.

Table 3 shows the regression result. First, each value of $\text{Incumbent}k_{il}$ implies that the incumbents submitted lower bids during the competitive periods than fringe firms. In Kyushu, Kyushu EPC submitted 13% lower bids, and Kansai EPC submitted 14% lower bids. In Chugoku, Chugoku EPC submitted 9% lower bids, and Kansai EPC submitted 13% lower bids. In Kansai, Kansai EPC submitted 17% lower bids, and Kyushu EPC submitted 15% lower bids. In Chubu, Kansai EPC and Chubu EPC also submitted lower bids, but the magnitude is smaller than other regions. Additionally, Chubu EPC submitted lower bids in Kansai, but not statistically significant. Therefore, the incumbents who had cartel agreements on procurement auctions competed aggressively with each other during the competitive period.

Second, during the cartel period, the fringe firms did not change their bidding behavior. In contrast, the incumbents changed their behavior. In particular, Kansai EPC submitted 25.5% and 24.5% higher bids in Kyushu and Chugoku, respectively, and Kyushu EPC also submitted 13% higher bids in Kansai. Kansai EPC increased the level of bids 6% in Chubu and Chubu EPC increased the level of bids 10% in Kansai, but these are not statistically significant. Therefore, the incumbents with the cartel agreements on procurement auctions submitted complementary (phantom) bids in other areas. These incumbents also increased the level of bids in their home regions. Kansai EPC submitted 20% higher bids, Chugoku EPC submitted 11% higher bids. Kyushu EPC increased bids 6%, but it is not statistically significant. However, given that Kyushu EPC submitted lower bids than the fringe firms and the fringe firms did not change their behavior, it can be conclude that Kyushu EPC increased the level of bids in Kyushu. This fact is also supported fact that Chubu EPC did not change its behavior in Chubu during the cartel period.

Next, I check the change in the winning bids. To do this, I regress the winning bids:

$$\log(\text{Win Bid}_l) = \beta X_l + \alpha_1 \text{Cartel}_l + F_{year} + F_{month} + F_{institution} + \varepsilon_l. \tag{2}$$

I separately run the regression (2) for each region. Note that X_l does not include bidder-level information.

Table 4 shows the regression result. During the cartel period, the winning bid increased in all regions. The magnitude is 9% in Kyushu and 8% in Chugoku. In contrast, the magnitude is 4% in Kansai and 3% in Chubu. In both areas, Kansai EPC and Chubu EPC, which did not have a cartel agreement on procurement auctions, still competed during the cartel period. Their competition may lead to a slight increase in the winning bids, although Kyushu and Chugoku had only one incumbent after the exit of the outside cartel member, Kansai EPC.

In summary, the results confirm the cartel description in 2.2. First, the cartel implemented a market allocation scheme in each region. Second, the non-designated cartel member submitted complementary bids. Third, some incumbents increased their bid level in own sales area Additionally, the level of winning bids increased in the area where the incumbents had the cartel agreement. This imply that public institutions' payments increased. Therefore, the cartel had negative impacts on electricity procurement auctions.

5 Competition and Market Outcomes

In Section 4, I confirmed the change in the cartel members' behavior from the competitive period to the cartel period. They indicate a decrease in the number of serious bidders. Therefore, the cartel members would likely continue to join auctions in other areas without cartels. In this section, I investigate a counterfactual scenario without the cartel and answer the following question: When the outside cartel members continue to join auctions in others' areas as serious bidders, how much do market outcomes improve from the competition among the incumbents and the fringes?

The analysis in Section 4 cannot answer the question because it just compares the competitive and

Table 3: Regression of Bids

Dependent Variable:	log (Bid)			
	Kyushu	Chugoku	Kansai	Chubu
Model:	(1)	(2)	(3)	(4)
Variables				
Contract Power	0.206***	0.301***	0.201***	0.195***
	(0.022)	(0.010)	(0.013)	(0.007)
Expected Usage	0.788***	0.688***	0.770***	0.813***
	(0.017)	(0.004)	(0.012)	(0.003)
Number Building	0.000	-0.002*	0.001***	0.000*
	(0.001)	(0.001)	(0.000)	(0.000)
Number Bidder	-0.005	-0.006	0.002	-0.011
	(0.002)	(0.005)	(0.006)	(0.005)
Distance	-0.002	-0.005	-0.008	-0.006
	(0.003)	(0.005)	(0.004)	(0.004)
Contract Days	0.000	0.000***	0.000	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Thermal Generation Cost	0.153	0.288**	0.142	0.128**
	(0.088)	(0.068)	(0.114)	(0.028)
Cartel Period	0.006	-0.012	-0.054***	-0.019
	(0.028)	(0.009)	(0.005)	(0.020)
Kyushu EPC	-0.138**		-0.162**	
	(0.040)		(0.046)	
Kansai EPC	-0.141***	-0.131***	-0.179**	-0.044
	(0.008)	(0.006)	(0.033)	(0.100)
Cartel Period × Kyushu EPC	0.036		0.130**	
	(0.045)		(0.040)	
Cartel Period × Kansai EPC	0.255***	0.245**	0.201***	0.062
	(0.009)	(0.052)	(0.033)	(0.105)
Chugoku EPC		-0.092*		
		(0.029)		
Cartel Period × Chugoku EPC		0.117**		
		(0.023)		
Chubu EPC			-0.136	-0.069
			(0.058)	(0.051)
Cartel Period × Chubu EPC			0.102	0.020
			(0.044)	(0.049)
Fixed-effects				
Year	Yes	Yes	Yes	Yes
Month	Yes	Yes	Yes	Yes
Institution	Yes	Yes	Yes	Yes
Fit statistics				
Observations	5,426	995	2,881	1,400
R^2	0.99633	0.99585	0.99065	0.99614
Within R^2	0.99007	0.98983	0.98516	0.99271

Clustered (Year) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Note: The control group is the fringe firms.

Table 4: Regression of winning bids

Dependent Variable:	log (Winnng Bid)			
	Kyushu	Chugoku	Kansai	Chubu
Model:	(1)	(2)	(3)	(4)
Variables				
Contract Power	0.195***	0.259***	0.213***	0.176***
	(0.020)	(0.016)	(0.005)	(0.016)
Expected Usage	0.795***	0.723***	0.761***	0.829***
	(0.019)	(0.016)	(0.008)	(0.009)
Number Building	0.001	-0.001	0.001***	0.000
	(0.001)	(0.001)	(0.000)	(0.000)
Number Bidder	-0.006*	-0.012*	-0.005	-0.012
	(0.002)	(0.004)	(0.008)	(0.006)
Distance	-0.002	-0.005	0.010**	0.001
	(0.006)	(0.007)	(0.003)	(0.002)
Contract Days	0.000	0.000***	0.000	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Thermal Generation Cost	-0.008	0.291	0.078	0.083*
	(0.060)	(0.139)	(0.076)	(0.031)
Cartel Period	0.090*	0.082***	0.040*	0.033
	(0.035)	(0.011)	(0.016)	(0.020)
Fixed-effects				
Year	Yes	Yes	Yes	Yes
Month	Yes	Yes	Yes	Yes
Institution	Yes	Yes	Yes	Yes
Fit statistics				
Observations	968	208	691	356
R^2	0.99835	0.99742	0.99501	0.99824
Within R^2	0.99536	0.99365	0.99206	0.99644

Clustered (Year) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

cartel periods. In this case, I cannot compare the change in the winning bid from the cartel situation to the competitive situation given an auction held in the cartel period. Additionally, I investigate the change in welfare in auctions.

To accomplish this, I use a structural model of procurement auctions, estimate the bidder's cost, and recover the equilibrium bidding functions. The difficulty in the estimation is that the structural estimation does not work to recover the cost of bidders during the cartel period. For example, when the Kansai EPC did not join an auction, no information is available to identify the cost, and as complementary bids do not have a clear map with the cost, they can not be used to recover costs. However, the data includes a sufficient number of competitive auctions, and hence, I estimate the cost distribution based only on the competitive auction data.

I rely on the nonparametric estimation method of auctions initiated by Guerre, Perrigne and Vuong (2000). Based on the institutional background and the feature of the procurement auction, the following model introduces asymmetric risk-averse bidders. I follow the identification and estimation based on Guerre, Perrigne and Vuong (2009) and Campo et al. (2011). The bidders are asymmetric in both cost distribution and risk-attitude. First, as I have shown, the incumbents and fringes have different cost structures, mainly based on how they supply electricity. Second, each bidder faces uncertainty in future payments because the bids are calculated based on the expected usage. Thus, the actual usage during the contract could be different, which changes the actual payment from the public institution.

While each auction has different auction characteristics, nonparametric estimation of cost conditional on auction characteristics suffers from the curse of dimensionality. To overcome the problem, I homogenize the bids based on Haile, Hong and Shum (2003) and estimate the density of idiosyncratic costs. In the following, I regard homogenized bids as bids and estimate idiosyncratic costs that remove the effects of auction characteristics.

5.1 Model

Consider a first-price sealed bid procurement auction with N risk-averse bidders. I assume three types of bidders are in the market: the home incumbent, the outside incumbent, and the fringe. Let h, o, and f be the index of the home incumbent, the outside incumbent, and the fringe, respectively. Let $\mathcal{N} = (N_h, N_o, N_f)$ be the tuple of the number of each bidder type, where N_k be the number of bidders of type $k = h, o$, and f. Note that I allow that $N_k = 0$ for some k. The cost of bidder i of type k is drawn independently from a distribution $F_k(\cdot)$. The distribution $F_k(\cdot)$ is absolutely continuous with density $f_k(\cdot) > 0$ on a compact support $[\underline{c}, \overline{c}]$. The density $f_k(\cdot)$ is assumed to be bounded away from zero and infinity on the support. The distributions assume exogenous participation; that is, the cost distribution does not depend on the number of bidders joining the auction. Let $U_k(\cdot)$ be the utility function of bidder with type k where $U(0) = 0$, $U(1) = 1$, $U'(\cdot) > 0$ and $U''(\cdot) \leq 0$. The expected payoff of each type of bidder is the following:

$$\begin{aligned}
&U_h(b_{h,i} - c_{h,i}) \Pr(b_{h,i} \leq \min_{j \neq i \in \mathcal{N}_h} b_{h,j}, b_{h,i} \leq \min_{j \in \mathcal{N}_o} b_{o,j}, b_{h,i} \leq \min_{j \in \mathcal{N}_f} b_{f,j}),\\
&U_o(b_{o,i} - c_{o,i}) \Pr(b_{o,i} \leq \min_{j \neq i \in \mathcal{N}_o} b_{o,j}, b_{o,i} \leq \min_{j \in \mathcal{N}_h} b_{h,j}, b_{o,i} \leq \min_{j \in \mathcal{N}_f} b_{f,j}),\\
&U_f(b_{f,i} - c_{f,i}) \Pr(b_{f,i} \leq \min_{j \neq i \in \mathcal{N}_f} b_{f,j}, b_{f,i} \leq \min_{j \in \mathcal{N}_h} b_{h,j}, b_{f,i} \leq \min_{j \in \mathcal{N}_o} b_{o,j}).
\end{aligned}$$

Pick a bidder i of type k. Let $s_k(\cdot) : [\underline{c}, \overline{c}] \to \mathbb{R}_+$ be the symmetric equilibrium strategy of bidder of type k. Assume that other bidders follow the equilibrium bidding strategy based on their types. By using the distributions of cost of each type and independence of the cost, the probability that bidder i wins in the auction by submitting $b_{k,i}$ is written as

$$\begin{aligned}&\Pr(b_{k,i} \leq \min_{j \neq i \in \mathcal{N}_h} b_{h,j}, b_{k,i} \leq \min_{j \in \mathcal{N}_o} b_{o,j}, b_{k,i} \leq \min_{j \in \mathcal{N}_f} b_{f,j})\\ &= [1 - F(s_k^{-1}(b_{k,i}))]^{N_k - 1} \prod_{j \neq k} [1 - F(s_j^{-1}(b_{k,i}))]^{N_j}.\end{aligned}$$

Substituting this representation into the expected payoff of the home incumbent, the maximization problem of bidder i is written as

$$\max_{b_{k,i}} U_k(b_{k,i} - c_{k,i})[1 - F(s_k^{-1}(b_{k,i}))]^{N_k - 1} \prod_{j \neq k} [1 - F(s_j^{-1}(b_{k,i}))]^{N_j}.$$

Differentiating the expected payoff with respect to $b_{k,i}$, the first-order condition is written as

$$1 = H_k(b_{k,i} \mid \mathcal{N}) \lambda_k(b_{k,i} - c_{k,i}).$$

where $\lambda_k(\cdot) = \frac{U_k(\cdot)}{U_k'(\cdot)}$ and

$$H_k(b_{k,i} \mid \mathcal{N}) = \frac{N_k - 1}{s_k'(s_k^{-1}(b_{k,i}))} \frac{f_k(s_k^{-1}(b_{k,i}))}{1 - F_k(s_k^{-1}(b_{k,i}))} + \sum_{j \neq k} \frac{N_j}{s_j'(s_j^{-1}(b_{k,i}))} \frac{f_j(s_j^{-1}(b_{k,i}))}{1 - F_j(s_j^{-1}(b_{k,i}))}.$$

Note that $\lambda_k'(\cdot) = 1 - \frac{U_k(\cdot) U_k''(\cdot)}{U_k'(\cdot)^2} \geq 1$, and hence $\lambda_k(\cdot)$ is strictly increasing and $\lambda_k(\cdot)$ is invertible. Therefore, the first-order condition can be written as

$$c_{k,i} = b_{k,i} - \lambda_k^{-1}\left(\frac{1}{H_k(b_{k,i} \mid \mathcal{N})}\right), \quad k = h, o, f. \tag{3}$$

Therefore, I can recover the cost by subtracting the markup from the bid.

5.2 Identification

The objects I need to identify are the cost distribution of each bidder type and the utility function of each bidder type. Guerre, Perrigne and Vuong (2009) provide an identification result of the cost distribution and the utility function.

Let $G_k(\cdot \mid \mathcal{N})$ be the distribution and $g_k(\cdot \mid \mathcal{N})$ be the density of the observed bids of bidders of type k with the set of bidders $\mathcal{N}$. Observe that the distribution of bids of type k and the cost distribution of type k has the following relationship:

$$G_k(b \mid \mathcal{N}) = \Pr(b_k \le b) = \Pr(c_k \le s_k^{-1}(b)) = F_k(s_k^{-1}(b)),$$

and then by differentiating both sides, I have

$$g_k(b \mid \mathcal{N}) = \frac{dG_k(b \mid \mathcal{N})}{db} = \frac{dF_k(s_k^{-1}(b))}{db} = \frac{f_k(s_k^{-1}(b))}{s_k'(s_k^{-1}(b))}.$$

Therefore, the function H_k in (3) can be written as

$$H_k(b_{k,i} \mid \mathcal{N}) = \frac{(N_k - 1)g_k(b_{k,i} \mid \mathcal{N})}{1 - G_k(b_{k,i} \mid \mathcal{N})} + \sum_{j \neq k} \frac{N_j g_j(b_{k,i} \mid \mathcal{N})}{1 - G_j(b_{k,i} \mid \mathcal{N})}.$$

Next, I identify $\lambda_k(\cdot)$ for $k = h, o, f$. Consider two auctions where the number of bidders is different. Let $\mathcal{N} = (N_h, N_o, N_f)$ and $\mathcal{N}' = (N_h', N_o', N_f')$ where $N_k < N_k'$ holds for at least one of k. As the number of bidders varies, the α-quantile of the bid distribution of type k varies as well. However, as the cost distribution of type k does not depend on the number of bidders, the α-quantile of the cost distribution of type k is the same in the two auctions. Let $b_k(\alpha; \mathcal{N})$ be the α-quantile of the bid distribution of type k in the auction with $\mathcal{N}$. From the first-order condition, as the α-quantile of the cost distribution of type k should be the same in two auctions, leading to

$$b_k(\alpha; \mathcal{N}) - \lambda_k^{-1}\left(\frac{1}{H_k(b_k(\alpha; \mathcal{N}) \mid \mathcal{N})}\right) = b_k(\alpha; \mathcal{N}') - \lambda_k^{-1}\left(\frac{1}{H_k(b_k(\alpha; \mathcal{N}') \mid \mathcal{N}')}\right),$$

for any $\alpha \in [0, 1]$, which are called the compatibility conditions. Based on the result in Guerre, Perrigne and Vuong (2009), it can be shown that $\lambda_k^{-1}(\cdot) = \sum_{t=0}^{\infty} \Delta b(\alpha_t)$ where $\Delta b(\alpha_t)$ is an identified sequence of differences in bid quantiles constructed from the compatibility conditions. As $\lambda^{-1}(\cdot)$ can be represented only by bids, it is identified.

5.3 Estimation

Step 1: Estimation of the risk parameter

First, for auctions where the set of the number of bidders is $\mathcal{N}$, estimate the distribution and density of bids of each bidder type by the empirical distribution and a kernel density estimator. The estimator is for $k = h$ and f,

$$\hat{G}_k(b \mid \mathcal{N}) = \frac{1}{L}\sum_{l=1}^{L}\frac{1}{N_{k,l}}\sum_{i=1}^{N_{k,l}}\mathbf{1}\{b_{k,i} \leq b,\ \mathcal{N}_l = \mathcal{N}\}, \tag{4}$$

$$\hat{g}_k(b \mid \mathcal{N}) = \frac{1}{Lh}\sum_{l=1}^{L}\frac{1}{N_{k,l}}\sum_{i=1}^{N_{k,l}} K\left(\frac{b - b_{k,i}}{h}\right)\mathbf{1}\{\mathcal{N}_l = \mathcal{N}\}, \tag{5}$$

where L is the number of auctions, N_k is the number of bidders of type k in $\mathcal{N}_l$, $K(\cdot)$ is a kernel function, and h is a bandwidth.

Let $b_k(\alpha_q; \mathcal{N})$ be the α-quantile of the bid distribution of type k in the auction with the set of bidders $\mathcal{N}$ for $q = 1, \ldots, Q$ where Q is the number of quantiles. As the between-compatibility condition is an equality condition, the risk parameter can be defined as the minimum distance estimator of the following minimization problem:

$$\min_{\theta_k \in \Theta} \sum_{q=1}^{Q}\Bigg[b_k(\alpha_q; \mathcal{N}) - \lambda_k^{-1}\left(\frac{1}{H_k(b_k(\alpha_q; N) \mid \mathcal{N})}; \theta_k\right) - b_k(\alpha_q; \mathcal{N}') + \lambda_k^{-1}\left(\frac{1}{H_k(b_k(\alpha_q; \mathcal{N}') \mid \mathcal{N}')}; \theta_k\right)\Bigg]^2,$$

where Θ is the parameter space of θ_k.

Step 2: Estimation of the cost density

Given the estimated risk parameter $\hat{\theta}_k$, I estimate the cost density of bidder i of type k. For each type of bidder, estimate the distribution and density of bids by the empirical distribution and the kernel density estimator from (4) and (5). By substituting these into the first-order condition (3), I obtain the pseudo cost of bidder i of type k in auction l as

$$\hat{c}_{k,il} = b_{k,il} - \lambda_k^{-1}\left(\frac{1}{H_k(b_{k,il} \mid \mathcal{N}_l)}; \hat{\theta}_k\right),\ k = h, o, f.$$

Additional details for estimation

To obtain the homogenized bids, I regress the bid of bidder i of type k in auction l on the observed auction characteristics:

$$\log(b_{il}) = \beta X_l + F_{year} + F_{month} + F_{institution} + F_{region} + F_{\mathcal{N},k} + \varepsilon_{ikl}.$$

X_l is the observed auction characteristics in auction l. F_{year}, F_{month}, $F_{institution}$, F_{region}, and $F_{\mathcal{N},k}$ are year, month, institution, region, set of number of bidders of each type and bidder type fixed effects, respectively. For the estimation, I use competitive auctions with $\mathcal{N} = (1, 1, 1)$, $(1, 1, 2)$, $(1, 0, 1)$, and $(1, 0, 2)$. The number of auctions for each configuration is 278 for $(1, 0, 1)$, 271 for $(1, 0, 2)$, 161 for $(1, 1, 1)$, and 130 for $(1, 1, 2)$.

For the estimation of the risk parameter, I consider the CRRA utility functions with $U(x) = x^{1-\theta}$ where $\theta \in [0, 1)$. I assume that the risk parameters of the home incumbent and the outside incumbent are the same but are different from the fringes. In other words, $\theta_h = \theta_o \neq \theta_f$. I estimate the risk parameters of the home incumbent and the fringes by using the auctions where the home incumbent and the fringes join. To do this, I pick up the auctions (1) one home incumbent and one entrant join, (2) one home incumbent and two fringes join. For the kernel function, I use the triweight kernel. As the kernel density estimation is biased at the boundary, I follow the boundary correction method proposed in Hickman and Hubbard (2015). This method also derives the optimal bandwidth h. To compute quantiles of bids of type k in auctions with $\mathcal{N}$, I compute Q quantiles of bids of each bidder type from the empirical distribution. Based on Zincenko (2018), I set $Q = L^{6/5}$.

5.4 Estimation Result

Table 5 reports the result of the risk parameter. The risk parameter of the incumbent is 0.83, and that of the fringe firms is 0.71. As θ is between zero to one and $\theta = 0$ implies risk-neutral, the incumbents and the fringe firms are pretty risk-averse. The result also implies that the incumbents are more risk-averse than the fringe firms. [11] Under the CRRA specification, the more a bidder is risk-averse, the more the bidder reduces markup. Compared to the risk-neutral case, the markup decreases by 83% and 71%, respectively. The incumbents reduce markups by 16% compared to fringe firms.

Figure 6 and Table 6 show the result of the cost estimation. First, the home incumbent has a cost advantage over other types. On average, the outsides have 7% larger costs, while the fringe firms have 4% larger costs. While the minimum and maximum have significant differences between bidders, the overall differences in costs among bidders are less than 10%.

There are several reasons why the differences arise. First, incumbents have power plants in their own regions, but fringe firms need to buy electricity via the wholesale market. Therefore, the home incumbents can supply electricity at a cheaper price compared to fringes. Second, the difference between home incumbents and outside incumbents can be explained by transmission cost. For example, when Kansai EPC transmits electricity from a power plant in Kansai to Kyushu, it pays transaction fees from Kansai to Chugoku and Chugoku to Kyushu. Therefore, even though an outside incumbent

[11] Compared to the values reported in the literature, the values are slightly higher. For example, in timber auctions, Campo et al. (2011) and Lu and Perrigne (2008) report the values between 0.55 - 0.77, and in oil and gas leases, Kong (2020*a*) and Kong (2020*b*) report the values between 0.2 - 0.7.

Type	θ_k	Std. Deviation	Lower 95% CI	Upper 95% CI
Fringe	0.71	0.073	0.56	0.84
Incumbent	0.83	0.044	0.74	0.91

Table 5: The result of CRRA parameters

Type	Mean	sd	Min	25%	75%	Max
Home	0.96	0.14	0.17	0.9	1.03	1.37
Outside	1.03	0.12	0.71	0.96	1.1	1.34
Fringe	1.0	0.12	0.07	0.94	1.08	1.43

Table 6: The summary of cost estimate

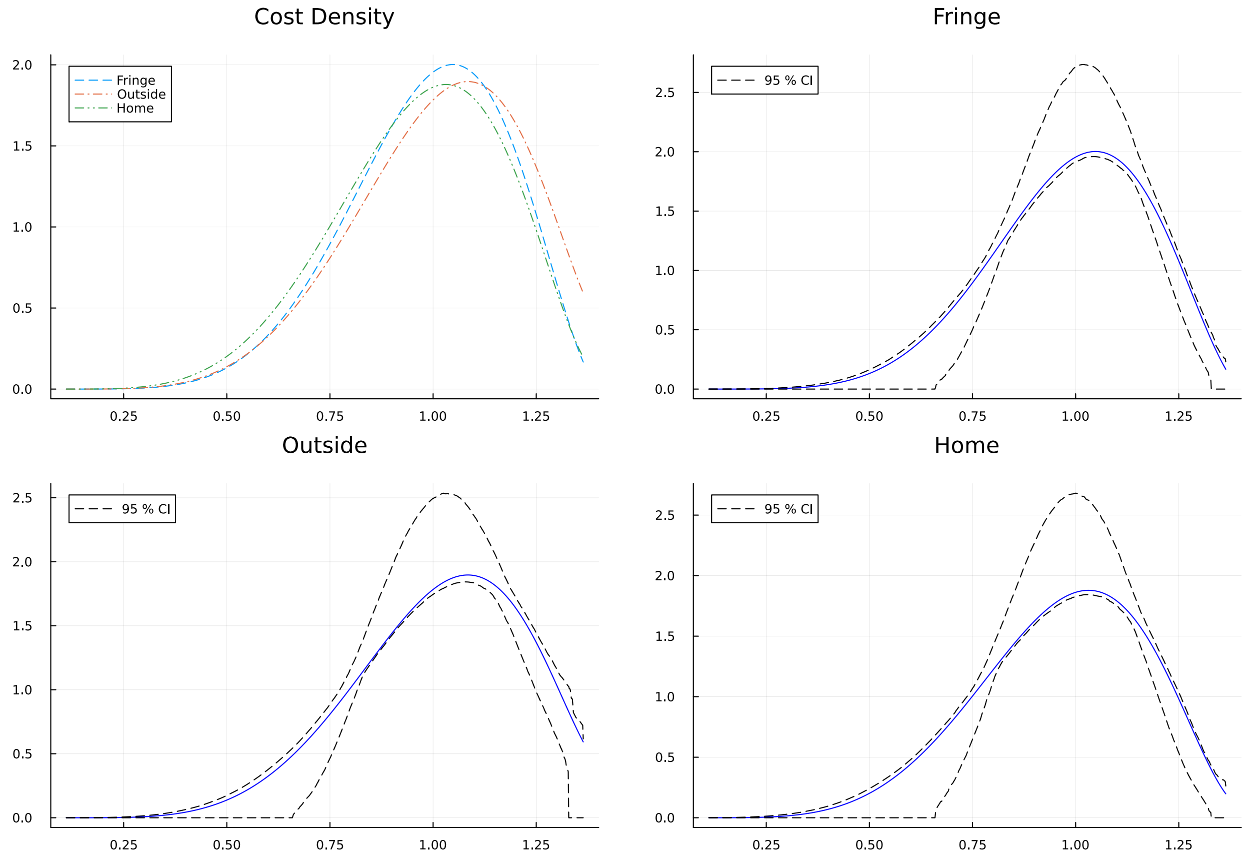
has a cost advantage in its own region, it loses its advantage due to transmission cost.

5.5 Counterfactual Simulation

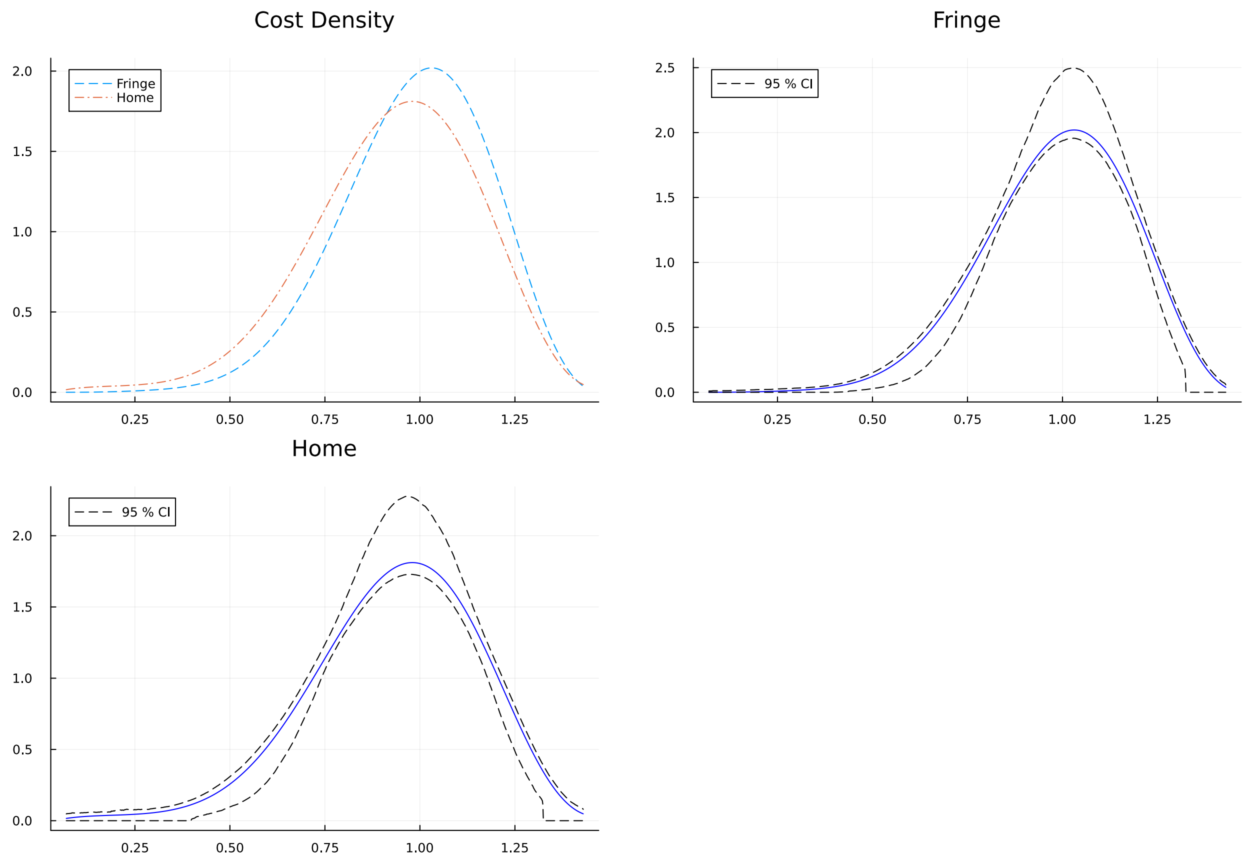
Based on the above estimation results, I have estimated costs and their corresponding homogeneous bids. Thus, I can infer the equilibrium bidding function given a configuration of each type of bidder. I use a second-order polynomial to approximate the equilibrium bidding function. Also, based on the cost estimate, the cost distribution of each type of bidder can be recovered. Given the approximated equilibrium bidding function and the cost distribution, I implement the following simulation.

1. Draw costs for one home, one outside, and two fringe firms.
2. Given the configuration of bidders, $\mathcal{N}$, compute the homogeneous bids by using the approximated equilibrium bidding function.
3. Pick up the minimum bid among the bidders and define it as the winner's bid.
4. Repeat Steps 1-3 for 1000 times and take the average of the winning bids

Table 7 shows the simulation result. First, Category (A) shows the average winning bids and winner costs. The values in the table are based on the homogeneous bids and the idiosyncratic costs. ΔBid and ΔCost show the change in the winning bids and the winner costs by adding one outside. Adding one outside incumbent to the auctions with one home incumbent and one fringe reduces the winning bids by 5.5%, and to the auction with one home incumbent and two fringes reduces the winning bids by 3.7%. The winner's cost also decreases. The change from $(1, 0, 1)$ to $(1, 1, 1)$ reduces the winner's cost by 3.4%, and change from $(1, 0, 2)$ to $(1, 1, 2)$ reduces the winner's cost by 2.4%.



(a) Density of cost distribution under CRRA with three types



(b) Density of cost distribution under CRRA with two types

Figure 6: The estimation result of cost density

Table 8 presents the average bids across bidder types and bidder configurations. When an outside incumbent is introduced, the average bids for all bidder types decrease. Notably, the outside incumbent exhibits a lower average bid compared to other types. The lower bids from outside incumbents also impact the winning rate of home incumbents. In two-type bidder auctions, the winning rate for home incumbents is around 65%, but this rate drops to 40% in three-type bidder auctions. Since the winning rate for fringe firms remains stable in both auction types, the reduction in the home incumbent's winning rate is solely attributable to the entry of an outside incumbent. Therefore, the average winning bids decrease when one outside incumbent is introduced.

Then, why do outside incumbents submit lower bids than other bidders? One possible explanation is that, as demonstrated, home incumbents have a cost advantage over other types, while outside incumbents likely face higher costs, prompting them to lower their bids in order to win auctions. This can be corroborated by the observed price-cost margins: the average margin for outside incumbents is 11%, whereas it is approximately 30% for home incumbents and fringe firms based on cost estimates and normalized bids.

Table 8 also displays the average winning costs for each bidder type. The average winning cost for home incumbents remains relatively unchanged even after adding an outside incumbent, and the winning cost for outside incumbents is similar to that of home incumbents. However, the average winning cost for fringe firms decreases by 4.5%. Given that the winning rate for fringe firms does not change with the addition of an outside incumbent, it follows that fringe firms must reduce their costs to remain competitive in auctions. Therefore, the decline in the average winning cost can be attributed to the victories of lower-cost fringe firms.

An important question is how much the winning bids during the cartel period were reduced by adding one outside bidder. Recall that the cartel contaminated the auctions held in Kyushu, Kansai, and Chugoku. Thus, pick up the auctions $(1,0,1)$, $(1,1,1)$, $(1,0,2)$, and $(1,1,2)$ held during the cartel period. Recall that the auctions with outside incumbents suffered from complementary bids, and hence, the number of serious bidders does not coincide with the number in the data. Therefore, for example, $(1,1,1)$ during the cartel period is not the same as the auctions with $(1,1,1)$ during the competitive period and similar to the auctions with $(1,0,1)$ as the number of serious bidders coincides. For each configuration of bidder, I multiply the winning bids by ΔBid. Category (B) shows the result. The average reduction of the winning bids ranges from 0.65 million yen to 7.07 million yen. The total reduction amounts to 242 million yen in Kyushu, 128 million yen in Kansai, and 230 million yen in Chugoku.

While the winning bids change improves public institutions' payoff, the welfare change is also important. The social welfare in procurement is defined as the expected winner cost,

$$-E[1\{b_i \leq \min_{i \neq j} b_j\} c_i].$$

The decrease in the winning cost improves the social welfare, and hence, introducing one outside incumbent improves the social welfare. However, there are some cases where the winner's cost is not the lowest cost in an auction, and hence, inefficiency arises. An auction is said to be efficient when the winner is the lowest-cost bidder in the auction. In Category (C), I show the simulation results of inefficiency. The share of inefficient auctions among 1000 simulations is 3.7% for $(1, 1, 1)$ and 3.0% for $(1, 1, 2)$, although the auctions with two types of bidders are all efficient. Even in these inefficient auctions, the efficiency loss is 0.008 and 0.004, respectively. These efficiency losses are small compared to the average homogenized bids (1.03 and 1.02). Therefore, more competitive auctions lead to some inefficiency, but the magnitude is small.

On the other hand, the cartel led to the outside incumbent's exit, which could lead to further inefficiency. For example, the outside incumbent is absent for the auction with $(1, 0, 1)$, but the outside incumbent can be regarded as the potential bidder. I compute the efficiency by including all potential bidders but the winner is determined only by using the bids of home incumbent and fringe firms. The last two rows show the result. The inefficiency due to the cartel is 26% in the auctions with $(1, 0, 1)$ and 19% in the auctions with $(1, 0, 2)$. While in these auctions, the share of inefficient auctions is zero when only using the actual bidders, the inefficiency due to the cartel is much more significant.

5.6 Does cheaper electricity generation reduce procurement costs?

So far, I have discussed the impact of competition on market outcomes. The simulation results I presented are based on homogenous bids and idiosyncratic costs, which exclude auction-level characteristics and fixed effects across auctions. However, changes in costs at the bidder level also influence market outcomes. For example, a more significant proportion of electricity generation is sourced from nuclear power plants. In that case, the procurement costs will likely decrease since nuclear power is cheaper than thermal generation. Naturally, lower costs result in more affordable winning bids.

In this section, I examine the effect of power plant configuration changes on procurement costs based on cost estimates. Table 9 provides the regression results of the estimated costs. These estimates are derived by adjusting the idiosyncratic costs with an auction-characteristics index (Γ), producing original costs that better reflect the auction environment. I then regress the estimated costs on auction characteristics and the share of each power plant type. The Agency for Natural Resources and Energy provides monthly data at the company level detailing the electricity generated by each type of power plant for each firm. It is important to note that fringe firms do not operate power plants.

$\mathcal{N}$	(1,1,1)	(1,0,1)	(1,1,2)	(1,0,2)
(A) Average wining bids and winner costs				
Winning Bid	0.93	0.98	0.9	0.93
Winner Cost	0.89	0.92	0.85	0.88
ΔBid (%)	-5.2		-3.7	
ΔCost (%)	-3.3		-2.5	
(B) Reduction in the winning bids				
Mean (Milion JPY)				
Kyushu	2.65	1.67	0.89	0.65
Kansai	3.85	-	3.19	-
Chugoku	2.06	7.07	5.89	2.33
Total (Milion JPY)				
Kyushu	242.81			
Kansai	128.0			
Chugoku	230.98			
(C) Inefficiency				
Inefficient auctions (%)	3.7	0.0	3.0	0.0
Efficiency loss	0.01	-	0.01	-
Inefficient auctions due to cartel (%)	-	26.1	-	19.0
Efficiency loss due to cartel	-	0.12	-	0.12

Table 7: Counterfactual Simulation Result

The results indicate that an increase in the share of thermal power generation raises procurement costs in Kyushu, Kansai, and Chubu. In Chugoku, the coefficient for thermal generation is negative, but it should be noted that Chugoku EPC relies more heavily on thermal power than other incumbents. In Chubu, where hydropower plants hold the second largest share, the cost decreases as the hydropower share increases. The scale of thermal generation remains relatively small.

In Kyushu and Kansai, nuclear power plants account for the second largest generation share, and the cost decreases when the nuclear share rises. Conversely, increases in hydropower and other renewable sources lead to higher procurement costs. This might seem counterintuitive, as hydropower and other renewables typically have lower marginal costs. However, a rise in their share implies a reduction in nuclear power's contribution. Nuclear power plants produce significantly more electricity than other types, so hydropower or other renewables cannot fully offset the reduced nuclear share. This shift increases reliance on thermal power, driving costs up.

$\mathcal{N}$	Fringe	Outside	Home
Average Bids			
$(1,0,1)$	0.9342	0.8450	0.8765
$(1,1,1)$	0.8851	0.8535	0.8737
$(1,0,2)$	0.9594	-	0.9714
$(1,1,2)$	0.9256	-	0.9347
Average Wining Cost			
$(1,0,1)$	0.8926	0.8884	0.8800
$(1,1,1)$	0.8803	0.8940	0.8816
$(1,0,2)$	0.9308	-	0.8833
$(1,1,2)$	0.9264	-	0.8821

Table 8: Summary of Average Bids and Average Wining Cost in the Simulation

6 Conclusion

This paper investigates the impact of a market allocation cartel among major Japanese electricity companies on electricity procurement auctions. The cartel operated from 2018 to 2020, during which each firm avoided entering others' regions. Using detailed auction data covering both the competitive and cartel periods, I find that cartel members significantly reduced participation and submitted higher, non-competitive bids in other firms' regions, leading to increased winning bids. A counterfactual analysis using a model of auctions with risk-averse bidders reveals that adding outside incumbents reduces winning bids and winning cost, but slightly lowering auction efficiency. The paper also highlights how changes in power plant composition, such as a shift toward nuclear generation, influence procurement costs. Overall, the cartel imposed financial burdens on public institutions, while increased competition led to lower costs with negligible efficiency losses.

	log(cost)			
	(1)	(2)	(3)	(4)
	Kyushu	Chugoku	Kansai	Chubu
expected usage	0.868***	0.842***	0.790***	0.873***
	(0.012)	(0.013)	(0.013)	(0.011)
Contract Power	0.085***	0.149***	0.176***	0.131***
	(0.013)	(0.016)	(0.014)	(0.013)
Thermal Generation Cost	0.348***	0.730**	0.304***	0.609***
	(0.063)	(0.222)	(0.085)	(0.054)
Number Buildings	0.001*	-0.000	0.001**	0.000
	(0.001)	(0.001)	(0.000)	(0.000)
Contract length	0.000*	0.000***	0.000**	0.000*
	(0.000)	(0.000)	(0.000)	(0.000)
Share of hydropower	0.026*	0.034	0.002	-0.003
	(0.011)	(0.057)	(0.003)	(0.003)
Share of thermal	0.021	-0.019	0.014**	0.005*
	(0.014)	(0.051)	(0.004)	(0.002)
Share of nuclear	-0.041**	0.004	-0.008***	0.000
	(0.013)	(0.006)	(0.002)	(0.001)
Share of other	0.008	-0.011	0.005**	-0.002
	(0.005)	(0.013)	(0.002)	(0.002)
month Fixed Effects	Yes	Yes	Yes	Yes
year Fixed Effects	Yes	Yes	Yes	Yes
region Fixed Effects	Yes	Yes	Yes	Yes
N	598	232	823	713
R^2	0.994	0.997	0.986	0.991
Within-R^2	0.988	0.993	0.982	0.988

Table 9: Regression of the estimated cost on auction characteristics and variables relating to electricity generation

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Appendix

A The detail of the cartel cases

A.1 Case 1: Kansai EPC and Kyushu EPC

This cartel targeted public institutions. Procurement auctions mainly determine the electricity suppliers for these buildings. In December 2017, Kansai EPC announced that since 2018, it would begin participating in electricity procurement auctions held in Kyushu. In response, Kyushu EPC joined procurement auctions in Kansai, leading both companies to submit competitive bids in both regions throughout 2018.

This competition reduced electricity prices for public buildings in both areas, decreasing the companies' profits from procurement auctions. To increase their profits, the officials from both companies held several meetings in mid-2018 and eventually reached a cartel agreement by October 2018.

The agreement between Kansai EPC and Kyushu EPC included three key terms. First, Kansai EPC would share its bids with Kyushu EPC before the auction deadlines in both regions. Second, Kyushu EPC, after reviewing Kansai's bids, would increase its bid prices. Third, Kyushu EPC would impose an upper limit on the total electricity supply in Kansai. During the cartel period, both companies regularly met to ensure compliance with the agreement. Consequently, Kansai EPC lost the majority of auctions held in Kyushu. At the same time, Kyushu EPC adjusted its bidding strategy to ensure that the total electricity supply in Kansai remained under the agreed threshold.

A.2 Case 2: Kansai EPC and Chugoku EPC

This cartel targeted not only public buildings but also private buildings. In November 2017, Kansai EPC announced it would enter the retail sales market and join procurement auctions in Chugoku starting in 2018. In response, Chugoku EPC entered the retail market in Kansai. Consequently, both companies proposed competitive contracts to customers in their respective retail markets, and they also submitted competitive bids in procurement auctions held in Chugoku.

However, in mid-2018, officials from both companies held several meetings and formed a cartel agreement to safeguard their profits in both regions by November 2018. The agreement between Kansai EPC and Chugoku EPC included two main provisions. First, both companies would limit their business activities in each other retail markets. Second, Kansai EPC would refrain from participating in procurement auctions where the expected usage was less than 300,000 kWh and would refrain from submitting bids below a specific price threshold. At the same time, Chugoku EPC would raise its bid prices. Both companies held regular meetings during the cartel period to maintain the agreement. As a result, they restricted their sales efforts in other territories and raised electricity prices within their areas. Additionally, both companies increased their bid prices in procurement auctions.

A.3 Case 3: Kansai EPC and Chubu EPC

This cartel targeted only private buildings and excluded public buildings. In November 2017, Kansai EPC entered the retail market in Chubu and proposed competitive contracts to customers. In response, Chubu EPC entered the retail market in Kansai, leading to severe competition between the two companies.

However, starting in mid-2018, officials from both companies held several meetings and reached a cartel agreement by November 2018. The agreement stipulated that both companies would restrict their activities in each other's retail markets and raise electricity prices in both regions to ensure profitability in their respective sales areas. During the cartel period, the agreement led to frequent meetings between both companies. Consequently, Kansai EPC and Chugoku EPC limited their sales activities in each other's regions and increased electricity prices within their territories.

B Additional Tables and Figures

Variable	Min	25-th	Median	75-th	Max	SD	Obs
Chubu							
Number Bidder	2	3	3	5	10	1	440
Expected Usage (mWh)	432	3,287	8,576	34,188	1,683,270	114,039	440
Contract Power (kW)	31	178	410	1,410	31,332	2,817	440
Number Building	1	1	1	3	388	26	440
Contract Length	212	364	364	365	1,095	162	440
Kansai							
Number Bidder	2	3	4	5	11	2	924
Expected Usage (mWh)	259	5,521	16,186	45,109	440,509	63,534	924
Contract Power (kW)	11	256	790	2,364	37,866	2,952	924
Number Building	1	1	1	8	432	31	924
Contract Length	242	364	364	365	1,460	110	924
Chugoku							
Number Bidder	2	3	4	6	12	2	268
Expected Usage (mWh)	301	3,121	9,571	27,788	807,781	76,785	268
Contract Power (kW)	15	112	332	833	13,739	1,479	268
Number Building	1	1	1	4	209	18	268
Contract Length	333	547	730	1,095	1,825	314	268
Kyushu							
Number Bidder	2	3	5	7	13	2	1,128
Expected Usage (mWh)	180	1,632	3,396	9,708	276,200	33,279	1,128
Contract Power (kW)	14	91	176	413	8,573	1,033	1,128
Number Building	1	1	1	1	147	9	1,128
Contract Length	121	364	364	365	1,095	66	1,128

Table 10: Summary of Auction Variables in Each Region

Bidder	Min	25-th	Median	75-th	Max	SD	Obs
Chubu							
Competitive Period							
Chubu EPC	785.0	5,523.4	22,480.5	57,675.1	1,196,534.1	168,285.0	145
Kansai EPC	1,357.2	8,422.4	28,638.1	68,945.6	1,342,659.6	198,284.4	117
Other	843.6	6,861.4	24,443.1	56,077.1	826,490.3	109,435.1	486
Cartel Period							
Chubu EPC	906.3	5,007.4	9,705.8	45,669.8	2,620,260.2	192,130.3	224
Kansai EPC	3,122.0	6,748.5	13,001.7	47,535.3	2,509,587.4	229,935.8	140
Other	921.4	6,003.9	17,022.8	57,488.4	882,842.5	92,456.8	545
Chugoku							
Competitive Period							
Chugoku EPC	489.2	3,348.5	11,031.3	37,662.4	391,225.8	66,984.9	139
Kansai EPC	7,858.4	20,515.5	46,444.8	67,975.9	356,465.3	76,616.8	20
Other	571.5	3,640.4	12,531.9	36,976.4	424,502.1	80,005.3	518
Cartel Period							
Chugoku EPC	1,091.9	8,827.9	29,946.2	59,109.6	970,066.1	142,513.5	113
Kansai EPC	9,803.7	42,536.8	60,183.7	99,383.1	197,317.6	61,035.7	10
Other	900.9	5,401.3	16,413.1	46,839.0	934,991.2	106,089.5	419
Kansai							
Competitive Period							
Chubu EPC	1,004.8	12,776.5	32,399.4	87,218.1	906,674.9	109,147.4	240
Kansai EPC	422.6	8,630.6	26,512.2	66,578.9	728,969.6	97,487.7	365
Kyushu EPC	671.8	12,825.5	30,838.7	88,242.6	564,467.5	90,974.8	108
Other	493.5	8,645.9	24,116.0	66,720.7	510,613.3	75,735.0	1,372
Cartel Period							
Chubu EPC	603.5	8,787.9	27,536.1	63,130.6	540,462.2	79,430.2	214
Kansai EPC	470.6	8,336.0	24,130.3	73,661.4	848,026.2	96,727.0	337
Kyushu EPC	1,258.8	10,044.2	32,251.6	86,048.9	497,470.1	78,537.4	170
Other	508.3	7,485.0	22,752.3	64,952.2	788,172.8	91,712.4	881
Kyushu							
Competitive Period							
Kansai EPC	1,182.1	4,532.8	6,396.7	19,074.4	303,559.5	45,443.9	138
Kyushu EPC	256.3	2,329.6	4,740.7	15,865.7	304,889.1	44,579.1	395
Other	283.5	2,749.7	5,561.6	11,508.8	323,715.0	32,963.1	2,497
Cartel Period							
Kansai EPC	4,565.0	13,272.3	34,875.2	71,166.8	318,907.6	51,075.8	94
Kyushu EPC	635.0	2,256.0	4,864.7	15,364.0	288,391.6	38,552.5	540
Other	624.0	2,166.9	4,329.4	9,333.1	318,449.8	32,792.1	2,359

Table 11: Summary of Bids (1000 JPY) in Each Region

Year	Min	Q25	Median	Q75	Max
PPSs					
2016	0	0.00000	0.120300	0.313000	449.9130
2017	0	0.00000	0.116000	0.289110	450.1000
2018	0	0.00000	0.107500	0.268000	429.6200
2019	0	0.00000	0.094040	0.252390	411.0100
2020	0	0.00000	0.109830	0.257800	169.7170
2021	0	0.00000	0.112000	0.270000	170.7935
2022	0	0.00000	0.120000	0.279000	170.9635
2023	0	0.00000	0.127675	0.298905	169.8870
Incumbent					
2016	0	21.69085	80.759980	192.214610	365.7294
2017	0	21.66320	80.754980	192.207260	365.9545
2018	0	21.60615	80.787980	188.635960	365.9585
2019	0	46.15702	91.151600	181.363520	654.7640
2020	0	0.17625	54.355880	106.456450	661.2640
2021	0	0.00400	21.593950	99.287820	661.2640
2022	0	0.00400	21.761950	99.296570	637.2640
2023	0	0.00400	21.761950	98.512520	616.1074

Table 12: Summary of the capacity of power plants by year (kWh)

Year	Min	Q25	Median	Q75	Max
PPSs					
2016	0	0	1	2	78
2017	0	0	1	1	88
2018	0	0	1	1	92
2019	0	0	1	1	101
2020	0	0	1	1	132
2021	0	0	1	1	362
2022	0	0	1	1	482
2023	0	0	1	1	417
Incumbent					
2016	0	30	114	170	232
2017	0	30	114	170	231
2018	0	30	113	170	231
2019	0	30	112	170	231
2020	0	1	30	142	231
2021	0	1	23	141	223
2022	0	1	23	141	224
2023	0	1	24	153	347

Table 13: Summary of the number of power plants by year