An Empirical Analysis of Entrant and Incumbent Bidding in Electric Power Procurement Auctions*

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Abstract

This paper explores the asymmetry between entrants and incumbents in electric power procurement auctions in Japan. In this market, entrants are considered to have a significant disadvantage in production cost structure, while incumbents have high opportunity costs of winning auctions. Using transaction prices, we empirically analyze the bidding patterns and the cost distributions of entrants and incumbents. We employ a structural model where the participation of entrants in an auction is endogenous. We also conduct counterfactual analyses under a price-preference policy to see whether such a policy can enhance competition and the participation of entrants.

The results indicate that the cost distribution of incumbents has a higher mean than that for entrants and that the opportunity cost of winning auctions for incumbents is economically significant. For the average auction, we find that price-preferential treatment does not have much effect on entrant participation. We also find that a preference for the weak bidder (namely, the incumbent) does not improve the government's procurement cost. In fact, government cost is minimized with a small preference for entrants, where the competition effect on the incumbent offsets the preference effect on entrants.

1 Introduction

This study investigates the bidding patterns of entrant and incumbent firms in electric power procurement auctions in Japan. In the Japanese retail electricity market, ten firms originally supplied electricity as local monopolists. However, beginning in 2000, partial liberalization

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allowed new firms, known as Power Producers and Suppliers (PPS), to enter the market and supply electricity to large users with power and voltage requirements greater than $2,000$kW and $20,000$V, respectively. With this wave of liberalization, public agencies have begun to utilize sealed-bid auctions for electric power supply contracts. The liberalization targets have since expanded, and the PPS are now permitted to participate in any auctions with power needs greater than 50kW .

Nevertheless, the participation rate of entrants in these auctions remains very low, implying the significant disadvantage of entrants compared with incumbents. In fact, the cost structures of entrants and incumbents in this market differ significantly. This is because all of the incumbent firms are vertically integrated and incorporate their own production divisions, while most entrants purchase their electricity from outside sources, including the Japanese electric power exchange market. Even for entrants with production divisions, cost disadvantages still arise because they only own thermal power stations. These incur higher costs generating electricity than the comparable nuclear power plants owned by most incumbents. Furthermore, the transmission network is operated by incumbents, and hence entrants must pay imbalance fees.[1] Therefore, entrants generally face higher costs in supplying electricity.

Nevertheless, practitioners have pointed out that incumbent bids in these auctions actually tend to be high despite their purported production cost structure. These high bids can then be explained by the opportunity costs of the incumbents from winning auctions. This is because the contracts auctioned off by public agencies are not major activities for the incumbents and their focus remains on large private users, to which they supply electricity at publicly announced rates, or at rates determined by a bargaining process.[2] Importantly, if incumbents submit low bids and win auctions run by public agencies, they will reveal their ability to supply electricity at lower rates to their private users. Then, when the contracts with these private users are to be renewed, these users may demand lower rates. That is,

[1] The imbalance fees range from 0.57 to 3.42 yen/kWh, with a fixed component of 346.50 to 656.25 yen/kW, depending on the area, time, and voltage.

[2] The amount of electricity sold at these auctions accounts for less than 1% of all electricity supplied by incumbents. However, it accounts for about 50% of the electricity supplied by PPS.

winning auctions at lower bids may mean the incumbents lose future profits from private users. If the incumbents consider this foregone profit as their opportunity cost of winning auctions, and when such opportunity costs are taken into account, the underlying cost of auction for the incumbents may exceed the cost for entrants.

The purposes of this study are first to empirically assess the differences in the distribution of costs for electricity contracts and bidding strategies for incumbents and entrants, and second to conduct policy experiments in the spirit of price-preference policies to enhance competition and the participation of entrants. It has been shown that when bidders have different cost distributions, strong bidders bid less aggressively when facing weaker bidders, thereby reducing the level of competition (Maskin and Riley 2000a). Asymmetry may also reduce the level of competition because the less efficient firms may be prevented from participating in the auction. In such an auction, the auctioneer may be better off implementing a price-preference treatment and exploiting the asymmetry (see Krishna 2002; Myerson 1981). Because the effect of such preferential treatment depends on extent of asymmetry, it is important to assess the existence and extent of asymmetry.[3]

We model the bidding and entry behavior of incumbents and entrants assuming that firms make an entry decision followed by a bidding decision. We nonparametrically estimate the cost distributions of an incumbent and entrants following Guerre et al. (2000) to recover the cost distributions from the bid distributions. However, because we only have access to winning bids, not all bids (including losing bids), we estimate the winning-bid distribution and use the theoretical relationship between the winning-bid and all-bids distributions to recover the latter. We then apply the approach in Guerre et al. (2000). This approach enables us to obtain cost estimates for the winning firm in each observed auction. We then calculate the entry costs that explain the present participation situation. Once we obtain the underlying cost distributions and entry costs, we undertake counter-factual analyses to see the effect of the different level of preferential treatment on the government procurement

[3] Under general assumptions, Cantillon (2008) has shown that the auctioneer's expected revenue is lower as bidders become more asymmetric. Accordingly, serious asymmetry may imply the greater potential to improve competition through a preferential policy.

cost.

A number of previous studies have empirically examined asymmetry among bidders arising from many different sources. For example, the extant work has shown that asymmetries arise from capacity constraints, as in Jofre-Bonet and Pesendorfer (2003), the possession of better information, as in Hendricks and Porter (1992), collusion among a group of bidders, as in Porter and Zona (1993) and Bajari and Ye (2003), the distance from places where the service is required, as in Bajari (1997) and Flambard and Perrigne (2006), and firm size, as noted by Laffont et al. (1995).

While asymmetries among bidders arising from these sources have already been examined in the literature, the asymmetries between incumbent and entrant firms have received little attention. The notable exception is De Silva et al.'s (2003) investigation of the differences in the bidding patterns of entrants and incumbents in road construction auctions in Oklahoma. De Silva et al.'s (2003) find that entrants are less efficient and their distribution of costs has greater dispersion. However, they seek asymmetries in firm experience or the information-gathering process, while we focus more on the structural differences between entrants and incumbents.[4]

Existing studies have also examined the effect of preference policies on auctioneer revenue. In general, preferences can take the form of discriminatory reserve prices, the discounting of the bids of preferred firms, or a set-aside policy. For instance, Krasnokutskaya and Seim (2008) investigated the California Small Business Program and found that the existing 5% preference to small business had virtually no effect on the cost of procurement or the total number of bidders. Likewise, Nakabayashi (2009) examined the effect of small business set-asides on Japanese public construction auctions. He found that approximately 40% of small businesses would exit from auctions were set-asides to be removed, thereby increasing government procurement costs. Many other studies have conducted policy experiments in this area. For example, Flambard and Perrigne (2006) found that a fixed

[4] While it is also surely in our interest to consider any asymmetry arising from experience or the information-gathering process, we focus on structural differences because we consider them especially large and economically significant in this particular market.

subsidy and discriminatory reserve prices can reduce the cost of snow removal contracts in Montreal because these policies enhance competition from stronger bidders. Similarly, Hubbard and Paarsch (2009) found that the participation effect is relatively unimportant and that for most cost-distribution assumptions, a positive cost-minimizing preference rate exists. Finally, Saini (2009) examined a dynamic setting where firms became more asymmetric as they became more capacity constrained, and found that the greater the rate of bid preference needed to be, the more farsighted firms were.

We find that the mean of the cost distribution of the incumbent is higher than that of the entrants for most auctions. This is even for auctions with high load-factor requirements, where the incumbents are considered to have a significant advantage in production cost structure. Our results imply that the incumbents' opportunity cost of winning auctions is economically significant. In our auctions, the mean cost of the incumbents is, on average, 1.25 times higher than that of the entrants. We also find that the entrants' rent is higher than that of the incumbent for a given auction. That is, as the theory suggests, strong bidders (the entrants) bid less aggressively than a weak bidder (the incumbent).

For the average auction, we find that the price-preferential treatment does not have much effect on the participation of entrants. Indeed, under the estimated participation cost, the number of bidders would increase only under a very high percentage of preferential treatment for entrants. However, in the case of a high preference for entrants, the government's cost of procurement increases significantly.

We also find that a preference for the weak bidder, the incumbent, does not improve the government's procurement cost, although the theory suggests a preference for weak bidders may enhance competition among strong bidders and thereby improve the government's procurement cost. The competition effect on entrants is not much, presumably because each entrant bids quite aggressively to compete with other entrants (not the incumbent), even with no preference policy for the incumbent. Therefore, the preference for the incumbent merely increases the probability of an incumbent with preferential treatment winning, and this increases the government's cost. The government cost is actually minimized with a small preference for entrants (5%) by making the incumbent bid more aggressively, while not significantly reducing the probability the incumbent winning.

2 Electricity procurement auction data

As discussed, the partial liberalization of the Japanese retail electricity market began in 2000, allowing new firms, known as PPS, to enter the market and supply electricity to large users with power and voltage requirements greater than $2,000$kW and $20,000$V, respectively. The liberalization target was later expanded to users with power and voltage requirements greater than 500kW and $6,000$V in 2004, and again to 50kW in 2005. Given the wave of liberalization, public agencies have started to utilize first-price sealed-bid auctions for electric power supply contracts for public places such as waterworks, roadway facilities, schools, hospitals, and markets.

Each public agency advertises auctions on its webpage, in its official gazette, or in newspapers, with detailed information including the required maximum (peak) power (kW), the amount of electricity to be supplied (kWh), the delivery period, the place of delivery, the qualifications needed for participating in the tendering process, and the time limit for tenders. The firm submitting the lowest bid wins the auction if the bid is lower than the reserve price, and it is paid the total of its bid times the tax rate. Although a reserve price exists, it is usually not announced (even after the bids have been opened). If the lowest bid is higher than the reserve price, then the contract is not offered. In this case, the agency either conducts a second auction or enters into bargaining with one of the bidders. In the case of the latter, a supplier will eventually supply the electricity at a negotiated rate. From the bidders' perspective, the supply of electricity to public agencies is often a secondary activity, and their focus remains on large private users where the prices are more often determined by a bargaining process.

2.1 The winning-bid data

This section describes our data set consisting of the winning bids of all electricity procurement auctions conducted throughout Japan between April 2004 and March 2008. The winning-bid data is from *Electric Daily News*, a newspaper specializing in electricity markets. The data contains information on the date when bids opened, the government agency (the auctioneer), the required maximum power (kW), the amount of electricity required (kWh), the contract period, the place of delivery, the winner of each auction, the winning bid, either the identification or number of other bidders, and other descriptive auction information, including whether there is a restriction on CO_2 emissions.[5] While the data contains a rich number of observations, its disadvantages are that it does not include losing bids and that identification of losing bidders is not revealed for many observations.

A total of 2,098 contracts were offered from April 2004 to March 2008.[6] Nineteen different firms participate in these auctions, with nine incumbents and ten entrants. We define the firms that operated before liberalization and that have continued to operate as incumbents (i.e. the former monopoly firms), and firms that entered the market after liberalization as entrants (i.e. PPS). In general, incumbent firms continue to operate only in their local areas following liberalization. Therefore, we do not observe any auctions where multiple incumbents bid.

Table 1 provides some summary statistics. We have 1,351 observations without missing information. As shown in the table, the auctions are not very competitive, with the average number of active participants ranging from 1.50 to 2.05. The entrants do not participate in all auctions, and the incumbent is the only bidder in many auctions. We can also see that the number of bidders increased in 2005, but decreased thereafter. This may reflect the

[5] The Environmental Conscious Contract Law has been enforced in Japan since November 2007. This law clarifies the public sector's responsibility to take into account not only economic concerns, but also the reduction of greenhouse gas emissions, when they sign a contract. Specifically, contracts concerning the purchase of electricity and official vehicles, as well as service contracts such as those with energy service companies (ESCO) and architects, are subject to law. In light of this law, public agencies have begun to set numerical targets, such as the maximum CO_2 emission coefficient, as a qualification for the participation in auctions.

[6] The Japanese fiscal year begins in April. Hereafter, we use "year" to indicate the fiscal year unless otherwise noted.

fact that the number of auctions with CO_2 emission restrictions have gradually increased since 2006. Because entrants usually only have thermal power stations that generate more CO_2, they tend to be disadvantaged in auctions with CO_2 emission restrictions (see Hattori and Saegusa 2010). Therefore, entrants are less likely to participate in auctions with CO_2 restrictions. Here *Green* is a dummy variable that takes a value of 1 if the auction has any restrictions on CO_2 emissions; zero otherwise. As shown, this applies to 42% of auctions in 2006 and 34% of auctions in 2007.

The winning bids per kWh (yen/kWh) have also been increasing during this period. Both the maximum (peak) power (kW) and the size (kWh) decreased until 2006, but increased in 2007. The downward trends in power and size until 2006 reflect the fact that the number of auctions of relatively small size increased as liberalization progressed. In 2007, we observe many public agencies that bundle several contracts for offer at one auction. This may also account for the increased size in 2007. *Load* refers to the load factor: the ratio between the average and maximum (peak) usage of electricity during the contract period. This is calculated as the required amount per year divided by the required capacity: (kWh) / (the maximum power (kW) $\times 24 \times 365$). The low-load factor induces inefficiency because firms need to hold capacity for peak usage that is not used for most of the time. The average load factor is around 40% during this period.

The load factor appears to play an important role in the firms' participation and bidding decisions. Table 2 presents summary statistics of the winning bids and participation rates by load factor. As shown in the second and third columns, winning bids decrease as the load factor increases, implying that firms can enjoy efficiency with high load factors. In the fourth column, we can see that the percentage of auctions with entrants decreases with the load factor, and similarly in the fifth column, the percentage of auctions with the entrant as winner decreases with the load factor. It then appears that entrants have a significant disadvantage in auctions with high load factors. As an explanation, Takagi and Hosoe (2007) argue that petroleum thermal generation, on which entrants depend, are peak power supplies and that it is difficult to supply electricity for a whole day with this form of generation. Therefore, in auctions requiring high load factors, entrants are likely to have a disadvantage. We can also see that entrants on average participate in only 44.0% of auctions, while incumbents participate in almost all auctions[7]. The last column shows, however, that the percentage of auctions where the entrant is the winner given the entrants' participation is very high, except when the load factor is between 60% and 80%. Put simply, once at least some entrants decide to participate in an auction, the incumbents are unlikely to win that auction.

2.2 Some evidence of asymmetry

In total, incumbents submitted 1,351 bids of which 867 won contracts, while 1,080 bids were submitted by entrants and 484 won contracts. Therefore, the winning rate of incumbents and entrants is 64.2% and 44.8%, respectively. Incumbents, then, are clearly more likely to win auctions. However, if we remove the auctions where an incumbent is the only bidder, incumbents submitted 594 bids of which 110 won contracts. The winning rate of incumbents and entrants in these auctions is 18.5% and 44.8%, respectively. Here, entrants are more likely to win auctions.

We also run a simple regression as follows:

$$y_i = X_i B + D + T + \varepsilon_i,$$

where the subscript i refers to the auction. Because we have winning-bid data, the data is at the auction level.[8] We specify the dependent variable, the winning bid per amount of electricity served (yen/kWh), throughout our analysis. The independent variables include three sets of controls: $X's$ controls for the auction-level variables, D is a vector of district fixed effects, and T is a vector of variables that control for the time trend. Because there is only one incumbent in each district, D can also be considered as incumbent fixed effects. We

[7] We observe only five auctions without incumbents.

[8] During the four years observed, some contracts for the same public places are repeatedly offered because most contracts are renewed each year. For simplicity, we pool the observations rather than using them as panel data.

use two types of T variables. The first is a vector of year dummies. This is because we wish to control for trends in such variables as oil prices and technological progress. The second T variable we use is the monthly spot transaction price of the Japan Electric Power Exchange (JEPX) market. JEPX is the only wholesale exchange market for electricity in Japan, and is one of the main input sources of entrants. Therefore, by controlling for JEPX prices, we can partially control for the entrants' input costs in supplying electricity. Furthermore, the JEPX price should also indirectly reflect the oil prices and technological progress that we would also like to control for using the T variable. In addition, the entrants can sell their electricity to the JEPX when the JEPX price is high, rather than supplying electricity to public agencies through auction. Therefore, the JEPX prices can effectively account for the opportunity cost of entrants in participating in auctions.

With respect to the auction characteristics X, we include the following variables. To start with, in order to distinguish between entrants and incumbents, we simply include an incumbent dummy variable that takes a value of 1 if the winner is an incumbent and zero otherwise. We also include the number of bidders. We expect that auctions will be more competitive and bids more aggressive as the number of bidders increases. The number of bidders, however, may have a negative effect on bids if the auction objects have a common value because of the phenomenon of winner's curse in common-value auctions. Because the winner's curse is more significant when the number of bidders is large, bidders may become less aggressive so as to avoid the winner's curse when the number of bidders increases.

The load factor is also included as an independent variable. Because bids appear to increase with the load factor, but not linearly, we include its square. We also include a high-voltage dummy that takes a value of 1 if the contract for auction is for voltage greater than $20,000$V. The peak power (kW) and the size (kWh) are also included. However, because the two variables kW and kWh are highly correlated, we include only one in the regression. These two variables are also highly correlated with the high-voltage dummy. Therefore, we present the regression results with and without the high-voltage dummy. We expect that the kWh size negatively affects winning bids as firms can enjoy scale economies with a larger size. For a similar reason, we expect that the contract length (*year*) has a negative effect on winning bids. The variable *green* is included to identify auctions with CO_2 emission restrictions.

In earlier auction studies using this type of reduced form regression, bidder characteristics (such as the winning rate and the backlogs of a bidder) are commonly included in the empirical specification. The winning rate is typically used to represent firm efficiency, while the backlog represents the firm's capacity constraints. Unfortunately, because we are unable to identify losing firms in most of the auctions in our dataset, we cannot construct these variables. This is a significant disadvantage of our data when undertaking reduced form analysis. As for the capacity constraint, however, we believe that it is not binding because the supply of electric power to the public sector is often a secondary activity for both incumbents and entrants.

Finally, we do not include a variable for project type (place of delivery) because it would appear that once we control for the load factor, the project type does not appear to matter much for electricity suppliers (see Takagi and Hosoe 2007).

Table 3 shows the estimation results for the basic specifications with and without the high-voltage dummy, kW, and kWh. The dependent variable is the winning bid per amount (yen/kWh). In the fifth and sixth specifications, the monthly spot price on the JEPX is used in place of the year dummies.

We can see similar results for the different specifications. The incumbent dummy does not have a statistically significant effect, although it is positive. The number of bidders has a negative and significant effect on the average bid, although this effect is not statistically significant when we include the high-voltage dummy. This may suggest that the electric power procurement auctions are likely to fit the private-value paradigm.[9] The high-voltage

[9] Gilley and Karels (1981) conclude that one of the basic qualitative predictions in the common-value paradigm is that "...a greater number of competitors on a tract will lower the optimal bid of the firm" (in higher-value auctions for oil tracts). This is because if a bid wins against a relatively large number of competitors, it is more likely that the object has been overvalued and, as a result, firms must take a more pessimistic view of winning bids when more competitors enter. However, Pinkse and Tan (2002) show that strategic behavior can cause bids to increase or decrease with the number of opponents under either the private- or common-value paradigm. Gilley and Karels (1981) also show that this does not always hold when the number of bidders is very small. Therefore, we cannot conclude that the auctions here can be modeled

dummy has a negative and significant effect: that is, high-voltage contracts are won with a lower bid. As expected, the load factor has a negative and significant effect on the winning bid, and this effect is not linear. The coefficients on size (kWh or kW) and contract length are also negative, implying that scale economies exist. The latter effect is, however, not statistically significant. The effects of size become insignificant when we include the high-voltage dummy. The variable *green* has a positive effect, implying that auctions with CO_2 emission restrictions are more costly for suppliers. However, this effect is also insignificant. Finally, as expected, the JEPX transaction price has a positive and significant effect on the winning bid.

Next, we include the dummy variable *single* that takes a value of 1 if no entrant participates in the auction and zero otherwise. Because we do not typically observe multiple incumbents in an auction, there is only one bidder (who is the incumbent) in the auction if single=1. We include this variable in order to control for the participation decision of entrants. As shown in Table 2, we find that entrants do not participate in all auctions. For example, entrants are observed in only 3.1% of auctions when the load factor is higher than 80%. Unfortunately, if we cannot control for all of the variables that affect the entrant's participation decision and the bidding behavior simultaneously, our results are likely to be biased. Gilley and Karels (1981) point out the importance of the link between the dichotomous bidding decision (bid, do not bid) and the bid-level decision, and suggest the use of Heckman's two-stage estimation (Heckman 1979). However, as we do not have losing bids and cannot identify the losing firms, we cannot employ this particular estimation method. Therefore, we control for this variable, *single,* and assume that it proxies for all of the auction characteristics on which entrants decide not to participate. Table 4 presents the estimation results including the dummy variable *single*. The incumbent dummy now has a positive and significant effect on the winning bid. That is, for similar types of auctions, the incumbent's winning bid is higher than that of the entrants. This may suggest that the incumbents' bid distribution is higher, implying that incumbents are actually weak bidders

using the private-value paradigm only on the basis of this result. Recent studies introduce selection tests for common- and private-value auctions (see, for example, Haile et al. 2003).

in these auctions.[10]

3 Model and estimation strategy

We employ a structural approach to recover the firms' underlying cost distributions and entry costs. The recovered structural elements can then be used for conducting the analysis of alternative economic policies. Similar to other work on auction participation, we model a potential bidder's decision as a two-stage process (Samuelson 1985, Levin and Smith 1994, McAfee and McMillan 1987). In the first stage, each potential bidder decides whether to participate in the auction. In the second stage, firms that choose to participate submit their bids.

In general, the literature analyzing endogenous participation differs in the timing of entry and the realization of the private value/costs (Li and Zheng 2007). That is, one typical model assumes that potential bidders learn their private values/costs before they decide whether to enter the auction, while another model assumes that potential bidders do not draw their private values/costs until after they decide to enter the auction. In the former model, entry cost is bid-preparation cost, while in the latter model, the entry cost consists of costs from both information acquisition, such as the cost of investigating the specification of the contract, and bid preparation. Samuelson (1985) represents the former model while Levin and Smith (1994) represents the latter; Li and Zheng (2007) test which model applies in reality to timber sale auctions in Michigan.

In the case of Japan's electricity procurement auctions, firms first have to register for auctions several weeks prior to the auction date. This registration can be considered as the "entry" process. However, we understand from actual auction participants that sometimes firms decline to bid, even after entry into the auction. This behavior may imply that firms do not know their private costs when they make the decision otherwise firms would never "enter and decline" if participation is costly and they know their private costs. Therefore,

[10] Maskin and Riley (2000a) have shown that when asymmetry among bidders' cost distributions exists in the sense of first-order stochastic dominance, their bids also exhibit first-order stochastic dominance.

we follow the latter model and assume that bidders do not draw their private costs until after they decide to enter. Specifically, we assume that incumbents participate in all of the auctions (as in reality) while entrants make their participation decision by comparing the expected profit conditional on participation to the cost of preparing the bid and acquiring information. We also assume that firms learn which other firms have entered the auction by the time of actual bidding once they decide to participate in the auction.

In the second stage, we consider an asymmetric auction model with independent costs. We assume cost independence based on the empirical finding in the last section that the number of bidders decreases with the winning bid. This generally fits the private-value paradigm (see footnote 8). Cost independence is a reasonable approximation, because firms have different opportunity costs resulting from their various principal activities. In procurement auctions, Bajari (1997), Jofre-Bonet and Pesendorfer (2003), Krasnokutskaya (2010) and Flambard and Perrigne (2006) have also assumed independence. Although a common component may exist, we consider it as negligible in this activity. The observed auctions have secret reserve prices: that is, the reserve prices are never announced. In fact, most reserve prices are not announced, even after the bids have been opened. However, many public documents show that the reserve price in electricity procurement auctions is generally the publicly listed power rate offered by the incumbents. Therefore, we assume that both incumbents and entrants know the reserve prices precisely, even though they are not announced. The reserve price introduces a truncation in the bid distribution if it is binding, and it causes the number of firms actually participating in the auction to vary from the potential number of firms. Here, however, we assume that the reserve price is not binding. We assume that entrants do not enter the industry unless they can supply electricity cheaper in the first place than the listed fee of their local incumbent. Therefore, the only factor that causes the number of actual firms to deviate from the number of potential firms is the participation cost in the first stage.

3.1 The second stage

We now consider the second stage. We apply the nonparametric approach in Guerre et al. (2000) to estimate the firms' costs and strategies. Flambard and Perrigne (2006) use the same approach for asymmetric bidders and a binding reserve price, and show that the independent private value (IPV) model with a binding reserve price is nonparametrically identified. Their approach involves first identifying the relationship between the bid and cost from the theoretical model. They then estimate the bid distribution nonparametrically, and recover the cost distribution using the theoretical relationship. Because we only observe winning bids, not all bids, we additionally need to identify the relationship between the winning-bid distribution and the all-bids distribution before fully applying this approach. That is, we first estimate the winning-bid distribution nonparametrically, and recover the all-bids distribution using the theoretical relationship. We then recover the cost distribution using the all-bids distribution thus obtained.

3.1.1 The bidding model

We consider a procurement auction in which n risk-neutral firms compete for a contract to provide electricity throughout the contract period. Before bidding starts, each firm i forms an estimate of its cost to complete the task. The cost estimate is then firm i's private information. Thus, firm i knows its own cost estimate but does not know the cost estimates of the other firms. The cost estimate for firm i is a random variable C_i with a realization denoted as c_i, and is drawn independently across all firms. We consider two types of firms. Type 1 (0) refers to the incumbent (entrant). Types 1 and 0 consist of $n_1 = 1$ and $n_0 = n - 1$ firms, respectively: we assume that there is only one incumbent, and the incumbent, as in reality, always participates in the auction. Firms are assumed to learn the number of participants n (and therefore, $n_0 = n - 1$) before they enter the second stage. Let c_1 and c_0 denote the costs of the incumbent and entrant, respectively, drawn respectively from distribution $F_1(\cdot)$ and $F_0(\cdot)$, defined on the common support $[\underline{c}, \overline{c}]$.[11] Both

[11] Under this common support assumption, firms always have a non-zero probability of winning the auction, and therefore tender bids once they enter the second stage and learn their private costs. However, as described

distributions are continuous, with densities $f_1(\cdot)$ and $f_0(\cdot)$. We consider a first-price sealed-bid auction. Maskin and Riley (2000b) establish the existence of Bayesian equilibrium in asymmetric auctions.

We assume that both the incumbent and entrants guess the reserve price p_1^e and p_0^e because this is undisclosed in this industry. We also assume that they guess the reserve price p correctly (i.e. $p_1^e = p_0^e = p$) for the reason described above. We assume that the reserve price is nonbinding. However, when the number of bidders is 1, that is, when the incumbent is the only participant ($n = n_1 = 1$), the incumbent bids the reserve price. In other cases, firm i must submit the bid that is lowest among the participants and lower than the reserve price in order to win the contract. In the following model, we consider the case where $n \neq 1$.

If firm i submits a bid b, given that it is lower than the reserve price, it will win the contract when $c_j \geq \phi_j(b)$ for all $j \neq i$, where ϕ_j is the inverse strategy function that maps the equilibrium bids to costs. At the Bayesian-Nash equilibrium, each firm i chooses its bid b to maximize its expected profit:

$$\max_b \pi_i(b, c_i) = (b - c_i) \prod_{j \neq i} \left[1 - F_j(\phi_j(b))\right]. \tag{1}$$

As we can see, firm i's expected profit is a markup times the probability that firm i is the lowest bidder. Differentiating (1) with respect to b gives the following two first-order conditions for type 1 and 0.

$$c_1 = b_1 - \frac{1}{(n-1)\frac{f_0(\phi_0(b_1)\phi_0'(b_1))}{1-F_0(\phi_0(b_1))}} \tag{2}$$

$$c_0 = b_0 - \frac{1}{\frac{f_1(\phi_1(b_0)\phi_1'(b_0))}{1-F_1(\phi_1(b_0))} + (n-2)\frac{f_0(\phi_0(b_0)\phi_0'(b_0))}{1-F_0(\phi_0(b_0))}} \tag{3}$$

earlier, some firms actually exist that enter auctions but decline to submit bids. These firms presumably decline to bid because they have learned there is no probability of winning. Therefore, to explain this behavior, we need to relax either the assumption of common support or the assumption of a nonbinding reserve price. However, as we do not observe the reserve price or where firms have declined to bid, we use these assumptions for simplicity.

with boundary conditions (Maskin and Riley (2000a))

$$\begin{aligned} \phi_k(\bar{c}) &= \bar{c} \text{ for } k = 0, 1 \\ \exists \beta \text{ s.t. } \phi_k(\beta) &= \underline{c} \text{ for } k = 0, 1 \end{aligned} \tag{4}$$

3.1.2 Identification and the estimation method of the bidding model

In a first-price sealed-bid auction, the bids and number of actual bidders are typically observed, while the bidders' costs and their distributions are not. The typical problem of identification reduces to whether $F_1(\cdot), F_0(\cdot)$ are identified from the observed bids and the number of actual bidders n.

Because the distributions and densities of costs are not observed, Guerre et al. (2000) and Flambard and Perrigne (2006) rewrite the above first-order conditions using only the distribution of observed bids, and nonparametrically estimate the latter. Let $G_1(\cdot)$ be the distribution of bids for the incumbent bidder with the density function $g_1(\cdot)$. Let $G_0(\cdot)$ be the marginal distribution of bids for the other bidders with the density function $g_0(\cdot)$. Because the observed bids are the equilibrium bids, we have, for every $b \in [\underline{b}, \bar{c}]$, $G_1(b) = F_1(\phi_1(b)) = F_1(c)$, and $G_0(b) = F_0(\phi_0(b)) = F_0(c)$. Similarly, $g_i(b) = G_i'(b) = f_i \cdot \phi_i'(b)$ for $i = 1, 0$. The system of equations (2) and (3) can be then rewritten as:

$$c_1 = b_1 - \frac{1}{(n-1)\frac{g_0^*(b_1)}{1-G_0^*(b_1)}} \tag{5}$$

$$c_0 = b_0 - \frac{1}{\frac{g_1^*(b_0)}{1-G_1^*(b_0)} + (n-2)\frac{g_0^*(b_0)}{1-G_0^*(b_0)}} \tag{6}$$

That is, knowledge of $G_1^*(\cdot), G_0^*(\cdot), g_1^*(\cdot), g_0^*(\cdot), n$ determines the costs c_1 and c_0 in Equations (5) and (6) for any bid value. We can then estimate the cost distribution using c_1 and c_0 for each observed bid: that is, the cost distributions are identified from the observed bids and the number of participants.

Given we only have access to winning bids, we need to transfer Equations (5) and (6) to those that relate to the cost and winning-bid distributions. Let $W_i(\cdot)$ be the distribution of bidder $i's$ winning bids. Then, as in Brendstrup and Paarsch (2003) and Athey and Haile (forthcoming), Berman's (1963) derivation yields the relation:

$$G_i(b) = 1 - \exp\left[-\int_{-\infty}^{b} \frac{dW_i(t)}{1 - \sum_{j=1}^{n} W_j(t)}\right] \tag{7}$$

for a given n (see the Appendix for derivation). Therefore, for each type, we have:

$$\begin{aligned}
G_1(b) &= 1 - \exp\left[-\int_{-\infty}^{b} \frac{dW_1(t)}{1 - W_1(t) - (n-1)W_0(t)}\right] && (8)\\
G_0(b) &= 1 - \exp\left[-\int_{-\infty}^{b} \frac{dW_0(t)}{1 - W_1(t) - (n-1)W_0(t)}\right] && (9)\\
g_1(b) &= [1 - G_1(b)] \times \frac{dW_1(t)}{1 - W_1(t) - (n-1)W_0(t)} && (10)\\
g_0(b) &= [1 - G_0(b)] \times \frac{dW_1(t)}{1 - W_1(t) - (n-1)W_0(t)}. && (11)
\end{aligned}$$

Then, we estimate the observed winning-bid distributions W_1^* and W_0^* and its density $w_1^* = dW_1^*$ and $w_0^* = dW_0^*$ nonparametrically and obtain $G_1^*, G_0^*, g_1^*, g_0^*$ from the above relationship. Once we obtain $G_1^*, G_0^*, g_1^*, g_0^*$, the cost of the winner corresponding to each observed auction is recovered as:

$$\begin{aligned}
c_1^w &= b_1^w - \frac{1}{(n-1)\frac{g_0^*(b_1^w)}{1-G_0^*(b_1^w)}} && (12)\\
c_0^w &= b_0^w - \frac{1}{\frac{g_1^*(b_0^w)}{1-G_1^*(b_0^w)} + (n-2)\frac{g_0^*(b_0^w)}{1-G_0^*(b_0^w)}} && (13)
\end{aligned}$$

where c_k^w and b_k^w are the cost and bid of a type-k winner. We can immediately see that the knowledge of $W_1^*(\cdot), W_0^*(\cdot), w_1^*(\cdot), w_0^*(\cdot), n$ determines the costs c_1^w and c_0^w for any winning bid value from Equations (8) to (13).

Next we control for heterogeneity in auctions. We consider L auctions indexed by l, $l = 1, ..., L$. Let X_l be a vector of variables characterizing the auction l. We assume that all of the information characterizing the auctioned object is available to the analyst, and that any unobserved heterogeneity arises only from the differences in the bidders' private costs, which are unobserved random terms in the model. Then, the winning-bid distribution can be written conditionally on X_l and the number of actual bidders n.

Following Guerre et al. (2000) and Brendstrup and Paarsch (2003), we nonparametrically estimate these winning-bid distributions and densities. We first estimate the joint distribution (defined below) and the joint density of winning bid b^w, the auction characteristics X, and the total number of actual bidders n as follows:

$$\begin{aligned}
\hat{W}_k^*(b^w, X, n) &= \frac{1}{Lh_{1k}h_{2k}} \sum_{l=1}^{L_k} \mathit{1}(b_{kl}^w \leq b^w) K_G \left(\frac{x - X_l}{h_{1k}}, \frac{n - n_l}{h_{2k}} \right), \\
\hat{w}_k^*(b^w, X, n) &= \frac{1}{Lh_{1k}h_{2k}h_{3k}} \sum_{l=1}^{L_k} K_g \left(\frac{b^w - {b^w}_{kl}}{h_{3k}}, \frac{x - X_l}{h_{1k}}, \frac{n - n_l}{h_{2k}} \right),
\end{aligned}$$

for $k = 0, 1$, where $\hat{W}_k^*(b^w, X, n) = \hat{W}_k^*(b^w|X, n) \cdot f_{xn}(X, n)$, L_k is the number of auctions where type k is the winner, $\mathit{1}(\cdot)$ is the indicator function, K_G, K_g, K_x are kernels defined on compact supports, the variables with subscript l are the values of these variables in auction l, and hs are smoothing parameters. We also nonparametrically estimate the joint density of X and n as follows:

$$\hat{f}_{xn}(X, n) = \frac{1}{Lh_x h_{2k}} \sum_{l=1}^{L} K_x\left(\frac{x - X_l}{h_x}, \frac{n - n_l^*}{h_{2k}}\right).$$

for $k = 0, 1$. Then, we obtain the conditional winning-bid distributions and densities by $\hat{W}_k^*(b^w|X, n) = \hat{W}_k^*(b^w, X, n)/f_{xn}(X, n)$ and $\hat{w}_k^*(b^w|X, n) = \hat{w}_k^*(b^w, X, n)/f_{xn}(X, n)$. Following Equations (8) to (11), we then obtain $\hat{G}_k^*(b|X, n)$ and $\hat{g}_k^*(b|X, n)$. Equations (12) and (13) can be rewritten as:

$$c_1^w = b_1^w - \frac{1}{(n-1)\frac{g_0^*(b_1^w|X,n)}{1-G_0^*(b_1^w|X,n)}} \tag{14}$$

$$c_0^w = b_0^w - \frac{1}{\frac{g_1^*(b_0^w|X,n)}{1-G_1^*(b_0^w|X,n)} + (n-2)\frac{g_0^*(b_0^w|X,n)}{1-G_0^*(b_0^w|X,n)}}. \tag{15}$$

The above procedure recovers the winner's cost. We calculate the type-k winner's rent by $b_k^w - c_k^w$.

In order to obtain the equilibrium strategies of the two types of firms, we need to obtain the corresponding cost for each bid, including the losing bids of firms. However, unlike previous studies, we do not observe all of the bids. Therefore, we rely on simulation. More specifically, we obtain T random draws from the estimated bid distribution $\hat{G}_k^*(b|X,n)$ for any observed value of X_l and n_l, by the inverse transform method (Brandimarte (2006)). For each draw b_k^t, we calculate the pseudo cost $\hat{c}_{1t}$ and $\hat{c}_{0t}$ from Equations (5), (6) using the estimated bid densities and distributions, $g_1^*, g_0^*, G_1^*, G_0^*$:

$$\hat{c}_1^t = b_1^t - \frac{1}{(n-1)\frac{\hat{g}_0^*(b_{1t}^t|X_l,n_l)}{1-\hat{G}_0^*(b_{1t}^t|X_l,n_l)}} \tag{16}$$

$$\hat{c}_0^t = b_0^t - \frac{1}{\frac{\hat{g}_1^*(b_{0t}^t|X_l,n_l)}{1-\hat{G}_1^*(b_{0t}^t|X_l,n_l)} + (n-2)\frac{\hat{g}_0^*(b_0^t|X_l,n_l)}{1-\hat{G}_0^*(b_0^t|X_l,n_l)}} \tag{17}$$

for given X_l. By plotting b_k^t against $\hat{c}_k^t$ for $k=0,1$, we can show the firms' bidding strategies of type 0 and 1.

3.1.3 Auction characteristics, choice of kernels, and bandwidths

In order to take into account auction heterogeneity, we control for the load factor, the peak power (kW), district, and the JEPX price because in Section 2.2 these factors were found to most substantially affect the winning bid.[12] We conduct a separate nonparametric estimation for each district in order to control for the district effect because the auction and participant characteristics differ significantly across districts. However, we only show the results for Tokyo district because of the limited number of observations in other districts. We also remove observations with a load factor of less than 10%, because in such auctions bids are extremely higher than in other auctions. We then have 408 observations. We

[12] The reduced form estimation in Section 2.2 shows that the auction characteristics that are statistically significant are dummy variables for a high-voltage auction and the load factor. To control for the high-voltage dummy in the nonparametric estimation, we should conduct a separate estimation for each dummy value. However, the number of observations in the high-voltage group is too small for nonparametric estimation. Therefore, instead of a high-voltage dummy, we use *peak-power* (kw) as it is continuous and has a strong positive correlation with the high-voltage dummy. In fact, if we drop the high-voltage dummy from the regression, the coefficient on peak power becomes negative and significant in the estimations in Section 2.2.

also exclude observations with single=1, because in such an auction the only bidder (the incumbent) bids the reserve price. The final number of observations is 241. Summary statistics for the Tokyo district are shown in Table 5.

Because of the relatively small size of our data set and the use of nonparametric estimators, we reduce the dimension of X_l by constructing a single variable to capture auction heterogeneity. We employ principal component analysis following Flambard and Perrigne (2006). Three variables characterize the auction, namely, the load factor, power, and the JEPX price. We construct the following variable $z_l = 0.6813L_l + 0.5100P_l - 0.5252t_l$, where L_l, P_l and t_l are standardized variables for load factor, power, and JEPX price, respectively. We obtain a z_l varying from -2.16 to 7.54 with a mean equal to 0 and a variance of 1.12.

Following Flambard and Perrigne (2006), we select the biweight kernel: $K(u) = (15/16)(1-u^2)^2 \mathit{1}(|u| \leq 1)$. $K_G(\cdot,\cdot)$ and $K_g(\cdot,\cdot,\cdot)$ are the products of two and three univariate biweight kernels, respectively. For the choice of bandwidth, we follow Simonoff (1996, p.105). The general form of the kernel estimator for multivariable x is $\hat{f}(x) = (1/(n\,|H|)) \sum_{i=1}^{n} K_d[H^{-1}(x-x_i)]$ where d is the dimension of x and H is a nonsingular $d \times d$ bandwidth matrix. To simplify the estimation, we employ a diagonal H :

$$H = diag(h_1, ..., h_d) = 2.623 \times (\frac{4}{d+2})^{1/(d+4)}(diag\Sigma^{\frac{1}{2}})n^{-1/(d+4)}.$$

Then, for our kernel estimators for winning-bid distributions, we have $h_{1k} = 2.623 \times \hat{\sigma}_{zk} \times L^{-1/6}, h_{2k} = 2.623 \times \hat{\sigma}_{nk} \times L^{-1/6}$ for $k = 1, 0$ where $\hat{\sigma}_{zk}$ and $\hat{\sigma}_{nk}$ are the empirical standard deviations of z and n in observations with a type-k winner. For our estimators of the winning-bid densities, we have $h_{1k} = 2.623 \times 0.969 \times \hat{\sigma}_{yk} \times L^{-1/7}$, $h_{2k} = 2.623 \times 0.969 \times \hat{\sigma}_{zk} \times L^{-1/7}$, and $h_{3k} = 2.623 \times 0.969 \times \hat{\sigma}_{nk} \times L^{-1/7}$ where $\hat{\sigma}s$ are defined similarly. For the estimator for the joint density of X and n, we have $h_x = 2.623 \times 1 \times \hat{\sigma}_{zk} \times L^{-1/6}$. The factor 2.623 is the correction arising from the use of a biweight kernel instead of a Gaussian kernel.

3.2 The first stage

In this subsection, we consider the first stage where firms decide whether they participate in the auction. Once a potential bidder enters an auction, it will incur a participation cost e_k, draws its cost realization, and submits a bid in the second stage. We assume that the participation cost differs between incumbents and entrants. More specifically, based on the observed fact that incumbents participate in all auctions, we assume that the participation cost for incumbents, e_1, is negligible, and that the incumbents participate in any auction. This may not be as strong an assumption as it at first sounds because the incumbents have a supply duty, and therefore must supply electricity to these public agencies, even when there are no participants in the auction. Therefore, as they have to investigate the contracts regardless, it is not a participation cost for the incumbent. Further, we assume that incumbents continue to operate only in their former monopoly areas. Therefore, there is always one incumbent bidder in each auction. We assume that the incumbents' decision in the first stage and their participation cost e_k for $k = 1, 2$ are common knowledge for all bidders.

We follow the entry process of McAfee and McMillan (1987) and Nakabayashi (2009), and assume that participation decisions are made sequentially. Specifically, we assume that entrants make their participation decision on the basis that there always exists one and only one incumbent in an auction. Entrants enter an auction until their expected profits are driven down to equal the entry cost e_0. We assume that the participation cost e_0 is binding because in each area we do not observe any auction where all of the potential entrants participate. For example, in the Tokyo area we have eight potential entrants operating in this area, while the observed maximum number of entrants in any Tokyo area auction is five. Therefore, the entrants are marginal bidders whose *ex ante* payoff is zero.[13]

An entrant's expected profit for auction l, given c_0 and n_0, is

$$\pi_{l0}(c_0, n_0) = (\beta(c_0, n_0) - c_0) \Pr ob(win|c_0, n_0).$$

[13] We temporarily ignore the fact that there must be an integer number of bidders.

Then their *ex ante* expected profit for auction l, given n_0, $V_{l0}(n_0)$, is:

$$V_{l0}(n_0) = \int_{c_0} \pi_{l0}(\hat{c}, n_0) dF_0(\hat{c}). \tag{18}$$

The unique entry equilibrium must satisfy

$$V_{l0}(n_0) = e_0$$

subject to $n_0 \leq n_0^h$ where n_0^h is the maximum number of entrants in the area. The participation cost e_0 differs by auction because of the auction characteristics.

Using the estimated results from the second stage, we obtain π_{l0} for any value of c_0 in Equation (18). Then, using the estimated cost density and the observed number of participants, we obtain V_{l0} for any observed auction, thereby obtaining the participation cost e_0.

4 Estimation results

Table 6 provides summary statistics on the estimated costs of winners (c_1^w and c_0^w) in the observed auctions in Tokyo. The average estimated costs of the type-1 (incumbent) and type-0 (entrant) winner are 9.03 yen/kWh and 10.11 yen/kWh, respectively, and the average rents are 0.39 yen/kWh and 0.34 yen/kWh, respectively, without controlling for auction characteristics. The cost of a type-1 (incumbent) winner is, on average, lower than that of a type-0 (entrant) winner, presumably because incumbents win auctions with high load factor requirements more often than entrants: put differently, the contracts with high load factor requirements are less costly. The incumbent's rent is probably higher for a similar reason: that is, contracts with high load factor requirements are more profitable. Table 7 provides the estimated costs and rents of winners on auction characteristics.[14] Once we control for auction characteristics in Tokyo area, we can see that the incumbent winner's

[14] Because the number of bidders should not affect firm costs, it only enters the regression for the firm rents.

cost is higher than that of entrants while the incumbent's rent is lower than that of entrants.

Next, we draw T random bids from the estimated bid distribution $\hat{G}_k^*(b|X,n)$ for all observed values of X_l and n_l, and obtain the corresponding cost distributions $F_1(c_1|X_l,n_l), F_0(c_0|X_l,n_l)$ for each (X_l,n_l) from Equations (16) and (17).[15] From $F_1(c_1|X_l,n_l), F_0(c_0|X_l,n_l)$, we obtain the mean of the cost distributions $E(c_1|X_l,n_l), E(c_0|X_l,n_l)$, and the standard deviations of the cost distributions $sd(c_1|X_l,n_l), sd(c_0|X_l,n_l)$ for each (X_l,n_l). Table 8 provides summary statistics of these estimated means and standard deviations of cost distributions. We can see that on average (average on (X_l,n_l)), the incumbent has a higher mean and a lower standard deviation. Figure 1 displays the estimated cost densities of entrants and the incumbent in the Tokyo area, given the median value of auction characteristics and the number of bidders (Peak power = 1,340kW, Load factor = 34.33%, JEPX price = 8.60 yen/kWh, one incumbent and one entrant). This is a typical cost density of two types. We can see that the density of the incumbent has a higher mean while that of the entrant has a higher variance. Figure 2 plots the estimated equilibrium strategies given the median values of the auction characteristics and two bidders in the Tokyo area. We can see that the incumbent bids more aggressively than the entrants: that is, as the theory suggests, for the same cost value, the incumbent submits a lower bid.

Our findings show that the incumbent has a higher cost for the electricity supply contracts despite its advantage in production cost structure. Its higher costs may then be explained by its opportunity cost of winning the auctions as discussed in the Introduction: winning auctions for public agencies at lower bids may lose future profits from private users for the incumbent. It appears, then, that the incumbent's opportunity cost of winning the auction is economically significant.

Table 9 shows the result from the regression of the difference of the mean cost of the incumbent and the entrants $(E(c_1|X_l,n_l) - E(c_0|X_l,n_l))$ on auction characteristics. We can see that the cost difference becomes smaller the higher the load factor. This implies that the incumbent's opportunity cost is lower for contracts with higher load factor require-

[15] For now, we set $T = 10000$.

ments. This may be because the incumbent already offers a low rate for private users whose electricity usage requires a high load factor.

Using the estimated costs for each observed auction characteristic and the number of participants, we calculate the participation cost of entrants. We calculate the participation cost for one observed auction with a mean value of z_l (peak power = 3,200kW, load factor = 33.1%, amount = $9,270$ thousand kWh, JEPX = 8.605yen/kWh) and $n = 5$. The calculated entry cost is $4,206$ thousand yen. This is comparable to the estimates in Krasnokutskaya and Seim (2008), though the auction objects are different in their case.

5 Counterfactual analyses

We use the above estimation results to assess the effect of hypothetical preferential treatment. We compare the costs to the government (the auctioneer) under different settings of the preference rate δ. With a bid preference rate of δ, if a preferred firm has tendered a bid of b, then the auctioneer would consider the preferred firm's tender a bid of $b/(1+\delta)$, but still pays b for the contract. As noted in Hubbard and Paarsch (2009), introducing preferential treatment has three effects. First, firms receiving preferential treatment can inflate their bids and still win the auction: they refer to this as the *preference effect*. Second, nonpreferred firms will behave more competitively than under the equal treatment of bids: this is the *competitive effect*. Finally, if preferential treatment changes firms' expected profit, it will also affect their participation behavior: this is the *participation effect*. We now examine the net effect of these three individual effects on government procurement costs under different bid preference rates.

In order to evaluate auction outcomes under alternative settings, we need to simulate bidding strategies that take the policy parameters into account. More specifically, we need to modify the first-order conditions (2) (3), which are based on the common support assumption, to those that incorporate the bid preference δ as follows (see Krasnokutskaya and

Seim (2008)). When a preference is given to incumbents:

$$
\begin{aligned}
c_1 &= b_1 - \frac{1}{(n-1)/(1+\delta)\frac{f_0(\phi_0(b_1/(1+\delta))\phi_0'(b_1/(1+\delta)))}{1-F_0(\phi_0(b_1/(1+\delta)))}} && (19)\\
c_0 &= b_0 - \frac{1}{\frac{(1+\delta)f_1(\phi_1(b_0(1+\delta))\phi_1'(b_0(1+\delta)))}{1-F_1(\phi_1(b_0(1+\delta)))} + (n-2)\frac{f_0(\phi_0(b_0)\phi_0'(b_0))}{1-F_0(\phi_0(b_0))}} && (20)
\end{aligned}
$$

with the boundary conditions,

$$
\begin{aligned}
\phi_0(\bar{c}) &= \bar{c} = \bar{b}_0, && (21)\\
\phi_1(\bar{b}_1) &= \bar{c} \textit{ and } \bar{b}_1 > \bar{b}_0. && (22)\\
\exists\beta \text{ s.t. } \phi_0(\beta) &= \underline{c} \textit{ and } \phi_1(\beta(1+\delta)) = \underline{c}
\end{aligned}
$$

where,

$$\bar{b}_1 = \arg\max_b (b-\bar{c})(1-F_0(b/(1+\delta))^{n_0}.$$

When a bid preference δ is given to entrants, the first order conditions are:

$$
\begin{aligned}
c_1 &= b_1 - \frac{1}{(n-1)(1+\delta)\frac{f_0(\phi_0(b_1(1+\delta))\phi_0'(b_1(1+\delta)))}{1-F_0(\phi_0(b_1(1+\delta)))}} && (23)\\
c_0 &= b_0 - \frac{1}{\frac{f_1(\phi_1(b_0/(1+\delta))\phi_1'(b_0/(1+\delta)))}{(1+\delta)(1-F_1(\phi_1(b_0/(1+\delta))))} + (n-2)\frac{f_0(\phi_0(b_0)\phi_0'(b_0))}{1-F_0(\phi_0(b_0))}} && (24)
\end{aligned}
$$

with the boundary conditions,

$$
\begin{aligned}
\phi_k(\bar{c}) &= \bar{c} \text{ for } k = 0, 1. && (25)\\
\exists\beta \text{ s.t. } \phi_1(\beta) &= \underline{c} \textit{ and } \phi_0(\beta(1+\delta)) = \underline{c}.
\end{aligned}
$$

The first-order conditions hold for $c_{m^{-1}} \in (\underline{c}, \bar{b}_m/(1+\delta))$ and $c_m \in (\underline{c}, \bar{c})$ where m is the preferred bidder. Nonpreferred bidders with cost $c_{m^{-1}} \in (\bar{b}_m/(1+\delta), \bar{c})$ cannot submit a winning bid that would cover their cost. We assume that in this range of cost realization, they bid their cost. This system of differential equations does not have a closed form solution and therefore needs to be solved numerically. We follow Marshall et al. (1994) who solve the differential equations forwards.[16] As noted by Marshall et al. (1994), the numerical determination of β is a critical component of the problem to be solved. We conduct a forward recursion algorithm starting at a lower boundary value β chosen to result in an endpoint that satisfies the upper boundary condition. We embed this forward algorithm in a routine that searches for a starting point that also satisfies the lower boundary condition.

The counterfactual analyses are again conducted for a particular auction that has a mean value of z_l (peak power = $3,200$kW, load factor = 33.1%, amount = $9,270$ thousand kWh, JEPX= 8.605yen/kWh). Table 10 presents the result from the counterfactual analyses. The upper panel presents the simulation results when preferential treatment is awarded to the entrants. δ is the preference rate. $E(rent1)$ and $E(rent0)$ are the (*ex-ante*) expected profit of the incumbent and entrants, respectively. $E(\text{cost})$ is the government's expected procurement cost. $E(incumbent\ win)$ is the expected rate of the incumbent winning. We can see that the preference for entrants does not have much effect on the number of bidders when the rate is small. Although the expected profit for entrants increases as the discount increases, the fifth entrant cannot enter because if it did the expected profit would be less than the participation cost. When the preference rate reaches 20%, the number of bidders jumps to nine. The expected profit of the incumbent decreases with the discount rate for entrants. This is firstly because the incumbent bids more aggressively the higher the preference to entrants, and secondly, because it becomes more difficult for the incumbent to win the auction. The expected winning bid decreases with the discount rate, reflecting discounted bids by the entrants and more aggressive bids by the incumbent. The government's procurement cost has nonmonotonic movement with the discount rate. We can see that the government cost is minimized with a preference rate of 5% for this auction. At this discount rate, the competitive effect on the incumbent offsets the preference effect on the entrants. However, as the preference rate increases, the effect of a more aggressive bid by the incumbent is offset because even with more aggressive bids, incumbents are unlikely

[16] Marshall et al. (1994) solves a high bid auction and suggest solving the problem backwards. Here, we consider a low-bid auction and solve the system forwards.

to win the auction.

The second panel presents the simulation results when a preferential treatment is awarded to the incumbent. Theory suggests a preference for weak bidders may enhance competition among strong bidders, and thereby improve the government's procurement cost. We can see, however, that a preference for the incumbent does not improve the government's procurement cost. Not surprisingly, the expected profit of the incumbent increases while that of the entrants decrease, with the preference rate for the incumbent. However, the competition effect on the entrants is not sufficient to offset the preference effect on the incumbent. The reason for this small competition effect may be that each entrant already bids aggressively, even without the preferential treatment for the incumbent, in order to compete with other entrants. Because of the small competition effect, the preference for the incumbent merely increases the probability of winning by an incumbent that already has preferential treatment, and this increases the government's cost.

6 Conclusion

This paper studies the bidding patterns of entrant and incumbent firms in electric power procurement auctions in Japan. In the Japanese retail electricity market, ten firms that supplied electricity acted as local monopolists. Partial liberalization started in 2000, allowing PPS to enter the market and to supply electricity to large users with power and voltage requirements greater than $2,000$kW and $20,000$V, respectively. Accompanying this liberalization wave, public agencies have begun to utilize sealed bidding systems for electric power supply contracts. Although PPS are now allowed to participate in any auctions with power requirements exceeding $50kW$, their participation rate remains very low, implying a significant cost disadvantage of entrants relative to incumbents. Conversely, the incumbents' opportunity costs of winning auctions are considered high because they have large outside customers already trading in the publicly announced power rate. We assess the extent of asymmetry between the incumbent and the entrants and whether preferential treatment on one or the other type can improve the participation of entrants and decrease the government's procurement costs.

We model the bidding and participation behavior of the incumbents and the entrants in a two-stage game and recover the cost distributions using the structural estimation method proposed by Guerre et al. (2000). Because we only have access to winning bids, we non-parametrically estimate the winning-bid distribution, and use the theoretical relationship between it and the all-bids distribution to apply the approach in Guerre et al. (2000). We then calculate the participation cost that explains the present participation situation using the estimated cost distributions.

We find that an incumbent has a much higher cost for a given auction than the entrants, despite its advantages in production cost structure. Our results indicate that the incumbent's opportunity cost of winning auctions is also economically significant: that is, the incumbent cannot win auctions with low bids because it will reveal its ability to supply electricity at lower rates to outside customers.

Having estimated the bid and cost distributions, we are able to simulate auction outcomes under alternative scenarios for price-preference policy. We find that a preference for the weak bidder, the incumbent, does not improve the government's procurement cost, although theory suggests a preference for weak bidders may enhance competition among strong bidders and thereby improve the government's procurement cost. In fact, government cost is minimized with only a small preference for entrants (5%) by making the incumbent bid more aggressively while not significantly reducing the probability of the incumbent winning.

Some points that should be considered remain outstanding in our approach. First, we do not consider heterogeneity among entrants. In reality, entrants have very different characteristics, such as size. However, because our data set does not permit the identification of entrants when they do not win, it is not possible to consider the heterogeneity among entrants here. We are currently gathering all auction bids (not just the winning bid) for further study. Second, our study considers only the static effects of preference treatment. Further research is needed to assess preference policy in a dynamic setting.

A Appendix

The identification of each marginal bid distribution G_i from the observation of the winning bid is formally equivalent to the identification of the competing risks model with independent non-identically distributed risks (see Brendstrup and Paarsch (2003); Athey and Haile (forthcoming)). The distribution of the winning bid of firm i, $W_i(y)$, is the union of two disjointed events, b_i being $\min(b_1, ..., b_n)$ and $b_i \leq y$.

$$
\begin{aligned}
W_i(y) &= \Pr(Y \leq y, \text{winner is } i) \\
&= \int_{-\infty}^{y} \prod_{j \neq i} [1 - G_j(t)]\, g_i(t) dt \\
&= \int_{-\infty}^{y} \frac{\prod_{j=1}^{n} [1 - G_j(t)]}{1 - G_i(t)} g_i(t) dt \\
&= \int_{-\infty}^{y} \frac{1 - \Pr(y \leq t)}{1 - G_i(t)} g_i(t) dt \\
&= \int_{-\infty}^{y} \frac{1 - \sum_{j=1}^{n} W_j(t)}{1 - G_i(t)} g_i(t) dt \\
&= \int_{-\infty}^{y} - \left[1 - \sum_{j=1}^{n} W_j(t) \right] d \log(1 - G_i(t))
\end{aligned} \tag{26}
$$

where n is the number of bidders who actually participated in the auction. Rearranging the above equation, we obtain the relationships between the winning-bid distribution and the all-bids distribution and between the winning-bid density and the all-bids density as follows.

$$
\begin{aligned}
dW_i(y) &= -\left[1-\sum_{j=1}^{n} W_j(y)\right] d\log(1-G_i(y)) \\
d\log(1-G_i(y)) &= -\frac{dW_i(y)}{1-\sum_{j=1}^{n} W_j(y)} \\
\log(1-G_i(y)) &= -\int_{-\infty}^{y} \frac{dW_i(t)}{1-\sum_{j=1}^{n} W_j(t)} \\
1-G_i(y) &= \exp\left[-\int_{-\infty}^{y} \frac{dW_i(t)}{1-\sum_{j=1}^{n} W_j(t)}\right] \\
G_i(y) &= 1-\exp\left[-\int_{-\infty}^{y} \frac{dW_i(t)}{1-\sum_{j=1}^{n} W_j(t)}\right] \\
g_i(y) &= \exp\left[-\int_{-\infty}^{y} \frac{dW_i(t)}{1-\sum_{j=1}^{n} W_j(t)}\right] \times \frac{dW_i(t)}{1-\sum_{j=1}^{n} W_j(t)} \\
&= [1-G_i(y)] \times \frac{dW_i(t)}{1-\sum_{j=1}^{n} W_j(t)}
\end{aligned}
$$

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FY	# of auctions	# of bidders	Winning bids (yen/kWh)	Peak power (kW)	Amount (thousand kWh)	Load	Green
2004	335	1.50	14.25	2110.04	9565.24	0.44	0.00
2005	279	2.05	14.75	2047.39	8774.40	0.41	0.00
2006	324	1.97	15.11	1680.45	6757.03	0.38	0.42
2007	413	1.75	15.74	2165.51	9685.31	0.38	0.32
Total	1351	1.80	15.02	2011.04	8765.15	0.40	0.20

Table 1: Auctions from FY2004 to FY2007

Load factor	# of auctions	Win bid of incumbent	Win bid of entrant	% with entrant	% entrant wins	%entrant win given entrant entry
-10%	59	37.08	27.12	83.1%	83.1%	100%
$10-20\%$	125	20.24	20.23	56.0%	52.8%	94.3%
$20-40\%$	524	16.09	15.48	50.2%	45.8%	91.3%
$40-60\%$	413	12.87	12.32	42.1%	27.9%	66.1%
$60-80\%$	198	11.05	10.62	18.7%	6.6%	35.1%
$80\%-$	32	10.56	11.50	3.1%	3.1%	100%
$Total$	1351	14.23	16.41	44.0%	35.8%	81.5%

Table 2: Load factor and bid difference between incumbent and entrant

	(1)	(2)	(3)	(4)	(5)	(6)
Incumbent wins	0.150	0.153	0.244	0.249	0125	0.242
	(0.275)	(0.275)	(0.277)	(0.277)	(0.277)	(0.277)
Number of bidders	−0.201	−0.201	−0.330***	−0.335***	−0.340***	−0.344***
	(0.122)	(0.123)	(0.122)	(0.122)	(0.120)	(0.120)
High voltage	−1.173***	−1.160***				
	(0.213)	(0.206)				
Load	−0.550***	−0.551***	−0.550***	−0.549***	−0.547***	−0.546***
	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)
Load^2	0.004***	0.004***	0.004***	0.004***	0.004***	0.004***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
KW	−0.007		−0.051**		−0.049**	
	(0.022)		(0.021)		(0.021)	
KWh		−0.002		−0.008**		−0.007**
		(0.004)		(0.003)		(0.003)
Contract length	−0.020	−0.011	−0.049	−0.029	−0.061	−0.041
	(0.239)	(0.160)	(0.161)	(0.162)	(0.160)	(0.161)
Green	0.161	0.119	0.001	0.008	−0.099	−0.091
	(0.234)	(0.239)	(0.242)	(0.242)	(0.215)	(0.215)
JEPX					0.074***	0.075***
					(0.027)	(0.027)
Constant	30.168***	30.142***	30.179***	30.075***	29.534***	29.420***
	(0.592)	(0.593)	(0.599)	(0.600)	(0.667)	(0.668)
F(P-value)	0.000	0.000	0.000	0.000	0.000	0.000
Adj. R-squared	0.652	0.652	0.645	0.644	0.645	0.645
# of obs.	1349	1349	1349	1349	1349	1349

Notes: Dependent variable is average bid (yen/kWh). (1) to (4) include district and year dummies. (5) and (6) include district dummies. SEs are in parentheses.

Table 3: Estimation results:Basic specification

	(1)	(2)	(3)	(4)	(5)	(6)
Incumbent wins	0.704**	0.711**	0.694**	0.687*	0.654*	0.647*
	(0.342)	(0.342)	(0.346)	(0.346)	(0.346)	(0.346)
Number of bidders	−0.362***	−0.363***	−0.464***	−0.465***	−0.467***	−0.467***
	(0.136)	(0.136)	(0.137)	(0.137)	(0.135)	(0.136)
Single	−0.988***	−0.994***	−0.795***	−0.772**	−0.740**	−0.717*
	(0.365)	(0.364)	(0.361)	(0.367)	(0.368)	(0.367)
High voltage	−1.123***	−1.218***				
	(0.214)	(0.206)				
Load	−0.554***	−0.555***	−0.553***	−0.552***	−0.550***	−0.549***
	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)
Load^2	0.004***	0.004***	0.004***	0.004***	0.004***	0.004***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
KW	−0.010		−0.055***		−0.053**	
	(0.022)		(0.021)		(0.021)	
KWh		−0.003		−0.008**		−0.008**
		(0.004)		(0.004)		(0.003)
Contract length	−0.021	−0.010	−0.051	−0.029	−0.065	−0.043
	(0.159)	(0.160)	(0.161)	(0.162)	(0.160)	(0.161)
Green	−0.008	0.009	0.023	−0.015	−0.132	−0.122
	(0.239)	(0.239)	(0.242)	(0.242)	(0.216)	(0.216)
JEPX					0.067**	0.068**
					(0.028)	(0.028)
Constant	30.865***	30.836***	30.740***	30.611***	30.106***	29.966***
	(0.645)	(0.644)	(0.652)	(0.651)	(0.724)	(0.723)
F(P-value)	0.000	0.000	0.000	0.000	0.000	0.000
Adj. R-squared	0.654	0.654	0.646	0.645	0.646	0.646
# of obs.	1349	1349	1349	1349	1349	1349

Notes: Dependent variable is average bid (yen/kWh). (1) to (4) include district and year dummies. (5) and (6) include district dummies. SEs are in parentheses.

Table 4: Estimation results: Controlling for auctions with incumbent only

Variables	# of obs.	Mean	Std. Dev.	Median
Winning bid (yen/kWh)	241	14.56	2.95	14.27
Peak power (thousand kW)	241	2.48	3.70	1.34
Load factor (%)	241	36.59	14.98	34.33
# of actual bidders	241	3.38	1.34	3.00
Incumbent dummy	241	0.19	0.39	0.00
JEPX (yen/kWh)	241	10.12	2.820	8.60

Table 5: Summary statistics of Tokyo area

Variables	Mean	S.D.
Incumbent		
Bid	14.13	3.33
Cost	9.03	4.92
Rent	0.39	0.22
Entrants		
Bid	15.01	2.58
Cost	10.11	4.32
Rent	0.34	0.20

Table 6: Summary statistics of estimated winner's cost and rent in Tokyo area

Dependent var.	Cost	Rent
Incumbent wins	1.750^{**}	-0.103^{***}
	(0.611)	(0.0334)
Number of bidders		-0.048^{***}
		(0.013)
Load	-66.903^{***}	2.580^{***}
	(6.383)	(0.334)
Load^2	56.130^{***}	-2.385^{***}
	(7.458)	(0.391)
KW	-0.283^{**}	0.012^{**}
	(0.116)	(0.006)
JEPX	-0.435^{***}	0.030^{***}
	(0.092)	(0.005)
Constant	30.060^{***}	-0.359^{***}
	(1.737)	(0.109)
F(P-value)	0.000	0.000
Adj. R-squared	0.518	0.387

Notes: SEs are in parentheses.

Table 7: Regression of estimated winner's cost and rent

Variables	Mean	S.D.
Incumbent		
Mean of cost	16.98	3.72
S.D. of cost	3.34	1.49
Entrants		
Mean of cost	13.57	2.95
S.D. of cost	4.34	1.34

Table 8: Summary statistics of estimated mean and standard deviation of cost distributions in Tokyo area

Variables	Difference $(E(c_1) - E(c_0))$	
Load	-9.526	$(1.307)^{***}$
KW	-0.134	$(0.077)^{*}$
JEPX	0.385	$(0.069)^{***}$
Constant	3.262	$(0.972)^{***}$
F(P-value)	44.30	
Adj. R-squared	0.364	
# observations	228	

Notes: SEs are in parenthesis.

Table 9: Regression on the difference between estimated mean cost of incumbent and entrants in Tokyo area

Discount on entrants (δ)	# bidders	E(rent1) (yen/kWh)	E(rent0) (yen/kWh)	E(winbid) (yen/kWh)	E(cost) (yen/kWh)	E(incumbent wins)
0	4	0.187	0.485	13.825	13.825	0.154
0.05	4	0.114	0.505	13.232	13.821	0.105
0.10	4	0.065	0.515	12.681	13.859	0.068
0.15	4	0.040	0.520	12.132	13.860	0.047
0.20	9	0.344	0.950	12.519	15.012	0.088
Discount on incumbents (δ)	# bidders	E(rent1) (yen/kWh)	E(rent0) (yen/kWh)	E(winbid) (yen/kWh)	E(cost) (yen/kWh)	E(incumbent wins)
0	4	0.181	0.488	13.815	13.815	0.148
0.05	4	0.282	0.475	13.797	13.906	0.152
0.10	4	0.391	0.467	13.738	13.973	0.162
0.15	4	0.557	0.443	13.718	14.113	0.184
0.20	4	0.683	0.439	13.594	14.137	0.190

Table 10: Simulation results of bid discount program

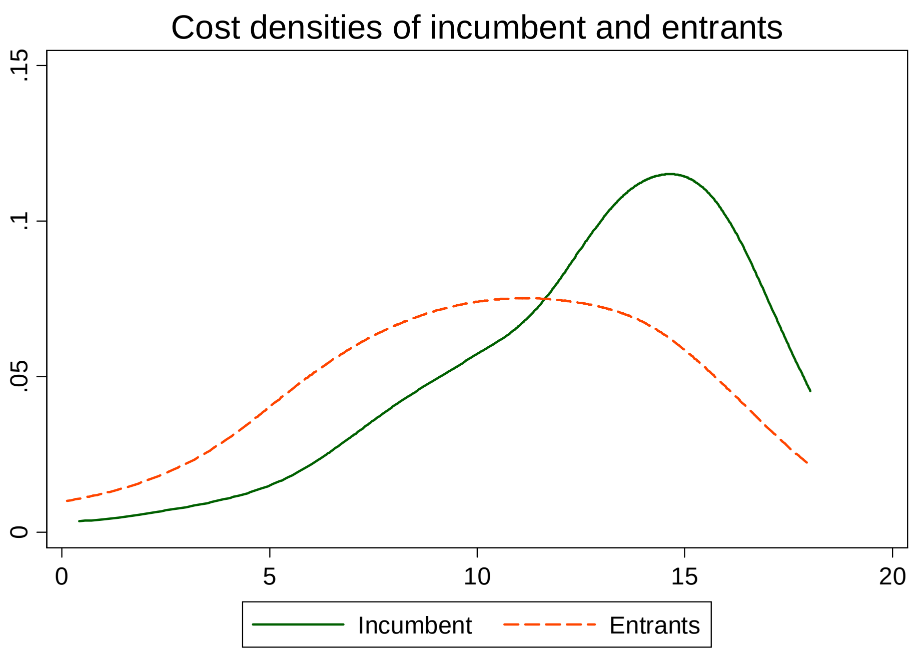

Figure 1: Estimated cost densities of incumbent and entrants for the median covariates (Peak power = 1340kW, Load factor = 34.33%,JEPX price = 8.60 yen/kWh, one incumbent and one entrant)

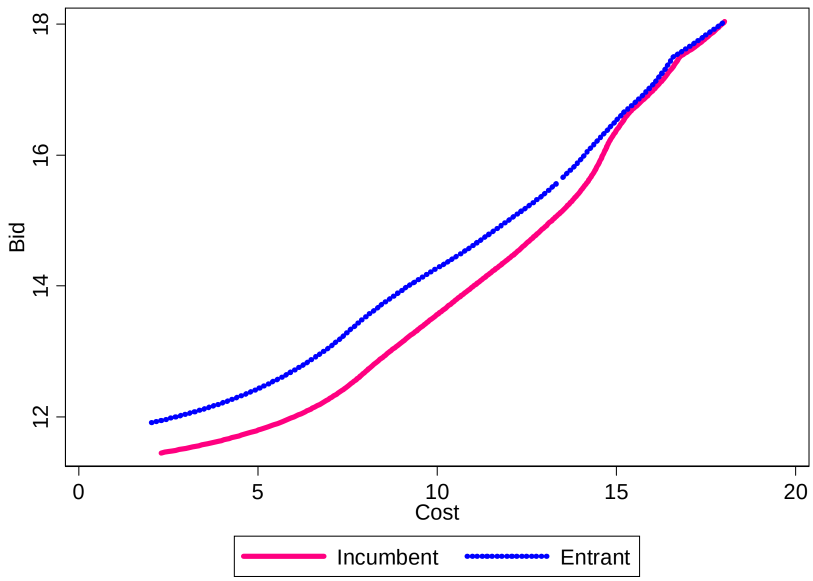

Figure 2: Equilibrium bidding strategies of incumbent and entrants for the median covariates (Peak power =1340kW, Load factor = 34.33%, JEPX price = 8.60 yen/kWh, one incumbent and one entrant)