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# A Structural Estimation Approach to an Asymmetric Auction Model for the Japanese Retail Power Market

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# A Structural Estimation Approach to an Asymmetric Auction Model for the Japanese Retail Power Market

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## Abstract

In this paper, we develop a structural auction model and quantify the effects of policy measures aiming to enhance competition in the Japanese retail power market. We employ a theoretical model that incorporates asymmetries between the incumbent and entrants in terms of both the cost and information structures, where the costs of the former are assumed common knowledge, and empirically estimate the structural parameters characterizing their cost distributions using public power procurement data. We then conduct counterfactual simulations to quantify two competition-promoting policy measures: a bid preference program for entrants, and an increase in the number of potential bidders. We take a parametric approach to estimate the structural model successfully in contrast to a nonparametric approach that previous studies took. Our simulation results show that these procompetitive measures would barely increase participation by potential entrants but would elicit more aggressive incumbent bidding behavior. Further, a modest bid-preferential rate would improve welfare and reduce the probability of realizing inefficient allocations associated with a costly winning bidder.

JEL Classification: L94, H57, C54

Keywords: electric power industry; auction data; public procurement; structural estimation; asymmetric information structure; competition policy

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# 1. Introduction

There has long been heavy regulation of utilities of all forms in most countries. Accordingly, in the early stages of deregulation, huge incumbents, which had previously monopolized regional and sometimes national markets under regulated regimes, typically play a dominant role alongside just a few smaller entrants. In evidence, Corfe and Gicheva (2017) report very high concentration ratios and Herfindahl–Hirschman indices (HHIs) for fixed and mobile phone, broadband, electricity, and gas services in the UK. There is also high industry concentration among airlines, not only in the US with just four major carriers, but in other countries with industries comprised of legacy and low-cost carriers (see Fu et al. (2015) for China and Sun (2017) for Korea). Similarly, the Agency for the Cooperation of Energy Regulators (2015) reports high concentration rates for the three major suppliers in retail electricity and gas markets in EU member states. In this regard, Japan is no exception, with its Electricity and Gas Market Surveillance Commission (2018) showing that the nine Japanese regional retail markets have extremely high HHIs and are comparable with those in the most concentrated countries of France, Latvia, Estonia, and Croatia.

In 1995, Japan initiated a series of regulatory reforms to shift toward a more market-oriented power industry by deregulating entry into the wholesale power market. Retail market deregulation commenced in the market segment for large industrial and commercial customers using 2,000 kilowatt (kW) or more of ultra-high voltage (UHV) power. Since then, the scope of deregulation has gradually expanded to other middle-sized customers using 500 kW or more of high voltage (HV) power in 2004, and again to those using 50 kW or more in 2005. These deregulated market segments covered more than 60% of the total power demand in 2006, with deregulation eventually reaching all customers in 2016.

Initially, new entrants to this market mainly started their business using third-party power plants while developing their own plants, eventually accounting for a 5% share of the deregulated retail market in 2014. However, because of their limited supply capacity, entrants typically focus on large customers using UHV power in large cities, especially in the service area of the Tokyo Electric Power Company (TEPCO). These entrants engage in power procurement auctions very actively and exploit their cheaper supply costs to win out over incumbents in auctions for large customers once they decide to participate in the auction.

The Agency for Natural Resources and Energy (2004, 2006) examined auction data for power supply to government and other public entities in Japan and found that with just a few exceptions, the average power charges in auctions with multiple bidders were about 0.7 yen per kilowatt-hour (kWh) lower in auctions with a single bidder, where only one incumbent participates.[1] Problematically, we cannot attribute this difference in power charges solely to the participation of entrants, because the entrants first endogenously decide entry and only then bid after considering the impact of the auction attributes for their profits. For instance, Hattori (2010) found that entrants were more likely to participate in potentially profitable auctions with lower load factors, larger contract demand, and UHV power supply, using auction data for 2004–2006.[2] Hosoe and Takagi (2012) concluded that participation by entrants lowered power charges by about 0.48 yen/kWh in auctions on average while controlling for the endogeneity bias caused by their participation decisions. However, their closed-form models only describe bidder diversity (or the asymmetry between them) with dummy explanatory variables.

There are two major sources of asymmetry between an incumbent and entrants in the retail power market. One is their business activities, including the types and sizes of facilities they possess, their major customers, and their scale of business. These are often

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[1] The average power charge divides the winning bids (in yen) by the power demand (in kWh). Unless otherwise noted, we simply refer to this as the power charge in our study.

[2] The (annual average) load factor is defined as follows: Load factor (%) = planned power demand (kWh) ÷ [contract demand (kW) × 365 (days) × 24 (hours) × contract period (years)] × 100 (%). Given total power demand, a lower load factor implies that capacity is more likely to be idle and thus customers are costly to serve.

readily observable and related to the difference in cost structures between market players. The other is institutional asymmetry in information structure. Here, the incumbents have long served the market and usually disclosed their cost information (e.g., plant portfolios and fuel consumption and power generation by power station) in detail under the previous regulatory regime.

With this information, other players can precisely infer the supply costs of incumbents for individual auctions, such as in Hosoe (2015) using fuel efficiency data. In contrast, there is little disclosure of the information about entrants, such as the capacities of their third-party suppliers and their own new plants, their deals in the power exchange market, and through bilateral contracts. Accordingly, most information about entrants is private and most information about an incumbent is common knowledge. This type of asymmetry leads to different actions taken by the incumbent and entrants.

To model procurement auctions with such highly asymmetric players, Brendstrup and Paarsch (2004) and Suzuki (2010) applied a nonparametric approach to estimating bidders' cost distributions, based on earlier work by Guerre et al. (2000). After estimating the bidders' cost densities, they obtained the optimal bidding functions as numerical solutions of the boundary value problem for the partial differential equations, as derived from the first-order conditions of the bidders.

This nonparametric approach has an advantage in that it could identify the bidders' cost distributions without specifying their parametric functional form, rather through the densities and distributions of the bid data. Nevertheless, at the cost of flexibility in the functional form, nonparametric estimations of densities suffer from possible biases or inconsistencies near the data endpoints. See, for example, Hickman and Hubbard (2015). In addition, it is widely recognized that the numerical methods used for solving boundary value problems are inherently unstable, especially near boundary points (Fibich and Gavish, 2011).

In general, the estimation biases and numerical instabilities inherent in the nonparametric estimation and numerical solution methods of partial differential equations affect the estimated auction outcomes: namely, winning bids, profits, participation probabilities, and inefficiencies. Those numerical difficulties then deteriorate the preciseness of the counterfactual simulations using the estimated auction outcomes. Eventually, Suzuki (2011) reinstated participation costs in the auctions as in Levin and Smith (1994). Her counterfactual simulations, like those of Krasnokutskaya and Seim (2011), showed that the number of participants would double (from four to nine bidders) with a 20% preference rate for bids by entrants. However, in her estimations, the participation costs for an average auction were some 4.2 million yen (5.3% of the winning bids of that auction) and these appear much too large for procurement auctions held regularly every year.[3]

In this study, we follow the theoretical frameworks in Vickrey (1961) and Martínez-Pardina (2006) and develop a parametric model for power procurement auctions, whereby the incumbent and entrants are heterogeneous in their cost distributions and information structure. In contrast to the nonparametric approach of earlier studies, we take a parametric approach, where we prespecify the functional forms of bidders' cost distributions. We also assume the asymmetries not only in the cost distributions of the incumbent and entrants, but also in the cost information disclosed to other participants. Incorporating these into the theoretical model, we explicitly obtain the parametric bidding functions of each participant, depending on common knowledge. For our estimation, we use data for nearly 800 power procurement auctions held in the early stage of the retail market deregulation in TEPCO's service area. Taking advantage of the structural approach, we then conduct counterfactual policy simulations to demonstrate the effects of procompetitive policies on the auction participant behavior and market outcomes, including power charges and the efficiency of resource allocation. These provide clear quantitative policy implications for the drastic

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[3] The attributes of the average auction in Suzuki's (2011) simulations are 3,200 kW of maximum power use, 9.3 million kWh of planned power demand, 80 million yen for the winning bid, and a 33% load factor.

regulatory reforms following the Fukushima Dai-ichi Nuclear Disaster in March 2011.

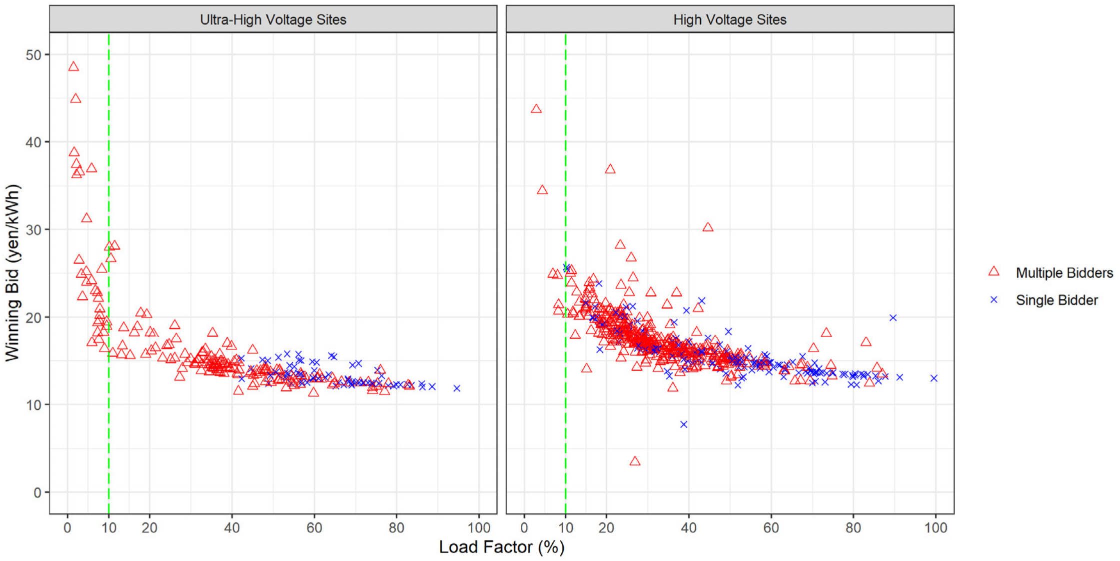
The remainder of the paper proceeds as follows. Section 2 discusses the basic statistics of our auction sample, and Section 3 presents Martínez-Pardina's (2006) theoretical model for power procurement auctions assuming asymmetry in player costs and information structures. Section 4 describes our estimation method for the structural auction model as based on indirect inference. Section 5 discusses our estimation and policy simulation results, examining how procompetitive policies affect the behavior of both bidders and market outcomes. Section 6 concludes.

## 2. Power Procurement Auction Data

Our sample comprises auctions for power procurement by government and other public entities in TEPCO's service area. We use auction data for supply in 2009 and 2010 that disclose whether entrants bid.[4] As shown by Figure 2.1, the power charges [total bid amount (yen) ÷ planned power demand (kWh)], observed as winning bids, exhibit a downward-sloping curve reflecting the two-tier tariff system, based on capacity and demand charges. Following Hosoe and Takagi (2012), we use the subsample of auctions with load factors of 10% or more partly because the power charges in auctions with load factor below 10% are highly volatile given idiosyncratic factors and partly because the market segment with load factors around 20–60% are more competitive given the active participation of entrants. The resulting sample size is 793 auctions, consisting of 216 UHV auctions and 577 HV auctions.

[4] In Japan, there is no full disclosure of the results of power procurement auctions. For example, losing bids are not publicly available. The names of bidding losers are also not necessarily reported; only the number or presence of losers. As the information about the presence of losers is most often available, we rely on this information to provide as many observations as possible.

Figure 2.1: Winning Bids and Load Factors




Our auction data provide details of contracts and winning bids, including the site name, supply voltage (V), power demand (kWh), maximum load (kW), winning bids (yen), and names of winners. However, we cannot necessarily detect either the losers' names or their bids, but we can observe whether there were multiple bidders. Because TEPCO bids in almost all auctions as the default bidder, the observation of multiple bidders immediately implies entrant participation.[5] The descriptive statistics summarize winning bids and entrant participation by market segment (Table 2.1). In multiple-bidder cases, the number of bidders (including the default bidder of the incumbent) is at most three. Entrants very actively participate in the market segments with load factors less than 50% and usually beat the incumbent.

However, from the descriptive statistics we cannot obtain any clear evidence that entrant participation always lowers winning bids. For example, while the winning bids in

[5] In our sample period, TEPCO withdrew from some auctions because it could not meet the qualification for "green contracts", which required a low carbon emission level. We omit these irregular samples from our analysis.

multiple-bidder auctions are lower than in single-bidder auctions in the market segment with load factors of 50–70%, this does not hold for UHV auctions with load factors of 30–50%. This indicates that entrants focus on those market segments where they are competent and choose bids low enough, but not too low, to beat the incumbent by exploiting information about the incumbent's costs and inferred bid patterns.

Table 2.1: Descriptive Statistics

| | Subtotal | 10–30% | 30–50% | 50–70% | 70%– | Subtotal | 10–30% | 30–50% | 50–70% | 70%– | Total |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **Ultra-High Voltage Sites** | w/ Participation of Entrants | | | | | w/o Participation of Entrants | | | | | |
| Winning Bid | 14.57 | 17.81 | 14.38 | 12.81 | 12.29 | 13.36 | -- | 14.07 | 13.69 | 12.55 | 14.18 |
| (St. dev.) [yen/kWh] | (2.57) | (3.74) | (1.05) | (0.58) | (0.60) | (1.09) | | (1.00) | (1.05) | (0.62) | (2.28) |
| Power Demand | 20.62 | 8.00 | 12.71 | 49.3 | 27.02 | 27.32 | -- | 16.35 | 27.19 | 31.37 | 22.79 |
| (St. dev.) [million kWh] | (59.50) | (8.10) | (5.85) | (123.87) | (11.43) | (29.17) | | (13.26) | (36.34) | (15.15) | (51.75) |
| Supply Capacity | 4.26 | 3.57 | 3.55 | 6.71 | 4.01 | 4.46 | -- | 4.21 | 4.41 | 4.61 | 4.32 |
| (St. dev.) [thousand kW] | (6.24) | (1.85) | (1.47) | (12.89) | (1.63) | (3.35) | | (3.45) | (3.85) | (2.19) | (5.47) |
| Bidders | 2.91 | 2.76 | 3.27 | 2.39 | 2.36 | 1.00 | -- | 1.00 | 1.00 | 1.00 | 2.3 |
| (St. dev.) | (1.01) | (1.04) | (0.98) | (0.79) | (0.48) | (0.00) | | (0.00) | (0.00) | (0.00) | (1.22) |
| Contact Period | 1.12 | 1.24 | 1.04 | 1.23 | 1.00 | 1.04 | -- | 1.00 | 1.08 | 1.00 | 1.09 |
| (St. dev.) [year] | (0.41) | (0.57) | (0.20) | (0.61) | 0.00 | (0.26) | | (0.00) | (0.35) | (0.00) | (0.37) |
| Green Contracts | 0.59 | 0.48 | 0.67 | 0.52 | 0.55 | 0.4 | -- | 0.38 | 0.46 | 0.30 | 0.53 |
| Awarded to an Entrant | 0.79 | 0.97 | 0.95 | 0.48 | 0.18 | 0.06 | -- | 0.00 | 0.10 | 0.00 | 0.56 |
| Observations | 146 | 29 | 75 | 31 | 11 | 70 | 0 | 8 | 39 | 23 | 216 |
| **High Voltage Sites** | w/ Participation of Entrants | | | | | w/o Participation of Entrants | | | | | |
| Winning Bid | 17.33 | 18.99 | 16.23 | 14.48 | 14.52 | 15.81 | 19.29 | 16.03 | 14.53 | 13.62 | 16.89 |
| (St. dev.) [yen/kWh] | (2.44) | (2.20) | (1.44) | (0.83) | (1.89) | (2.50) | (2.32) | (1.46) | (0.82) | (1.25) | (2.56) |
| Power Demand | 3.51 | 2.90 | 3.30 | 6.62 | 8.2 | 3.7 | 0.87 | 2.6 | 5.17 | 6.16 | 3.56 |
| (St. dev.) [million kWh] | (5.66) | (6.88) | (3.09) | (6.37) | (6.32) | (3.14) | (0.97) | (2.29) | (3.10) | (2.60) | (5.06) |
| Supply Capacity | 0.95 | 1.04 | 0.84 | 1.07 | 0.99 | 0.78 | 0.41 | 0.71 | 1.02 | 0.91 | 0.90 |
| (St. dev.) [thousand kW] | (1.12) | (1.50) | (0.58) | (0.64) | (0.47) | (0.58) | (0.44) | (0.59) | (0.60) | (0.40) | (0.99) |
| Bidders | 2.89 | 2.99 | 2.86 | 2.62 | 2.5 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 2.34 |
| (St. dev.) | (1.11) | (1.28) | (0.91) | (0.94) | (1.02) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (1.27) |
| Contact Period | 1.14 | 1.15 | 1.12 | 1.12 | 1.22 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.10 |
| (St. dev.) [year] | (0.43) | (0.46) | (0.38) | (0.39) | (0.70) | (0.01) | (0.00) | (0.00) | (0.02) | (0.00) | (0.37) |
| Green Contracts | 0.54 | 0.67 | 0.43 | 0.32 | 0.8 | 0.45 | 0.86 | 0.54 | 0.32 | 0.06 | 0.52 |
| Awarded to an Entrant | 0.91 | 0.99 | 0.94 | 0.47 | 0.5 | 0.07 | 0.25 | 0.02 | 0 | 0.03 | 0.67 |
| Observations | 409 | 191 | 174 | 34 | 10 | 168 | 36 | 48 | 53 | 31 | 577 |

Based on the site name, we categorized samples into several facility types we expect to correlate with the profitability of auctions: namely, office buildings, garbage-disposal facilities, school buildings, market sites, water and sewage plants, road facilities, hospitals, factories, and others, as detailed in Table 2.2. In what follows, we use data on the winning bids, a multiple-bidder dummy, a facility type dummy, load factor, supply voltage (UHV/HV), maximum load, and power demand for our structural estimation. We focus on the samples for power supply in 2009–2010 to avoid impacts of idiosyncratic shocks in other years, such as the 2007 oil price hike and TEPCO's nuclear power shutdowns caused by two huge earthquakes in 2007 and 2011.

The number of potential bidders for a specific auction is one of the key variables in auction models but is neither observable nor identifiable in our data set. Accordingly, we must guess the number of potential bidders based on the available circumstantial evidence. Many entrants have registered for the retail power business (79 firms at the end of 2012) but only a few actively participate in power procurement auctions. Table 2.1 and the finding by Hattori (2010) suggest that the number of actual bidders is, at most, 2–3 on average. Our dataset shows that eight and ten entrants participated in at least either one UHV or one HV auction, respectively. Following Li and Zheng (2009) and Li and Zhang (2015), we take account of the above observations of actual bidders and assume different numbers of potential bidders for subsamples in each market segment, as defined by load factor and supply voltage. For the numbers of potential bidders, we assume ten (eight) bidders for HV (UHV) auctions with load factors lower than 50%, nine (seven) bidders for those with 50–70% load factors, and eight (six) bidders for those with factor load exceeding 70%.[6]

[6] We do not find any significant differences in the estimation results even when we alternatively use the same numbers from six to ten for all the market segments in our robustness tests. See the Appendix for details.

Table 2.2: Auctions by Facility Type and Market Segment

| | Load Factor | | | | |
|---|---|---|---|---|---|
| | 10–30% | 30–50% | 50–70% | 70%– | Total |
| **Ultra-High Voltage Sites** | | | | | |
| Office Buildings | 8 | 46 | 15 | 4 | 73 |
| Garbage | 12 | 2 | | | 14 |
| School | | 5 | | | 5 |
| Factory | 1 | | | | 1 |
| Market | | 1 | 4 | | 5 |
| Water and Sewage | 3 | 3 | 34 | 28 | 68 |
| Road | 1 | 1 | 1 | | 3 |
| Hospital | | 5 | 7 | | 12 |
| Others | 4 | 20 | 9 | 2 | 35 |
| Total | 29 | 83 | 70 | 34 | 216 |
| **High Voltage Sites** | | | | | |
| Office Buildings | 128 | 90 | 16 | 9 | 243 |
| Garbage | 5 | 3 | 2 | | 10 |
| School | 30 | 24 | | | 54 |
| Factory | | | | | 0 |
| Market | 2 | 3 | | | 5 |
| Water and Sewage | 39 | 35 | 33 | 26 | 133 |
| Road | 1 | 7 | 1 | 1 | 10 |
| Hospital | | 20 | 20 | | 40 |
| Others | 22 | 40 | 15 | 5 | 82 |
| Total | 227 | 222 | 87 | 41 | 577 |

# 3. Theoretical Model

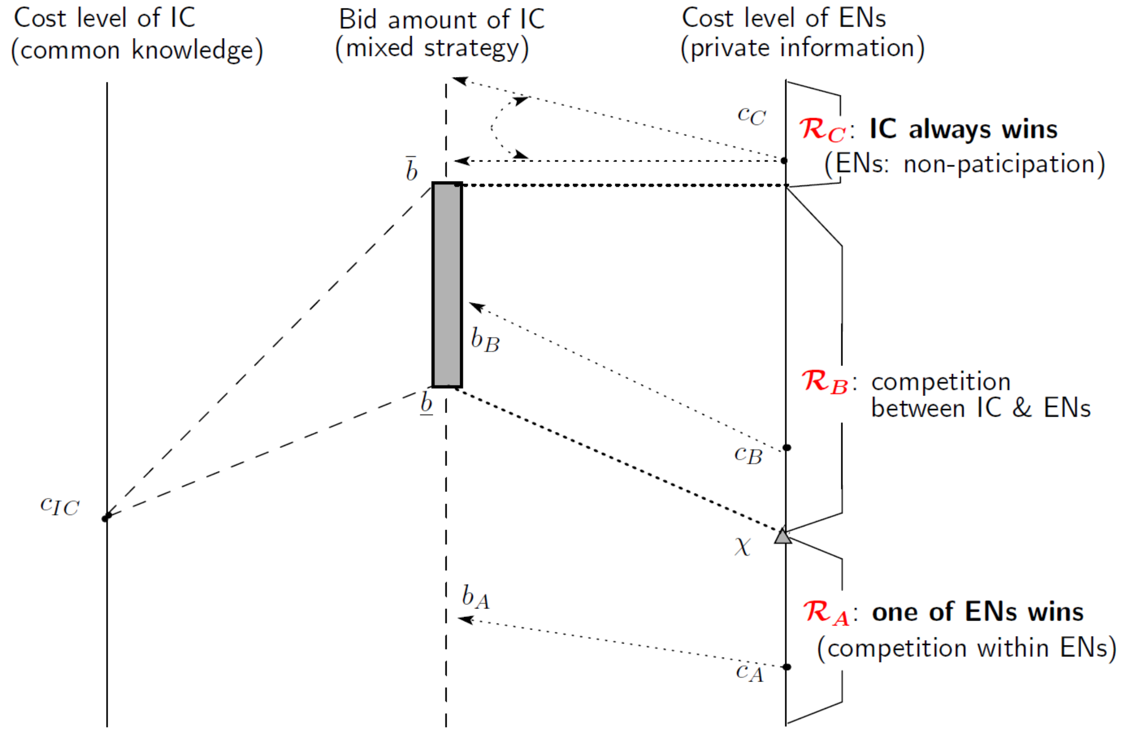
Following Martínez-Pardina (2006), we outline a theoretical model with asymmetry between the incumbent (i.e., TEPCO) and entrants in terms of both the cost distributions and information structure. In our context, the significance of asymmetry is twofold. The first lies in the asymmetry of the supply costs, which reflects differences in the fuel and facility portfolios. The second type of asymmetry in information structure is the key feature of our auction model, whereby we assume the incumbent's cost is common knowledge in an auction, whereas the entrants' costs are private information.

## 3.1 Setup

In our model, there is one incumbent firm and $n-1$ potential entrants with symmetric cost distributions. When *potential* bidders participate and bid in an auction, they are termed *actual* bidders. We assume that the cost level of the incumbent $c_1$, the number of potential bidders $n$, and their cost distribution functions are common knowledge. We denote $G(c_1) \equiv G(c_1; q_{IC})$ ($g(c_1)$) and $F(c_i) \equiv G(c_i; q_{EN})$ ($f(c_i)$) as the cost distribution (density) functions of the incumbent and entrant, where $c_i$ denotes costs of the $i$-th potential bidder and $q_{IC}$ and $q_{EN}$ are exogenous variables that influence the cost distribution function of the incumbent and entrant, respectively. These functions have support in the interval $[\underline{c}, \overline{c}]$.

In Martínez-Pardina's (2006) procurement game, an auctioneer first announces the details of the power procurement contracts for a first-price sealed-bid auction, such as total power demand (kWh), maximum load (kW), and contract duration (often one year). Entrants can then infer the incumbent's costs $c_1$ needed to fulfill the contract. Next, entrants examine their own costs $c_i$ ($i \geq 2$) and profits for the contract and decide whether to bid. Finally, the actual bidders choose their optimal bids, given the incumbent's costs and the number of potential bidders $n$. The incumbent randomly decides its bid along a bidding distribution $H(x)$ with an upper limit $\overline{b}$ and a lower limit $\underline{b}$ (i.e., a mixed strategy), as illustrated in Figure 3.1.

Figure 3.1: Mixed-Strategy Equilibrium




Source: Adopted from Martínez-Pardina (2006) and modified by the authors.
Note: IC and EN denote incumbent and entrant, respectively. $\chi$ denotes the cost level of entrants with the optimal bid $\underline{b}$.

Depending on the costs of the incumbent and entrants, three different competition regimes arise:

A: Competition only among entrants

B: Competition between the incumbent and entrants

C: No competition (only the incumbent participates)

The parameter $\chi$ in Figure 3.1 plays a crucial role in switching among these three regimes. $\chi$ is the threshold cost level of entrants, where their optimal bid is equal to the lower bound of the incumbent's bid $\underline{b}$. If entrants' costs are below $\chi$, entrants are sufficiently competitive and always beat the incumbent and therefore compete with each other (region $R_A$). Note that region $R_A$, where only entrants can win, disappears when the incumbent's cost $c_1$ is lower than the threshold $\hat{c}$. The upper limit $\bar{b}$ of the incumbent's bidding distribution

$H(x)$ divides the region $R_B$ from the region $R_C$. In the region $R_C$, entrants have no cost advantage over the incumbents and thus do not participate.

Starting with the profit functions of bidders, we derive the parameters characterizing the mixed-strategy equilibrium, namely $\hat{c}$, $\overline{b}$, $\underline{b}$, and $\chi$ by following Martínez-Pardina (2006). In this study, we extend the original model by adding a device that describes a preferential treatment for entrants so that we can conduct counterfactual policy simulations later. In this extension, we discount by $1+\delta$ the bids submitted by entrants and compare them with the incumbent's bid to determine the winner. That is, when the incumbent bids $x$ in an auction, an entrant wins by submitting a bid less than $x\cdot(1+\delta)$.

## 3.2 Model Summary and Welfare Measures

The mixed-strategy equilibrium of the model is characterized by the following system of equations:

・The cost threshold of the incumbent $\hat{c}$:

$$\hat{c}=\frac{\frac{n-2}{1+\delta}\underline{c}+\overline{b}(\hat{c})\cdot\left(1-F((1+\delta)\cdot\overline{b}(\hat{c}))\right)^{n-1}}{(n-2)+\left(1-F((1+\delta)\cdot\overline{b}(\hat{c}))\right)^{n-1}}$$

$$\overline{b}(\hat{c})=\hat{c}+\frac{1}{(n-1)\cdot(1+\delta)}\frac{1-F((1+\delta)\cdot\overline{b}(\hat{c}))}{f((1+\delta)\cdot\overline{b}(\hat{c}))},$$

where

$$\overline{b}(\hat{c})=\hat{c}+\frac{1}{(n-1)\cdot(1+\delta)}\frac{1-F((1+\delta)\cdot\overline{b}(\hat{c}))}{f((1+\delta)\cdot\overline{b}(\hat{c}))}.$$

・The upper bound bid of the incumbent $\overline{b}$:

$$\overline{b}=c_1+\frac{1}{(n-1)\cdot(1+\delta)}\frac{1-F((1+\delta)\cdot\overline{b})}{f((1+\delta)\cdot\overline{b})}.$$

・The lower bound bid of the incumbent $\underline{b}$ and the cost threshold of entrants $\chi$:

- If $\chi > \underline{c}$, $(\underline{b}, \chi)$ satisfies the following:

$$\{1-F(\chi)\}^{n-1} \cdot (\underline{b}-c_1) = \{1-F((1+\delta)\cdot \overline{b})\}^{n-1} \cdot (\overline{b}-c_1),$$

$$(n-2)\cdot(\underline{b}-\chi) = (n-1)\cdot(\underline{b}-(1+\delta)\cdot c_1).$$

- If $\chi = \underline{c}$, the lower bound is defined as:

$$\underline{b} = c_1 + \{1-F((1+\delta)\cdot \overline{b})\}^{n-1} \cdot (\overline{b}-c_1).$$

・The bid distribution (density) of the incumbent $H(x)$ ($h(x)$):

$$h(x) = \eta(x)\cdot \exp\left\{ -\int_{\underline{b}}^{x} \eta(y)dy \right\},$$

where

$$\eta(x) = \frac{1}{x - \frac{1}{1+\delta}\cdot F^{-1}\left[1-\{1-F((1+\delta)\cdot\overline{b})\}\cdot\left(\frac{\overline{b}-c_1}{x-c_1}\right)^{n-1}\right]} - \frac{n-2}{n-1}\frac{1}{x-c_1}.$$

・The bidding functions of an entrant $b_A(c), b_B(c)$:

- If $c_i < \chi$ (region $R_A$):

$$b_A(c_i) = c_i + \frac{\int_{c_i}^{\chi}\{1-F(y)\}^{n-2}dy}{\{1-F(c_i)\}^{n-2}} + \frac{\{1-F(\chi)\}^{n-2}}{\{1-F(c_i)\}^{n-2}}\cdot((1+\delta)\cdot\underline{b}-\chi).$$

- If $\chi \le c_i \le \overline{b}$ (region $R_B$), according to (7),

$$b_B(c_i) = (1+\delta)\cdot\left\{c_1 + \left(\frac{1-F((1+\delta)\cdot\overline{b})}{1-F(c_i)}\right)^{n-1}\cdot(\overline{b}-c_1)\right\}.$$

- If $c_i > \overline{b}$ (region *Rc*),

No entrant participation.

We solve this system given the cost distributions *F*(*c*) and *G*(*c*) and the number of potential bidders $n$.

Based on the equilibrium solution, we can evaluate the auction results and derive welfare measures for producers (i.e., auction participants) and consumers. The expected profit of the incumbent is:

$$\pi_{IC} = \int_{\underline{c}}^{\overline{c}}\left[\int_{\underline{b}}^{\overline{b}}\{1-F((1+\delta)\cdot\overline{b}(c_1))\}^{n-1}\cdot\frac{\underline{b}(c_1)-c_1}{x-c_1}(x-c_1)\cdot h(x\mid c_1)dx\right]dG(c_1).$$

The expected profit of entrants is:

$$\pi_{EN} = \int_{\hat{c}}^{\overline{c}}\left\{\int_{\underline{c}}^{\chi}\left(b_A(c^*)-c^*\right)dF^*_{1,n-1}(c^*)+\int_{\chi}^{\overline{b}}\overline{H}\left(\frac{b_B(c^*)}{1+\delta}\right)\cdot\left(b_B(c^*)-c^*\right)dF^*_{1,n-1}(c^*)\right\}dG(c_1),$$

where $F^*_{k,n-1}(c)$ is the distribution function of the $k$-th smallest order statistic of the sample from $F$ of size $N$ and density is denoted as $f^*_{k,n-1}(c)$. The expected consumer cost (i.e., the expected winning bid) $C$ is defined as follows:

$$C = \int_{\underline{c}}^{\overline{c}}\left\{\int_{\underline{b}}^{\overline{b}} x\cdot\{1-F((1+\delta)\cdot\overline{b}(c_1))\}^{n-1}\cdot\left(\frac{\overline{b}-c_1}{x-c_1}\right)\cdot h(x\mid c_1)dx\right\}dG(c_1)$$

$$+\int_{\hat{c}}^{\overline{c}}\left[\int_{\underline{c}}^{\chi} b_A(c^*)dF^*_{1,n-1}(c^*)+\int_{\chi}^{\overline{b}}\overline{H}\left(\frac{b_B(c^*)}{1+\delta}\right)\cdot b_B(c^*)\cdot dF^*_{1,n-1}(c^*)\right]dG(c_1),$$

because the winning entrant must have the lowest cost among potential entrants. The first term $C$ is the expected payment to the incumbent; the second is the payment to the (lowest-cost) entrant. We assume the electricity supplied by the incumbent and entrants to have the same level of quality and thus yield the same consumer benefits. Therefore, a positive change in consumer cost is equivalent to a negative change in consumer surplus.

The social cost $S$ is the sum of the expected producer and consumer cost:

$$S = \int_{\underline{c}}^{\bar{c}} \left\{ \int_{\underline{b}(c_1)}^{\bar{b}(c_1)} c_1 \cdot \left\{1 - F(\bar{b})\right\}^{n-1} \cdot \left( \frac{\bar{b} - c_1}{x - c_1} \right) \cdot h(x \mid c_1) dx \right\} dG(c_1)$$

$$+ \int_{\hat{c}}^{\bar{c}} \left[ \int_{\underline{c}}^{\chi} c^* dF_{1,n-1}^*(c^*) + \int_{\chi}^{\bar{b}} \overline{H} \left( \frac{b_B(c^*)}{1+\delta} \right) \cdot c^* \cdot dF_{1,n-1}^*(c^*) \right] dG(c_1).$$

We interpret this measure as a proxy of social welfare for the same reason as the abovementioned consumer cost and surplus.

# 4. Estimation Method

Figure 3.1 shows that the model contains several unknown parameters: $\bar{b}$, $\underline{b}$, $\hat{c}$, and $\chi$. These can be computed by solving the abovementioned system of simultaneous equations, given the incumbent's and entrants' cost distribution functions, $G(\bullet)$ and $F(\bullet)$, respectively, which can be determined by estimating the parameters of these distribution functions. We assume that costs are log-normally distributed random variables and relate to the auction-specific variables using the moments of the cost distributions. We discuss the estimation method of the unknown parameters while specifying the structural model.

## 4.1 Estimation Model

Denote the cost level of the $i$-th entrant in the $\ell$-th auction as $c_{i,\ell}$. The costs are assumed to be independently and identically log-normally distributed among entrants:[7]

$$\log c_{i,\ell} \sim N(\mu_\ell^{EN}, (\sigma_\ell^{EN})^2),\ i = 2,3,\ldots,n_\ell,\ \ell = 1,2,\ldots,L.$$

Then, the density is:

$$f(c_{i,\ell};\boldsymbol{\theta}_{EN}) = \frac{1}{c_{i,\ell}\cdot\sqrt{2\pi(\sigma_\ell^{EN})^2}}\exp\left\{-\frac{(\log c_{i,\ell}-\mu_\ell^{EN})^2}{(\sigma_\ell^{EN})^2}\right\},$$

where the mean $\mu_\ell^{EN}$ and the variance $(\sigma_\ell^{EN})^2$ of the log-cost are related to the individual auction-specific variable vector $\mathbf{x}_\ell$, such that:

$$\mu_\ell^{EN} = \beta_0 + \beta_1\cdot x_{1,\ell} + \cdots + \beta_{K-1}\cdot x_{K-1,\ell},$$

$$\sigma_\ell^{EN} = \exp\{-\gamma_0^{EN} - \gamma_1^{EN}\cdot x_{1,\ell} - \cdots - \gamma_{K'-1}^{EN}\cdot x_{K'-1,\ell}\}.$$

Similarly, the cost of the incumbent is assumed to be log-normally distributed, $\log c_{1,\ell} \sim N\left(\mu_\ell^{IC}, (\sigma_\ell^{IC})^2\right)$, where $\mu_\ell^{IC}$ and $(\sigma_\ell^{IC})^2$ are:

$$\mu_\ell^{IC} = \beta_0^{IC} + \beta_1^{IC}\cdot x_{1,\ell} + \cdots + \beta_{K-1}^{IC}\cdot x_{K-1,\ell},$$

$$\sigma_\ell^{IC} = \exp\{-\gamma_0^{IC} - \gamma_1^{IC}\cdot x_{1,\ell} - \cdots - \gamma_{K-1}^{IC}\cdot x_{K'-1,\ell}\}.$$

For notational simplicity, the structural parameters to be estimated are stacked into a single vector $\boldsymbol{\theta}' = (\boldsymbol{\theta}'_{IC}, \boldsymbol{\theta}'_{EN}) = (\boldsymbol{\beta}'_{IC}, \boldsymbol{\gamma}'_{IC}, \boldsymbol{\beta}'_{EN}, \boldsymbol{\gamma}'_{EN})'$.

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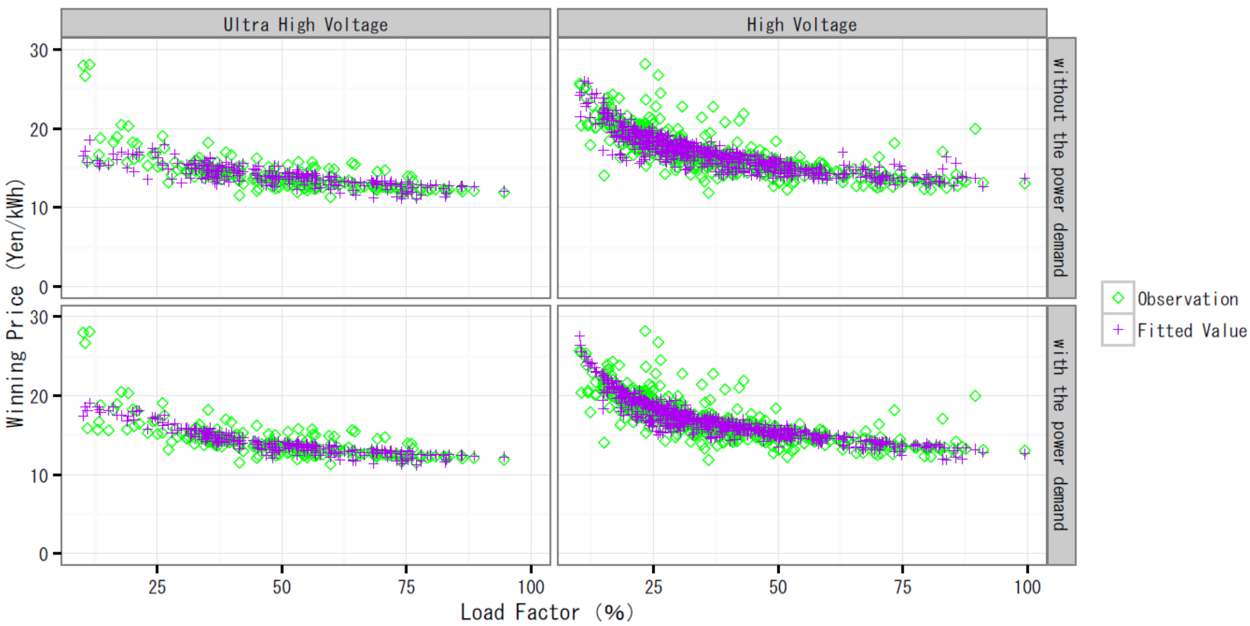
[7] Instead of this simplifying assumption, we could assume unobserved auction-specific heterogeneity for cost distributions, as described by Jofre-Bonet and Pesendorfer (2003), closed-form parametric models by assuming the other parametric distribution with unobserved heterogeneity, or some mixing distribution with general, nonparametric heterogeneity, as described by Heckman and Singer (1984). Given that these have some drawbacks in interpretation, identification, and computation, our chosen approach leads to reasonable goodness of fit and is useful for our simulation purposes.

As the auction-specific variable influencing the means and variances of the cost, we employ the level and the inverse of load factor (%), the power demand (kWh), and the number of actual bidders, as well as dummy variables for 2010 and "green contract" auctions.[8]

Following Campo et al. (2003), we use the number of actual bidders to control for the auction-specific heterogeneity. As the number of actual bidders is a sufficient statistic for unobserved auction-specific heterogeneity, by conditioning this number we can estimate the structural (infinite-dimensional) parameters without the effect of the unobserved heterogeneity. Although we often expect the power demand variable (kWh) to control for the scale of demand, it does not exhibit either significant effects on the cost distributions or clear improvements in the goodness of fit, as demonstrated in Figure 4.1. Therefore, we report the estimation results excluding this variable.

Figure 4.1: Goodness of Fit of Models with and without the Power Demand Variable




[8] Only bidders that meet a certain low-carbon emission qualification can participate in green contract auctions.

To estimate the structural parameters, we employ a simulation-assisted minimum chi-square method or an indirect inference method (Gourieroux et al., 1993). We do not derive the likelihood function under our parametric assumptions because formidable complexities in the likelihood function are caused by the incompleteness of the data, which have missing information about losing bids and censoring of the nonparticipating bids, and the requirements of multiple numerical integrations to evaluate the likelihood. Our alternative approach with the simulation-based method can reduce this burden and ensure feasible inferences. We discuss the simulation-based estimation method below.

## 4.2 Indirect Inference and Auxiliary Models

Indirect inference investigates the structural parameter $\boldsymbol{\theta}$ in the structural model through the parameter $\boldsymbol{\xi}$ in an auxiliary model. As this auxiliary model captures key characteristics of the data but does not always represent the data generation process itself, it is a misspecified model with some explanatory power for the data. The parameter vector $\boldsymbol{\xi}$ is a device to infer the structural parameter $\boldsymbol{\theta}$, known as an auxiliary parameter to distinguish it from the structural parameter. Indirect inference provides a level of correspondence with the estimated auxiliary parameter if an auxiliary model reasonably captures the characteristics of the data. The original sample implicitly depends on the true structural parameter $\boldsymbol{\theta}_0$; thus, the auxiliary parameter estimate using the original sample depends on the structural parameter in the form $\hat{\boldsymbol{\xi}} = \hat{\boldsymbol{\xi}}(\boldsymbol{\theta}_0)$. When we have a sample generated from the structural model with the other structural parameter value $\breve{\boldsymbol{\theta}}$, the auxiliary parameter from the sample can be written as $\tilde{\boldsymbol{\xi}} = \tilde{\boldsymbol{\xi}}(\breve{\boldsymbol{\theta}})$. Whereas the auxiliary parameter $\hat{\boldsymbol{\xi}}$ is estimated from the original sample, the auxiliary parameter $\tilde{\boldsymbol{\xi}}$ would be obtained from the artificial sample with the structural parameter value $\breve{\boldsymbol{\theta}}$. If the vector $\hat{\boldsymbol{\xi}}$

is nearly equal to $\tilde{\boldsymbol{\xi}}$, it is naturally conjectured that the vector $\breve{\boldsymbol{\theta}}$ is also close to $\boldsymbol{\theta}_0$.

Let us outline the estimation procedure. We contrast two series of observations: the winning price $y_\ell$ and the dummy variable indicating entrant participation $d_\ell$ with their solutions from the structural model. We select an auxiliary model to capture features of these endogenous variables, as discussed below.

1. Given the structural parameter value $\boldsymbol{\theta}$ and the auction-specific variables $\{\mathbf{x}_\ell\}_{\ell=1}^{L}$, we set the cost distributions of the incumbent and entrants. We simulate the costs $\{c_{1,\ell}^{(r)}, c_{2,\ell}^{(r)}, \dots, c_{n,\ell}^{(r)}\}_{\ell=1}^{L}$ and solve the structural model. Consequently, we have a sample of the winning bid and the participation dummy $\{y_\ell^{(r)}, d_\ell^{(r)}\}_{\ell=1}^{L}$ corresponding to $\boldsymbol{\theta}$.
2. Using the generated sample $\{y_\ell^{(r)}, d_\ell^{(r)}\}_{\ell=1}^{L}$, we estimate the auxiliary model and obtain the auxiliary parameter estimates $\boldsymbol{\xi}^{(r)}$.
3. By repeating the above steps for $r = 1, 2, \dots, R$ times, we obtain a sequence of auxiliary parameter estimates $\{\boldsymbol{\xi}^{(r)}\}_{r=1}^{R}$. We denote their average value by $\bar{\boldsymbol{\xi}}_R = R^{-1}\sum_{r=1}^{R}\boldsymbol{\xi}^{(r)}$.
4. We search the structural parameter value $\boldsymbol{\theta}$ such that the simulation-based auxiliary parameter $\bar{\boldsymbol{\xi}}_R$ is sufficiently close to the auxiliary parameter $\bar{\boldsymbol{\xi}}$ from the original sample.

In selecting auxiliary models, computational simplicity is as important as the explanatory power of the data. There have been several auxiliary models proposed. For example, Rossi and Santucci de Magistris (2018) discussed the identification issues in stochastic volatility models using simple linear time series models as auxiliary models. Gallant and Tauchen (1996) proposed the use of a semi-nonparametric density function for an auxiliary model. Their auxiliary model flexibly captures features of the data-generating process and can provide an efficient estimator (the efficient method of moments). However, the literature does not explore well the inclusion of exogenous variables in semi-nonparametric density functions. In contrast, our approach is easy to implement by employing a switching regression model to describe the participating behavior and the winning bid determination.[9] Hosoe and Takagi (2012) indeed demonstrated that the switching regression model for the winning bid and the entrant participation dummy variable performed well in light of the goodness of fit.

The auxiliary model is:

$$y_{j,\ell} = \mathbf{x}'_{\ell}\,\boldsymbol{\varphi}_j + u_{\ell},\;\; j = 0,1,\; \ell = 1,2,\ldots,L,$$

$$d_{\ell} = \mathbf{l}\{\mathbf{z}'_{\ell}\,\boldsymbol{\psi} + v_{\ell} > 0\},$$

where $\mathbf{l}\{\bullet\}$ is an indicator function that returns unity (or zero) when the condition in the parentheses holds (or does not hold) (i.e., one or more entrants decide(s) (not) to participate in the auction $\ell$). The suffix $j = 1(0)$ indicates the status that entrants (do not) participate in the auction. The distribution of the error term is assumed as follows:

$$\begin{pmatrix} u_{j,\ell} \\ v_{\ell} \end{pmatrix} \sim N\left(\mathbf{0}, \boldsymbol{\Sigma}_{j,\ell}\right),\;\; \boldsymbol{\Sigma}_{j,\ell} = \begin{pmatrix} \exp\{2\cdot\mathbf{w}'_{\ell}\,\boldsymbol{\eta}_j\} & 0 \\ 0 & 1 \end{pmatrix},\; j = 0,1,$$

where the auxiliary parameters are stacked into a vector $\boldsymbol{\xi} = (\boldsymbol{\varphi}_1', \boldsymbol{\varphi}_0', \boldsymbol{\eta}_1', \boldsymbol{\eta}_0', \boldsymbol{\psi}')'$.

The switching regression model can capture the two aspects of the power procurement auctions. First, the participation decision of entrants is modeled by a binary response model. Second, determinants of the winning bid are investigated by a regression model. Comparing their cost levels $c_i$ with the upper bound bid by the incumbent $\bar{b}$, entrants decide whether to participate or not, as described in the binary choice model. The winning bids in the region $R_A$ (i.e., without entrant participation) possess the features of the

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[9] Li and Zhang (2015) took a similar approach. They used the auxiliary model with two equations: a count data regression equation for explaining the number of actual bidders and a linear regression equation for examining the determinants of all submitted bids.

incumbent's bid distribution $H(\bullet)$. In contrast, the winning bids in the regions $R_B$ and $R_C$ (i.e., with entrants' participation) embody the features of both types' bid distributions.

In the auxiliary model, we analyze the dependent variable for each regime in the switching regression to summarize the sample information into the auxiliary parameter estimates, with which we can identify the structural parameters in the bid distributions of the incumbent and entrants.

The log-likelihood function of the auxiliary model is given as:

$$\log \mathcal{L}(\{y_\ell, d_\ell, \mathbf{x}_\ell\}_{\ell=1}^{L}; \xi) = \sum_{\ell=1}^{L} d_\ell \cdot \log\left(\frac{1}{\sigma_{1,\ell}} \phi\left(\frac{y_\ell - \mathbf{x}'_\ell \boldsymbol{\varphi}_1}{\sigma_{1,\ell}}\right)\right)$$

$$+ \sum_{\ell=1}^{L} (1-d_\ell) \cdot \log\left(\frac{1}{\sigma_{0,\ell}} \phi\left(\frac{y_\ell - \mathbf{x}'_\ell \boldsymbol{\varphi}_0}{\sigma_{0,\ell}}\right)\right)$$

$$+ \sum_{\ell=1}^{L} d_\ell \cdot \log \Phi(\mathbf{z}'_\ell \boldsymbol{\psi}) + \sum_{\ell=1}^{L} (1-d_\ell) \cdot \log \Phi(-\mathbf{z}'_\ell \boldsymbol{\psi}),$$

where $\mathbf{x}_\ell$ is an auction-specific variable vector, comprising the load factor, the inverse of the load factor, a green contract dummy, a time dummy for 2010, and power demand. The standard deviations $\sigma_{j,\ell}$ in the likelihood function are parameterized as $\sigma_{j,\ell} = \exp\{\mathbf{w}'_\ell \boldsymbol{\eta}_j\}$, $j = 0,1$, $\ell = 1,2,\ldots,L$, where $\mathbf{w}_\ell$ comprises the load factor, the inverse of the load factor, and power demand. We also assume that that the determinants of participation are included in $\mathrm{z}_\ell$ (load factor, green contract dummy, time dummy for 2010, and power demand). Therefore, there are 21 parameters in the auxiliary model for the UHV auction sample. Alternatively, the number of parameters for the HV auction sample is 18, obtained by deleting the inverse of the load factor from $\mathbf{x}_\ell$ and $\mathbf{w}_\ell$.[10]

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[10] As for variable selection in the auxiliary model, we use the information criterion proposed by Barigozzi et al. (2015).

### 4.3 Estimating Structural Parameters

This section addresses the estimation method of the structural parameters $\boldsymbol{\theta}' = (\boldsymbol{\theta}'_{GEU}, \boldsymbol{\theta}'_{PPS})$. The auxiliary estimate from the original sample is:

$$\hat{\boldsymbol{\xi}}_L = \arg\max_{\boldsymbol{\xi}} \mathcal{L}(\{y_\ell, d_\ell, \mathbf{x}_\ell\}_{\ell=1}^L; \boldsymbol{\xi}) = \arg\max_{\boldsymbol{\xi}} \sum_{\ell=1}^{L} l(\boldsymbol{\xi}; y_\ell, d_\ell, \mathbf{x}_\ell).$$

Given a structural parameter vector $\boldsymbol{\theta}$ and the auction-specific covariates, we generate an $r$-th simulation-based sample, $\{y_\ell^{(r)}(\boldsymbol{\theta}), d_\ell^{(r)}(\boldsymbol{\theta}), \mathbf{x}_\ell\}_{\ell=1}^L$. Using this simulated sample, we compute the $r$-th auxiliary estimate:

$$\hat{\boldsymbol{\xi}}_L^{(r)}(\boldsymbol{\theta}) = \arg\max_{\boldsymbol{\xi}} \sum_{\ell=1}^{L} l(\boldsymbol{\xi}; y_\ell^{(r)}(\boldsymbol{\theta}), d_\ell^{(r)}(\boldsymbol{\theta}), \mathbf{x}_\ell).$$

We repeat the above steps $R$ times, and obtain a sequence of the simulation-based auxiliary estimates, $\{\hat{\boldsymbol{\xi}}_L^{(1)}(\boldsymbol{\theta}), \hat{\boldsymbol{\xi}}_L^{(2)}(\boldsymbol{\theta}), \ldots, \hat{\boldsymbol{\xi}}_L^{(R)}(\boldsymbol{\theta})\}$ and its mean:

$$\overline{\boldsymbol{\xi}}_{L,R}(\boldsymbol{\theta}) = \frac{1}{R} \sum_{r=1}^{R} \hat{\boldsymbol{\xi}}_L^{(r)}(\boldsymbol{\theta}).$$

We choose the structural parameter $\hat{\boldsymbol{\theta}}_L$ to minimize the following quadratic form with a weighting matrix $\boldsymbol{\Omega}$:

$$\hat{\boldsymbol{\theta}}_L = \arg\min_{\boldsymbol{\theta}} S_L(\boldsymbol{\theta}) = \arg\min_{\boldsymbol{\theta}} (\hat{\boldsymbol{\xi}}_L - \overline{\boldsymbol{\xi}}_{L,R}(\boldsymbol{\theta}))' \boldsymbol{\Omega} (\hat{\boldsymbol{\xi}}_L - \overline{\boldsymbol{\xi}}_{L,R}(\boldsymbol{\theta})).$$

$\boldsymbol{\Omega}_L$, the optimal choice of the weighting matrix, is given as follows:

$$\boldsymbol{\Omega}_L = \mathbf{A}_L \mathbf{B}_L^{-1} \mathbf{A}_L,$$

where

$$\mathbf{A}_L = \frac{1}{L} \sum_{\ell=1}^{L} \frac{\partial^2 l(\hat{\boldsymbol{\xi}}_L; y_\ell, d_\ell, \mathbf{x}_\ell)}{\partial \boldsymbol{\xi} \partial \boldsymbol{\xi}'}, \ \mathbf{B}_L = \frac{1}{L} \sum_{\ell=1}^{L} \frac{\partial l(\hat{\boldsymbol{\xi}}_L; y_\ell, d_\ell, \mathbf{x}_\ell)}{\partial \boldsymbol{\xi}} \frac{\partial l(\hat{\boldsymbol{\xi}}_L; y_\ell, d_\ell, \mathbf{x}_\ell)}{\partial \boldsymbol{\xi}'}.$$

There remains an identification problem. Let $\boldsymbol{\theta}$ be a $K \times 1$ vector, and $\boldsymbol{\xi}$ be a $J \times 1$ vector. The necessary conditions for the identification of the structural parameters are that $J \geq K$ , and that the rank of the Jacobian of the probability limit of the auxiliary $\hat{\boldsymbol{\xi}}$ with respect to the structural parameters is of full column rank $K$ (Gourieroux et al. (1993)). Therefore, it follows that we attain identification if we successfully obtain the covariance matrix estimate.

Given that these identification conditions are satisfied, the asymptotic distribution of the structural parameter estimator is:

$$\sqrt{L}(\hat{\boldsymbol{\theta}}_L - \boldsymbol{\theta}_0) \xrightarrow{d} N\left(\mathbf{0}, \frac{1+R}{R} \cdot \mathbb{V}[\hat{\boldsymbol{\theta}}_L]\right),$$

and the estimator of the asymptotic covariance $\mathbb{V}[\hat{\boldsymbol{\theta}}_L]$ is given as:

$$\mathbb{V}_L[\hat{\boldsymbol{\theta}}_L] = \left(\mathbf{Q}'_L \, \mathbf{B}_L^{-1} \mathbf{Q}_L\right)^{-1}, \quad \mathbf{Q}_L = \frac{1}{L}\sum_{\ell=1}^{L} \frac{\partial^2 l(\overline{\xi}_{L,R}(\hat{\boldsymbol{\theta}}_L); y_\ell, d_\ell, \mathbf{x}_\ell)}{\partial \boldsymbol{\xi} \partial \boldsymbol{\theta}'},$$

where $\overline{\boldsymbol{\xi}}_{L,R}(\hat{\boldsymbol{\theta}}_L)$ is a simulated auxiliary parameter estimate given the structural parameter vector $\hat{\boldsymbol{\theta}}_L$. Note that the asymptotic covariance can be rewritten as:

$$\operatorname{plim}_{L\to\infty} \mathbb{V}[\hat{\boldsymbol{\theta}}_L] = \operatorname{plim}_{L\to\infty} \left(\mathbf{Q}'_L \, \mathbf{B}_L^{-1} \mathbf{Q}_L\right)^{-1} = \operatorname{plim}_{L\to\infty} \left(\frac{\partial \hat{\boldsymbol{\xi}}'(\hat{\boldsymbol{\theta}}_L)}{\partial \boldsymbol{\theta}} \boldsymbol{\Omega}_L \frac{\partial \hat{\boldsymbol{\xi}}(\hat{\boldsymbol{\theta}}_L)}{\partial \boldsymbol{\theta}'}\right)^{-1}.$$

Along with the usual minimum chi-square methods, the model is overidentified if $J > K$ . The minimized criterion function normalized by $R/(1+R) \cdot L$ asymptotically follows a chi-squared distribution with $J - K$ degrees of freedom under the maintained assumption that the structural model is correctly specified:

$$\frac{R}{1+R} \cdot L \cdot \mathcal{S}_L(\hat{\boldsymbol{\theta}}_L) \xrightarrow{d} \chi^2_{J-K}.$$

In their computation, we note that the global minimum is difficult to identify using derivative-based optimization algorithms because the criterion function $\mathcal{S}_L(\boldsymbol{\theta})$ features a number of local minima and nonsmooth points. Therefore, we employ a simulated annealing method to find the global minimum (e.g., Goffe and Ferrier (1994)).[11] We use DeinoMPI 1.1.0 and Ox 6.2 + oxmpi (Doornik (2010)) for estimation, and R 3.1.1 (R Development Core Team (2010)) for various policy simulation implementations.

# 5. Results of Model Estimation and Policy Simulations

## 5.1 Estimation Results

Table 5.1 provides the estimation results for the structural parameters, with $R$ =20 simulation replications for calculating the criterion function.[12] Based on these estimated parameters, we can recover the incumbent's cost level in each market segment as exemplified in Table 5.2.

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[11] Chernozhukov and Hong (2003) proposed an alternative estimation strategy for simulation-based estimators based upon a Markov chain Monte Carlo method. We do not use their method as we find it slow and the results are sensitive to the starting points (see Kormilitsina and Nekipelov (2012)).

[12] Although the asymptotic properties are guaranteed even in the case of $R = 1$, the coefficient estimates and fitted values are not stable because of the relatively small sample size. We can obtain stable estimates when setting the replication size to greater than five. We seldom find significant differences between the result with $R = 5$ and that with $R = 20$.

Table 5.1: Estimation Results: Cost Distribution Structural Parameters ($R = 20$)

| | Ultra–High Voltage Sites | | | | High Voltage Sites | | | |
|---|---|---|---|---|---|---|---|---|
| | Model 1 | | Model 2 | | Model 1 | | Model 2 | |
| | **Estimate** | **S.E.** | **Estimate** | **S.E.** | **Estimate** | **S.E.** | **Estimate** | **S.E.** |
| $\beta^{EN}$ | The mean parameter for Entrants | | | | | | | |
| Constant | 3.130 | 0.451 | 3.213 | 0.592 | 2.946 | 0.644 | 3.226 | 1.051 |
| Load Factor | –0.376 | 0.180 | -0.386 | 0.084 | -0.099 | 0.092 | -0.176 | 0.374 |
| Load Factor$^{-1}$ | – | – | – | – | 0.525 | 0.091 | 0.483 | 0.138 |
| Green Contract | 0.040 | 0.118 | 0.072 | 0.071 | 0.011 | 0.054 | 0.011 | 0.136 |
| Dummy for 2010 | –0.037 | 0.262 | –0.031 | 0.245 | –0.118 | 0.129 | –0.040 | 0.160 |
| Power Demand | – | – | –0.004 | 0.033 | – | – | –0.003 | 0.087 |
| log (no. of bidders) | 0.024 | 0.093 | –0.026 | 0.064 | 0.061 | 0.056 | –0.098 | 0.234 |
| $\gamma^{EN}$ | The variance parameter for Entrants | | | | | | | |
| Constant | 0.668 | 0.103 | 0.490 | 0.073 | 1.027 | 0.110 | 1.517 | 0.111 |
| Load Factor | 1.731 | 0.145 | 1.853 | 0.399 | 1.102 | 0.187 | 0.004 | 0.335 |
| log (no. of bidders) | –0.619 | 0.130 | –0.467 | 0.196 | 0.536 | 0.080 | –0.195 | 0.230 |
| $\beta^{IC}$ | The mean parameter for the Incumbent | | | | | | | |
| Constant | 3.308 | 0.430 | 3.370 | 0.415 | 2.739 | 0.256 | 2.637 | 0.651 |
| Load Factor | –1.786 | 0.187 | –1.655 | 0.256 | –0.712 | 0.070 | –0.842 | 0.311 |
| Load Factor$^{-1}$ | – | – | – | – | 1.027 | 0.126 | 0.829 | 0.267 |
| Green Contract | 0.036 | 0.361 | –0.045 | 0.061 | –0.054 | 0.076 | –0.060 | 0.502 |
| Dummy for 2010 | 0.131 | 0.117 | 0.089 | 0.161 | 0.101 | 0.078 | 0.054 | 0.402 |
| Power Demand | – | – | –0.010 | 0.070 | – | – | –0.001 | 0.084 |
| log (no. of bidders) | –0.059 | 0.149 | 0.077 | 0.072 | –0.019 | 0.127 | 0.273 | 0.210 |
| $\gamma^{IC}$ | The variance parameter for the Incumbent | | | | | | | |
| Constant | 9.564 | 0.235 | 9.950 | 1.269 | 1.709 | 0.254 | 0.930 | 0.322 |
| Load Factor | –8.008 | 1.337 | –0.007 | 0.083 | –0.055 | 0.136 | 0.104 | 0.495 |
| log (no. of bidders) | –1.791 | 0.286 | –2.227 | 0.470 | 0.017 | 0.157 | 2.094 | 0.624 |
| OID (p–value) | 13.709 (0.001) | | 23.210 (0.000) | | 5.369 (0.068) | | 39.635 (0.000) | |
| AIC | 45.408 | | 45.408 | | 45.408 | | 45.408 | |
| Goodness of Fit | | | | | | | | |
| Winning Bid | 0.700 | | 0.715 | | 0.709 | | 0.807 | |
| Entrant Participation | 0.850 | | 0.878 | | 0.640 | | 0.906 | |
| No. of Parameters | | | | | | | | |
| in Auxiliary Model | 18 | | 20 | | 21 | | 23 | |
| in Structural Model | 16 | | 18 | | 18 | | 20 | |

Table 5.2: Medians of Incumbent's Estimated Cost Distributions (yen/kWh)

| Load Factor | UHV Auctions | HV Auctions |
|---|---|---|
| 30% | 19.51 | 18.23 |
| 40% | 15.83 | 15.35 |
| 50% | 12.88 | 13.34 |
| 60% | 10.50 | 11.77 |

Source: Based on the estimation results of Model 1 shown in Table 5.1.

Our estimation results show that load factor affects log-unit supply costs negatively and nonlinearly, as depicted in Figure 2.1. In contrast, other variables, such as the green contract dummy, power demand, and the number of bidders, are not significant cost factors. Load factor positively affects the entrants' cost variations while it negatively impacts upon the incumbent's costs only with the UHV power supply. An increase in the number of bidders affects the variation in costs of both the incumbent and the entrants for the UHV power supply, but its impact tends to be positive and less clear for the HV power supply.

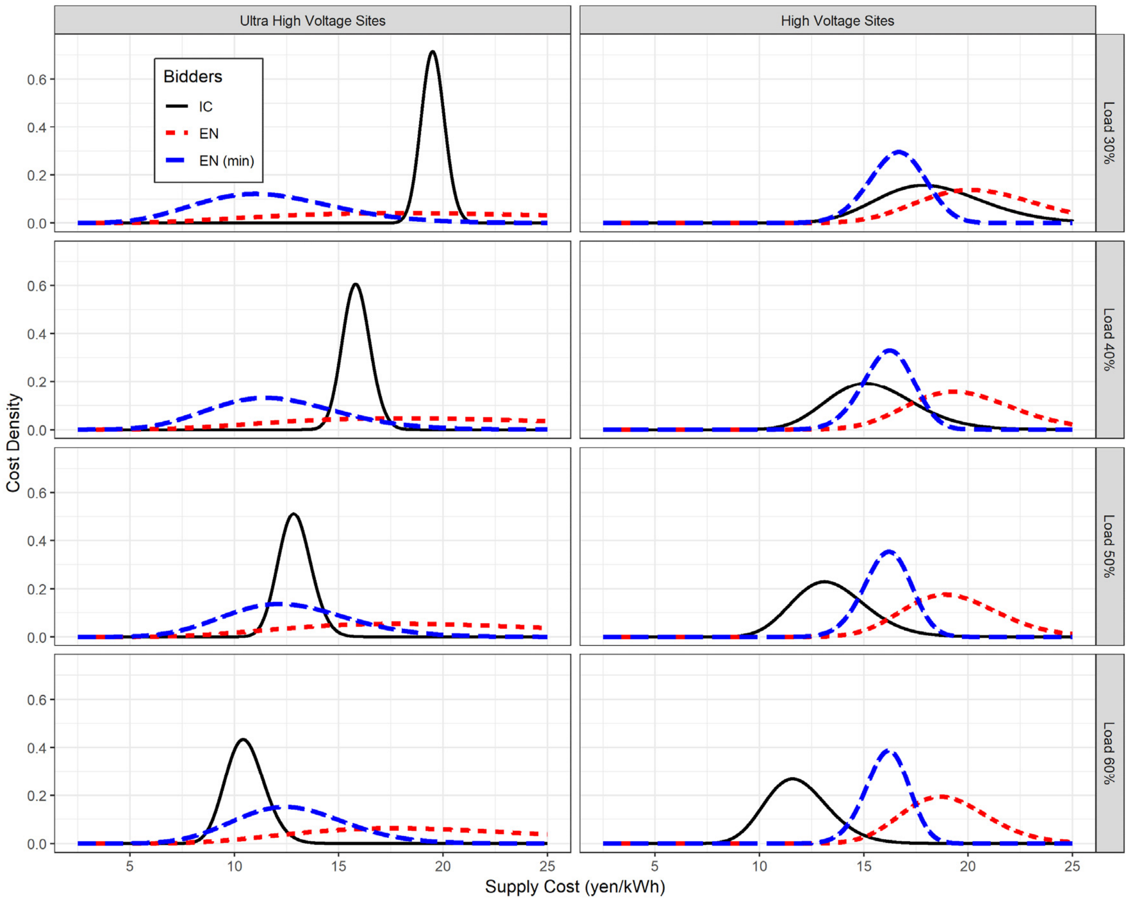
The overidentification (OID) test in the lower part of Table 5.1 favors the specification of the model without the power demand variable (Model 1) to that with it (Model 2). While some outliers weaken the OID test results for the UHV auction sample, but which we could easily trim to improve the model in terms of the minimum value of the criterion function, the goodness-of-fit statistics indicate our model estimates are successful.[13] Therefore, overall, we consider Model 1 to suffer no serious misspecification, and so conduct the following policy simulations using this model.

Using the coefficient estimates, we reconstruct and depict the cost density functions

[13] For the goodness-of-fit measure of the binary variable, we employ the measure of correct classification ratio, where we assign the value of one to the predicted dependent variable if the ratio of simulated auctions with entrant participation is equal to or greater than 0.5.

of the incumbent and entrants for the auctions in the eight market segments in 2010 (Figure 5.1). In this figure, EN (min) is the lowest order statistic of the sample from the entrant cost distribution, representing the cost of the most efficient entrant, which is thus most likely to win among all potential entrant bidders. The peaks in EN (min) indicate the supply cost gaps between UHV and HV auctions with the same load factor. These gaps are attributable partly to the difference in transmission costs between the UHV and HV power supplies, which entrants pay for using the incumbent's network. As the load factor rises, the cost distributions shift gradually leftward. This is most conspicuous in the incumbent's costs and matches the downward-sloping curves of the winning bids depicted in Figure 2.1.

Figure 5.1: Estimated Cost Densities of the Incumbent and Entrants




Comparing the cost distributions of the incumbent and entrants, we can identify the competitiveness of these players in each market segment. In the market segments for the UHV power supply with load factors of 30–40%, the distributions of EN (min) are located on the left-hand side and overlap a little with those of the incumbent. This significant cost advantage enables entrants to win almost perfectly as observed in Table 2.1. In contrast, the cost advantage for entrants diminishes in the market segments for the HV power supply and/or with a high load factor. The incumbent's cost distributions are often located to the left of those of the entrants, demonstrating its strong performance in supplying high load factor customers, whose load profile often matches that of the incumbent's plant portfolio.[14]

## 5.2 Policy Simulations

We use the estimated structural auction model to simulate two competition-promoting policies, namely (i) increasing the number of the potential bidders and (ii) introducing preferential treatment for entrants. Hubbard and Paarsch (2009) argued that competition-promoting policies could bring about three types of effects: a competitive effect, a participation effect, and a preference effect. The *competitive effect* refers to the changes in bids induced by a competition-promoting policy, which drives bidders to bid more aggressively to avoid being beaten. The *participation effect* refers to the effect on the participation probability of entrants, which we expect to promote competition mainly against the incumbent. The *preference effect* refers to the effect of a preferential treatment that causes inefficient allocation incidences by inviting and allowing inefficient (i.e., high-cost)

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[14] Incumbents are typically equipped with large baseload power plants, such as coal-fired thermal and nuclear plants. In contrast, entrants have not invested in sufficient own supply capacity in their short business history after deregulation and depend largely on third-party power supply from less fuel-efficient plants, excess capacity in the private power supply, wholesale supply by incumbents, and purchases through the power exchange.

bidders to win. We examine the impacts of these two policy interventions through these three effects on bidding strategies, bidders' profits, the probability of entrants' participation, and consumer costs (equivalently, power charges). As the latter policy intervention can be distortionary by allowing less cost-efficient entrants to win, we estimate the allocative efficiency of auctions given this preferential treatment.[15]

In our structural model context, these two policy interventions work as follows. While the incumbent always participates as the default bidder, entrants with costs lower than the upper bound of the incumbent's bid $\bar{b}$ are likely to participate in an auction. An increase in the number of potential bidders $n$ promotes entrants' participation (the participation effect). The incumbent reacts to this more active participation with more aggressive bids (the competitive effect). In particular, the incumbent's aggressive reaction lowers $\bar{b}$ to discourage entrant participation. However, the overall impact is ambiguous—whether the number of potential bidders $n$ positively or negatively affects the participation probabilities of entrants and the resulting auction outcomes.

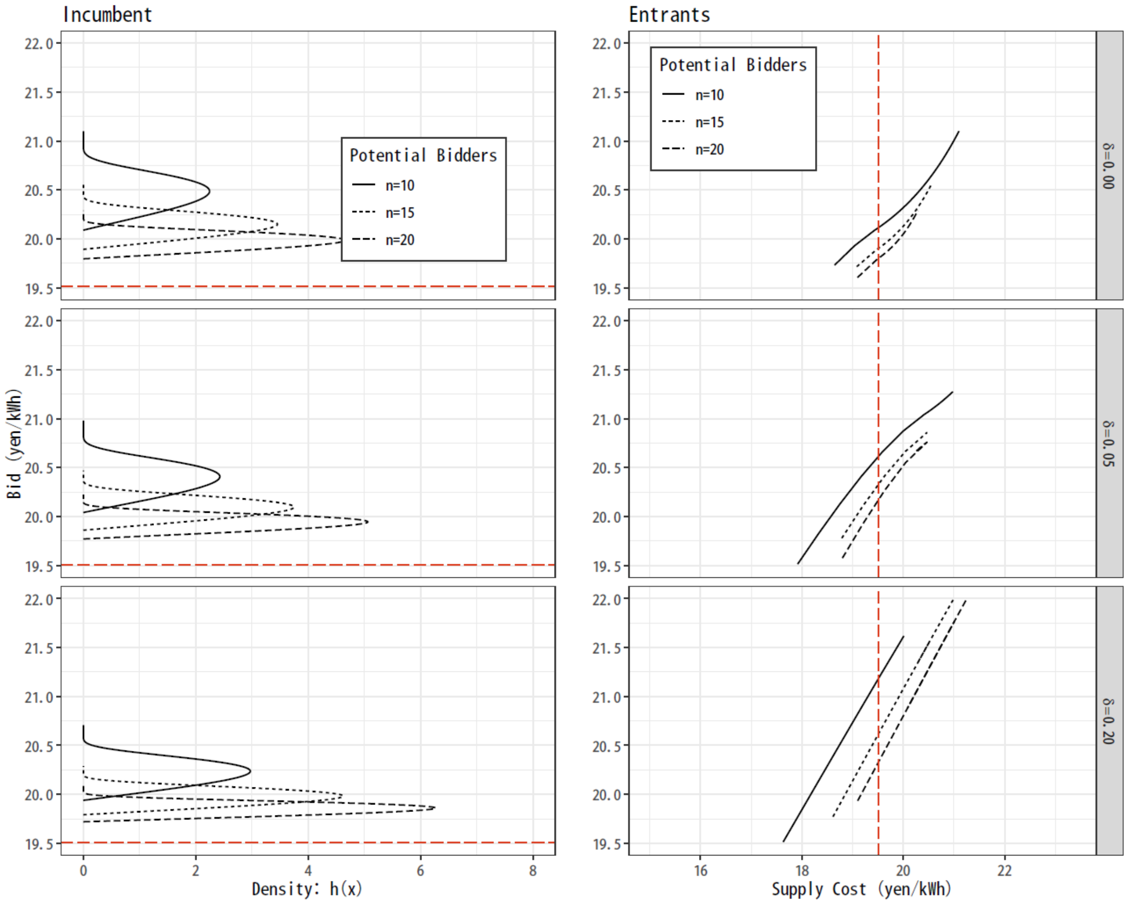
The second policy intervention, the preferential treatment for entrants' winning bids, can enhance the competitive effect with more aggressive incumbent's bids against the preferred bids. Alternatively, we could discount entrants' bids in the awarding process, and this could increase the number of bidders by inviting less cost-efficient bidders into the auction. When the latter preferential effect dominates the former competitive effect, allocative efficiency is impaired. This also needs empirical examination.

Using the parameter estimates in Table 5.1, we identify the bidding behavior. The bidding strategies are for a UHV auction with a load factor of 30% (Figure 5.2) and for an HV auction with a load factor of 50% (Figure 5.3). In these two figures, the incumbent's bid

[15] Although the regulatory authority cannot directly change the number of potential bidders, we assume that regulatory reforms in the power market and general administrative reforms in procurement auctions are able to reduce the pecuniary and nonpecuniary costs and facilitate entry.

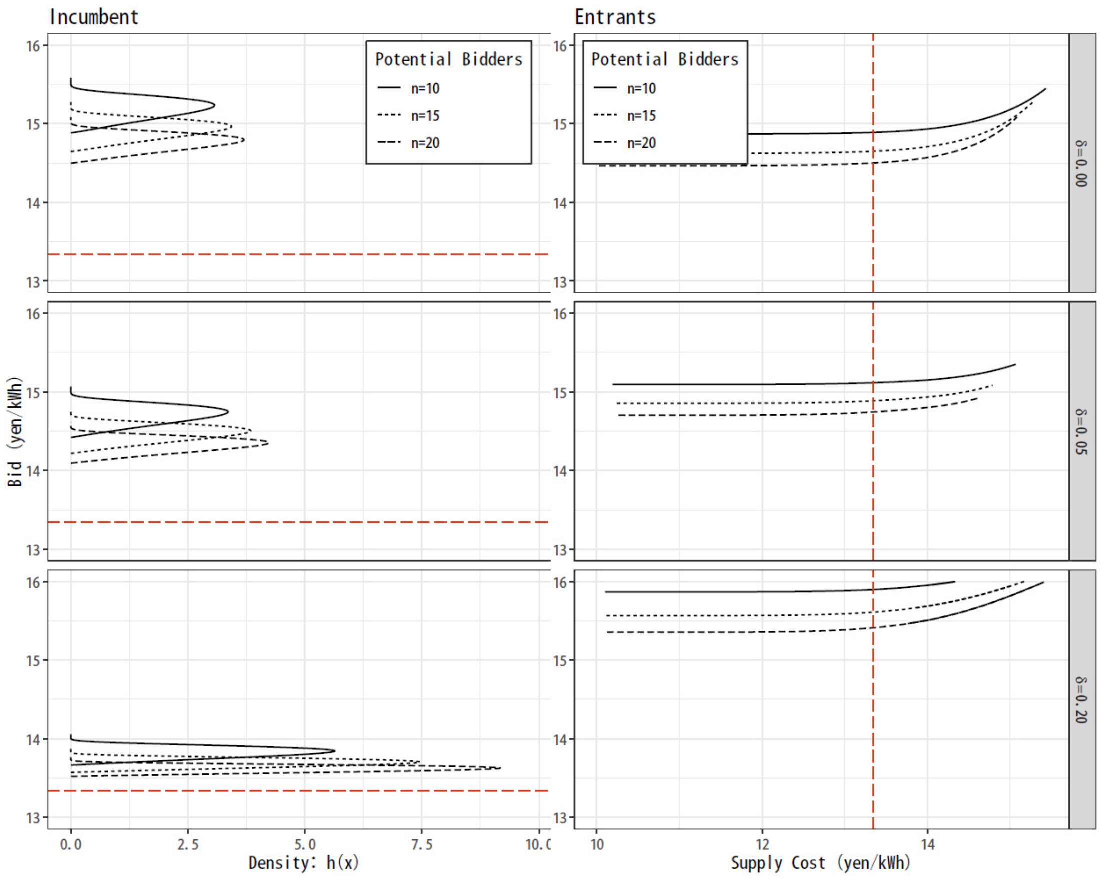
densities $h(x)$ are in the left-hand side panels, where the vertical axes indicate the bids (yen/kWh), and the horizontal axes the probabilities of random bids chosen by the incumbent in the mixed-strategy game. The bidding functions of entrants $b(c)$ are in the right-hand side panels, where the vertical axes are again the bids, and the horizontal axes the supply costs (yen/kWh). For example, the top left panel in Figure 5.2 shows that when $n = 10$ and the incumbent's cost $x$ is at its median level (19.51 yen/kWh), indicated by the red dashed lines, it draws a bid between 20.09 and 21.09 yen/kWh along the density. Entrants' bids generally depend on their supply costs $c$, as well as the incumbent's costs $x$. If the entrants' supply cost is at the same level, they submit a bid of 20.11 yen/kWh (the top right-hand panel in Figure 5.2).

Figure 5.2: Bidding Strategies of Incumbent $h(x)$ and Entrants $b(c)$ in UHV Auctions Load Factor of 30%




Note: The red dashed lines indicate the incumbent's median costs (19.51 yen/kWh).

Figure 5.3: Bidding Strategies of Incumbent $h(x)$ and Entrants $b(c)$ in HV Auctions with Load Factor of 30%




Note: The red dashed lines indicate the incumbent's median costs (13.34 yen/kWh).

In Figures 5.2 and 5.3, the entrants' bid functions show that the incumbent will bid more aggressively as the number of potential bidders $n$ increases or the preference rate $\delta$ rises. Note that the latter effect arises as long as the incumbent has an incentive to participate in that auction. That is, when a too-high preference rate $\delta$ expels the incumbent from the auction, entrants will play a typical symmetric auction game among themselves in the region $R_A$ in Figure 3.1.

A higher degree of competition lowers the upper bounds of the incumbent's bid $\overline{b}$, which works as a hurdle for entry and thus allows only relatively low-cost bidders to participate. Preferential treatment for entrants not only lowers this hurdle, but also allows less cost-efficient bidders to participate. This selection effect is important for the efficiency of resource allocation. As Figures 5.2 and 5.3 cannot depict this outcome, we discuss it further in Section 5.5.

## 5.3 Participation Probability

The order statistic from the estimated cost distributions indicates how many potential entrants would actually participate in an auction. Let $c^*_{k,n-1}$ be the $k$-th smallest order statistic of a sample of size $n$–1, (i.e., the number of potential entrant bidders). When the order statistic $c^*_{k,n-1}$ is less than or equal to the upper bound of the incumbent's bid $\overline{b}$, at least $k$ entrant bidders would participate in the auction. This probability is:

$$p(n,k,\delta) = \int_{\underline{c}}^{\overline{c}} \int_{\underline{c}}^{\overline{c}} \mathbf{1}\{c^*_{k,n-1}/(1+\delta) \le \overline{b}(c_1;n,\delta)\} dF^*_{k,n-1} dG(c_1),$$

where $F_{k,n-1}(c)$ is the distribution function of the order statistic $c^*_{k,n-1}$. We compute these for four typical market segments.

Figure 5.4 illustrates the participation probabilities in each market segment.[16] Participation is active for UHV or low load factor auctions. Auctions with many participants are rare. Without any policy interventions, the active range is up to six participants in UHV auctions and up to four participants in HV auctions. The effects of the increased potential bidders $n$ on the participation probabilities are most sizable in the UHV auctions with a load factor of 30%, which are anticipated to have four to seven bidders. For example, an increase of $n$ from 10 to 15 would raise the probability that an auction has five actual entrant bidders by 41 percentage points. The impact of the additional five bidders on the participation probability would reach 17 percentage points in the UHV auction with a load factor of 50%

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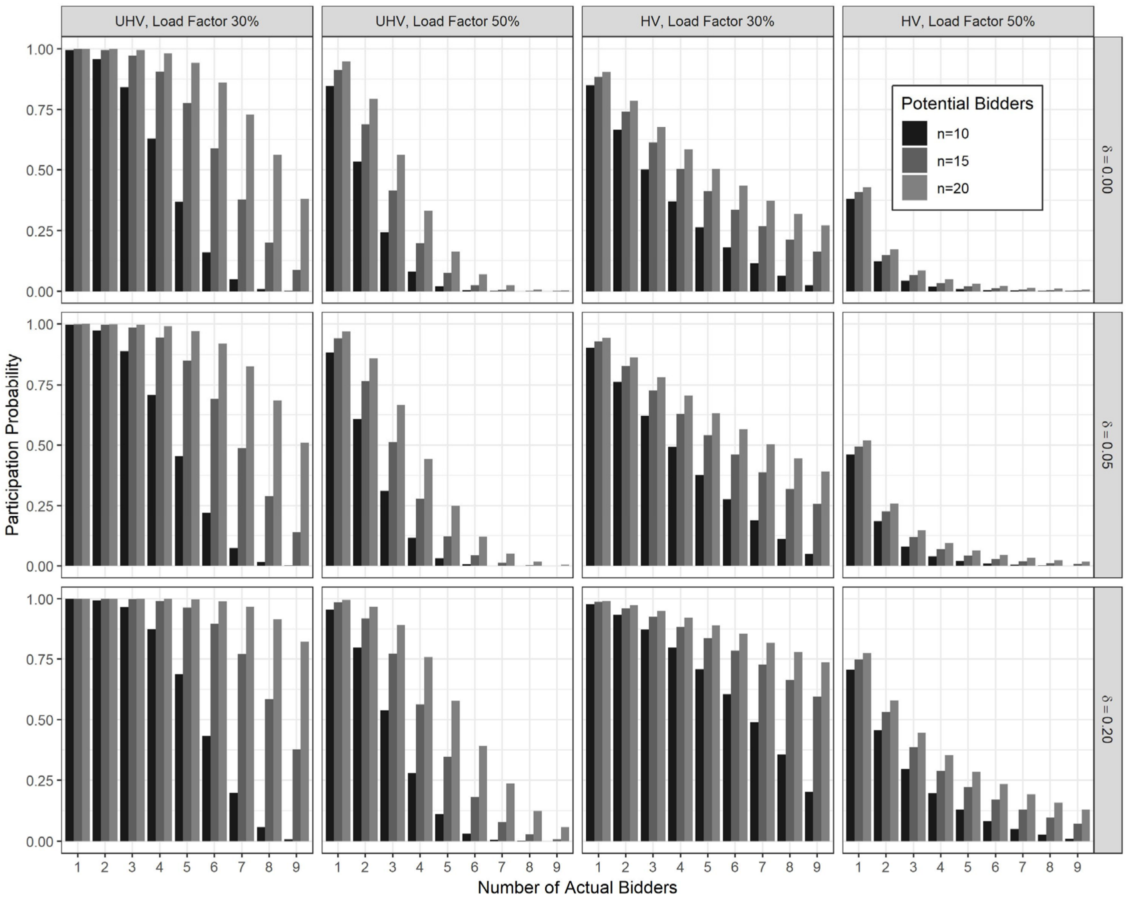
[16] While we assume $n$ = 6–10 in our model estimation depending on the market segment, we assume $n$ = 10 for ease of comparison of the simulation results between different market segments.

and 15 percentage points in the HV auction with a load factor of 30%. We attribute these large effects of $n$ to the potential cost advantage of entrants over the incumbent (additional bidders do not markedly contribute to increasing the participation probabilities in an auction that has one or two actual bidders, simply because their probabilities are often already saturated). However, the impact would be very low in the HV auction with a load factor of 50% and in the UHV auction with a load factor of 50% that attracts many (six or more) participants. In these cases, entrant participation is negligibly small in the status quo.

Figure 5.4: Participation Probabilities




The middle and the lower panels in Figure 5.4 show that the preference rate $\delta$ positively affects the participation probability. This outcome is brought about by the interplay between the competitive effect and the participation effect, which are triggered by the increase in $\delta$. On one hand, the incumbent would lower the upper bound of its bid $\overline{b}$ as a reaction to the discounted bids of entrants (the competitive effect on the incumbent's bid). The incumbent's aggressive bids cut entrants' profit margins and thus discourage their participation. On the other hand, the preferential treatment affords the opportunity to participate in auctions for less cost-efficient entrants, who could not participate without the preferential treatment (the participation effect on entrants).

While we anticipate both positive and negative influences, as shown in Figure 5.4, the participation effect will always dominate the competitive effect given this preferential treatment. For example, a 5% discount would boost the participation probability by up to 7–12 percentage points. However, the magnitude is not uniform across all cases. For the most part, the probability increase will be marked only in moderately or less competitive auctions attracting, for example, six or fewer participants in the UHV auction with a load factor of 30% even without the preferential treatment. In the HV auction with a load factor of 50%, the impact is visible only in auctions that can attract three or fewer participants without the treatment. We cannot expect that the policy would influence auctions with many (five to nine) participants. For further outreach, we require a larger discount of 20%, rather than 5%. This policy option makes us aware of a serious tradeoff between the participation effect and the distortionary effect induced by the preferential treatment, as discussed later.

## 5.4 Profits and Consumer Costs

The competition-promoting policies affect bidders' profits and consumers' costs (or equivalently their welfare) through the participation probabilities and winning bids. We provide these for the typical market segments for different numbers of potential bidders $n$ in Figures 5.5 and 5.6. An increase in $n$ (from 10 to 20) would make competition more severe and reduce the profits of both the incumbent and entrants in all market segments (Figure 5.5). However, the incumbent's profits are almost zero in the UHV auctions and thus not affected any further. The upward-sloping curves for "EN Total" indicate that an increase in the preference rate would increase (total) profits of all entrants only in the relatively less competitive market segments, characterized by lower load factors, fewer potential bidders, and/or HV power supply.

Figure 5.5: Profits of Incumbent and Entrants

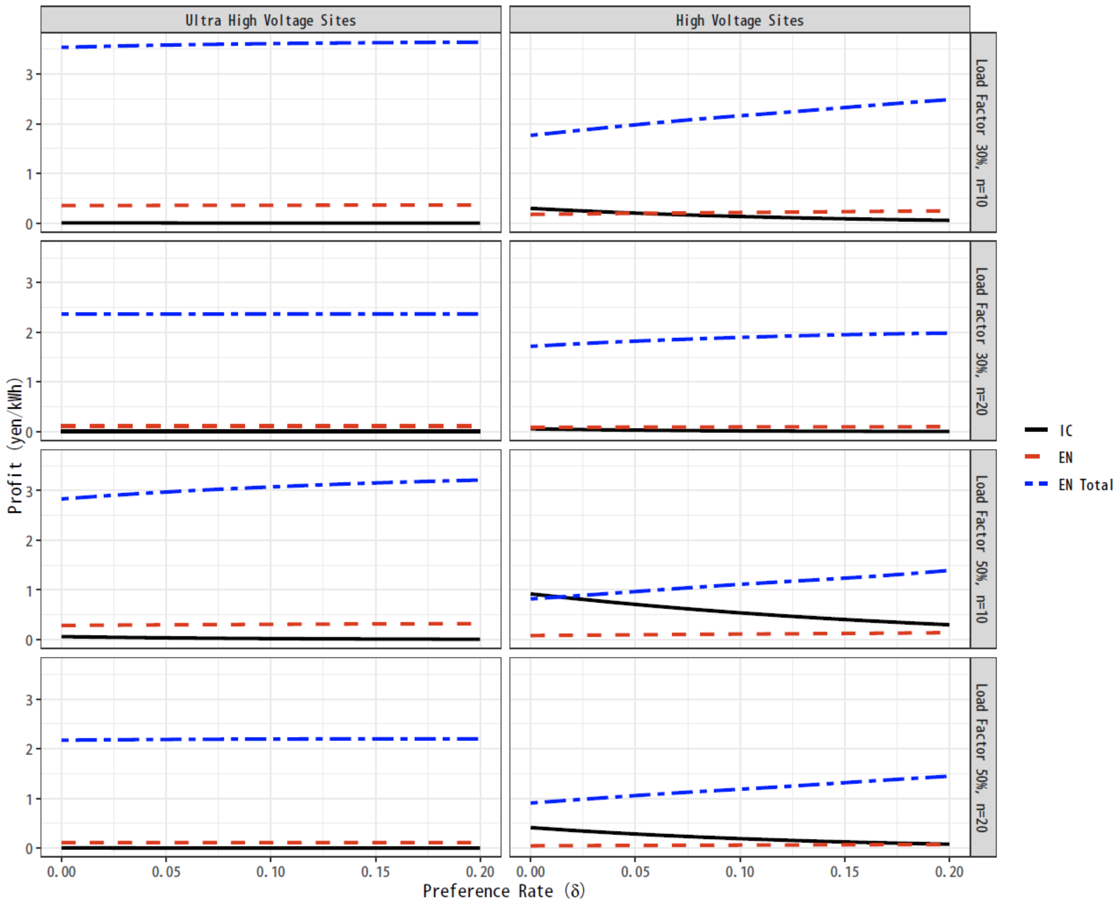
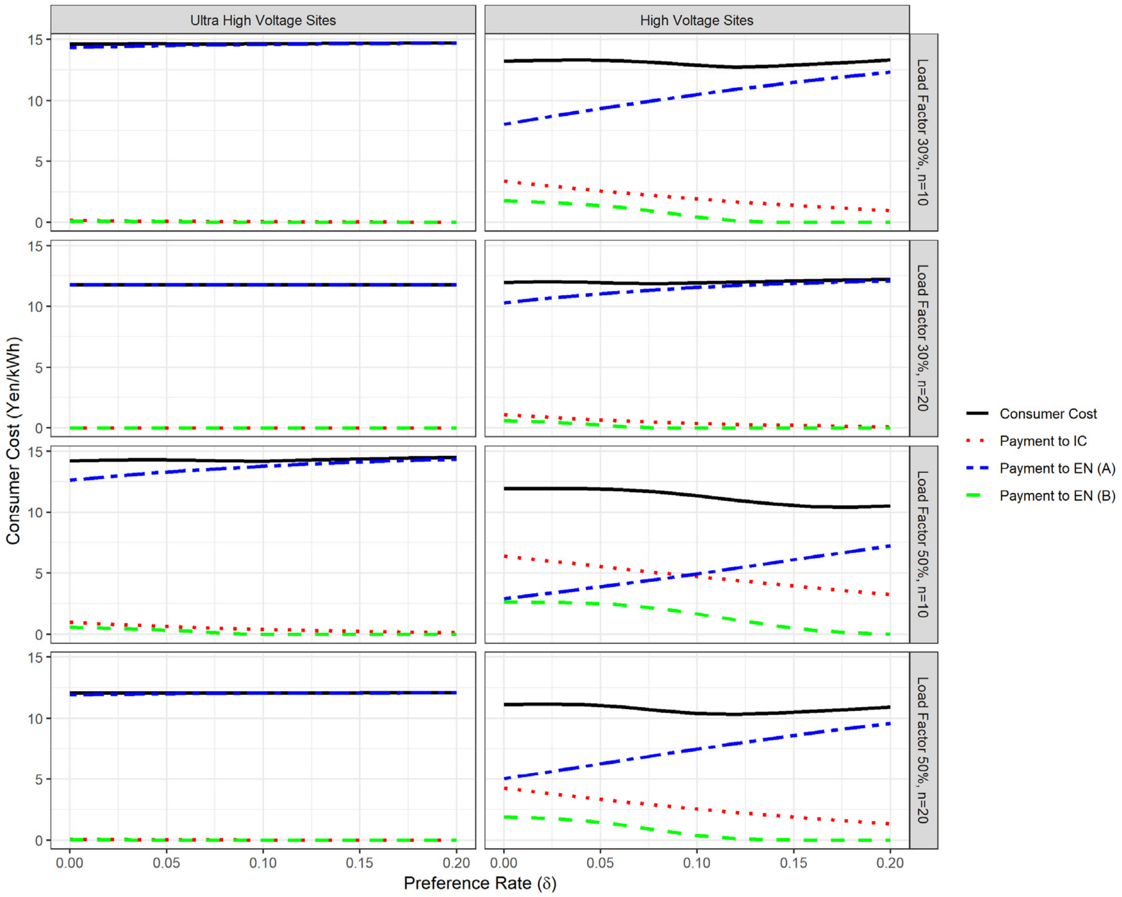



Figure 5.6 shows that an increase in $n$ would decrease payments to winning bidders just as it would decrease bidders' profits. In contrast, the impact of the preference rate $\delta$ on consumer costs is complex, especially in HV auctions, where switching among the three competition regimes is important. The payment to the incumbent and that to entrants in competition regime B (the incumbent vs. entrants) are decreasing in $\delta$ because the incumbent's aggressive bidding induced by the increase in $\delta$ (i.e., the competitive effect)

plays a crucial role.[17] Given that competition regime A (i.e., competition only among entrants without the incumbent) occurs, an increase in $\delta$ would allow entrants to raise their bids by that much to increase payments to themselves.

Figure 5.6: Consumer Costs




The consumer costs consist of the expected payments incurred in these three competition regimes. Because the payments are increasing and decreasing in $\delta$ , the consumer cost curves typically become U-shaped (see the right-hand side panels in Figure

[17] Competition regime C, where only the incumbent participates and wins, will not arise in these four typical market segments given our assumed parameters and the estimated model.

5.6). For an auction with a load factor of 50% and $n = 10$, the optimal $\delta$ that minimizes its consumer costs is approximately 10%. Although the reduction in consumer costs by controlling $\delta$ is very small (less than 1 yen/kWh) in highly competitive UHV auctions, it can be sizable (about 2–3 yen/kWh) in less competitive auctions. We can draw the same conclusion for social costs, being the sum of consumer costs and profits.

## 5.5 Inefficient Allocation

Inefficient allocation could emerge in both regions $R_A$ (entrants vs. entrants) and $R_B$ (incumbent vs. entrants) in Figure 3.1. When an entrant has a cost in region $R_B$, inefficient allocation can occur in two forms: (1) the incumbent bids too aggressively and defeats the lowest-cost entrant ($c_1 > c^* \in R_B$), and (2) the incumbent with the lowest-cost bids too passively and thus defeated by an entrant with higher costs ($c_1 < c^* \in R_B$). The probabilities of these are denoted as $p_{B+}$ and $p_{B-}$, respectively, and written as follows:

$$p_{B+} = \int_{\underline{c}}^{\overline{c}} \int_{\min\{\chi, c_1\}}^{c_1} H\left(\frac{b_B(c^*)}{1+\delta}\right) dF(c^*) dG(c_1) \quad c^* \in [\chi, \overline{b}],\ c_1 \in [\underline{c}, \overline{c}],$$

$$p_{B-} = \int_{\underline{c}}^{\overline{c}} \int_{c_1}^{\overline{b}} \left\{1 - H\left(\frac{b_B(c^*)}{1+\delta}\right)\right\} dF(c_i^*) dG(c_1) \quad c^* \in [\chi, \overline{b}],\ c_1 \in [\underline{c}, \overline{c}].$$

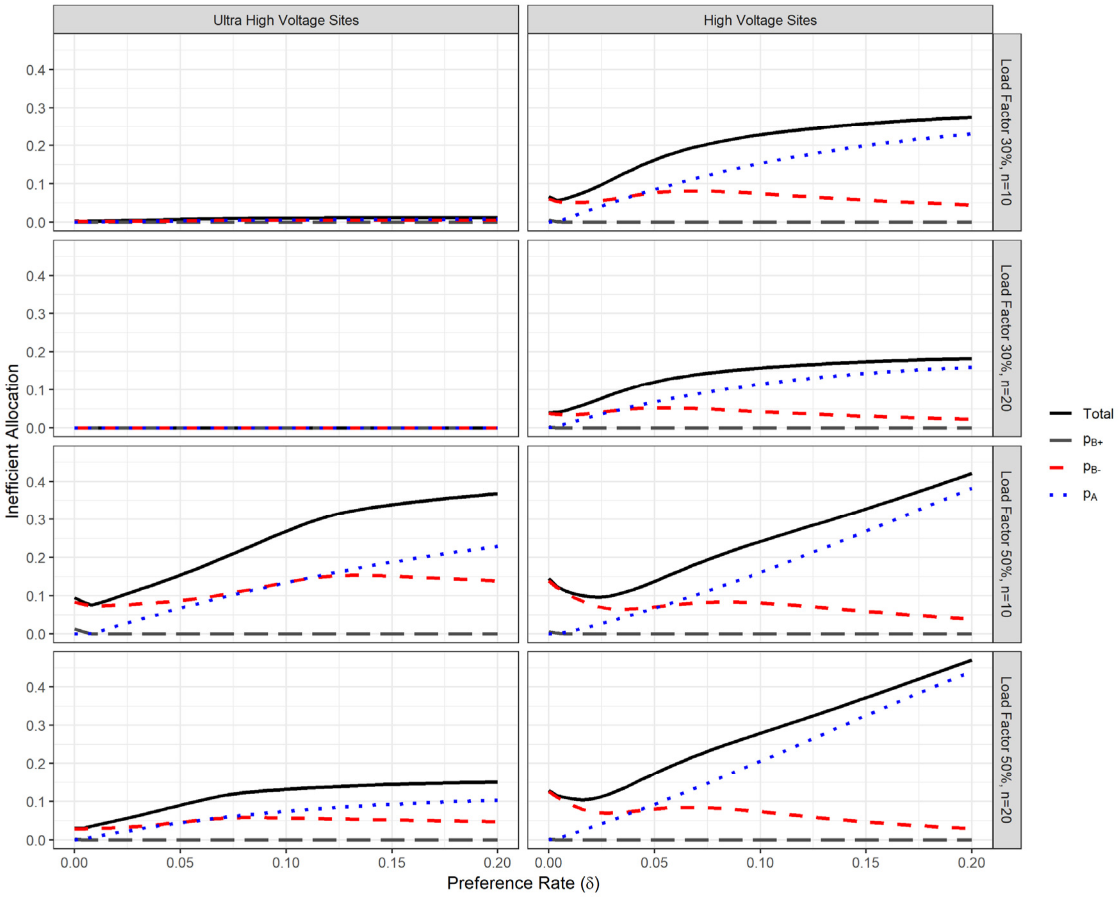
Inefficient allocation can also occur if the preferred entrants have higher costs (but in region $R_A$) than the incumbent ($c_1 < c^* \in R_A$) and win. This probability is:

$$p_A = \int_{\underline{c}}^{\overline{c}} \int_{c_1}^{\chi} dF(c^*) dG(c_1) \quad c^* \in [\chi, \overline{b}],\ c_1 \in [\underline{c}, \overline{c}].$$

The larger the preference rate $\delta$ is, the greater is the cost threshold $\chi$. Then, the winning probability of the preferred entrant increases, irrespective of the incumbent's cost level. The total probability that the most efficient bidder is defeated is the sum of the above three terms (Figure 5.7). Given our sample and estimated model, we find inefficient allocation would be caused mostly by the too passive bidding of the incumbent $p_{B-}$ and the too aggressive bidding of the entrants $p_A$.

We could mitigate this inefficient allocation by increasing the number of potential bidders $n$ and using a reasonably low preference rate $\delta$ (0–10%) that makes the incumbent aggressive. Notably, the latter implies that the inefficiency curve has a bliss point within a reasonable range of the preference rate while Hubbard and Paarsch (2009) concluded that an increase in the preference rate would always increase inefficiency. This may well reflect the unique context of the regulatory reform that commenced recently in the Japanese retail market. Here, the incumbent (TEPCO) faced very little competition before and in the early stage of retail market deregulation and thus could sacrifice large rents as a reaction to entry.

Figure 5.7: Probability of Realizing Inefficient Allocation




Note: $p_A$ is the probability that an entrant with a higher cost in the region $R_A$ wins because of preferential treatment; $p_{B-}$ is the probability that an entrant with a higher cost in the region $R_B$ wins because of preferential treatment and a passive bid by the incumbent; and $p_{B+}$ is the probability that entrants with a lower cost in the region $R_B$ lose because of an aggressive bid by the incumbent.

As a bliss point exists, we could improve allocative efficiency by fine-tuning the preference rate for each market segment. In HV auctions with a high load factor, we could set the preference rate at 1.6–2.4% to lower the probability of inefficiency by 2.4–4.8 percentage points (compared with the case without any preferential treatment). We now find two different bliss points. In the HV auctions with a 50% load factor, this loss-minimizing preference rate is much lower than the consumer cost-minimizing preference rate, which is around 10%. The gap between these two optimal preference rates indicates a need for a second-best policy option that manages the tradeoff between efficiency and consumer costs. However, in other market segments, the optimal preference rate should be (practically) zero, such that market intervention through a preference program would always incur efficiency losses.

## 6. Conclusion

This paper developed a structural auction model and quantitatively examined the effects of policy measures to enhance competition in the Japanese retail power market. We used the theoretical model in Martínez-Pardina (2006) with asymmetries between an incumbent and entrants in both the cost distributions and information structure. We explicitly generated simulation-based solutions of the model as a form of the participation decision of new entrants and the bidding functions of participants. We then matched these to observations of the participation states and winning bids through the auxiliary model in the indirect inference method. This method enabled us to obtain structural parameter estimates with a reasonable goodness of fit.

Our estimation results showed significant cost gaps between the incumbent and entrants in HV auctions with high load factors, where entrants do not participate actively owing to their cost disadvantages. The cost gaps at the same time encourage entrants to choose carefully the profitable market segments in which to participate. These are mostly UHV auctions with low load factors.

Based upon the estimated model, we conducted counterfactual simulations and found that an increase in potential bidders would raise participation probabilities in market segments with active participation and discourage entrant participation in market segments with inactive participation. This is because the preferential treatment for entrants would induce aggressive bidding by the incumbent that would prevent further participation by entrants. Such competition-promoting policies would then result in moderate reductions in consumer costs.

We also found that we could alleviate inefficient resource allocation caused by too aggressive or passive bidding behavior by setting the preference rate at 2–3% for HV auctions or by increasing the number of potential bidders. Nonetheless, about 10% of these auctions would continue to suffer from inefficient allocation. In contrast, we could minimize consumer costs with a modest preference rate. It is noteworthy that this consumer cost-minimizing preference rate is higher than the inefficiency-minimizing rate, suggesting a tradeoff between the two policy targets.

Further elaborations are possible by introducing uncertainty about the number of potential bidders (e.g., An et al. (2010) and Shneyerov and Wong (2011)) and unobserved heterogeneity into their cost distributions (e.g., Campo et al. (2003)). We could also carry out semi/nonparametric estimation of deep structural parameters, as described in Li and Zheng (2009) and Suzuki (2011). Other factors, such as bidder supply capacity and its uses for auctions before they participate in an auction, and bidders who won in the previous year, may also affect bidding behavior. We could investigate all these effects by considering the dynamic behavior of bidders (e.g., Jofre-Bonet and Pesendorfer (2003)) in future work.

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# Appendix: Alternative Specifications

There are several options for specifying the estimation model: one is the specification of the bidders' cost distribution functions, and another is the variable selection in the structural model. We discuss these alternative specifications in our analysis.

We used a log-normal cost distribution in the main text but could also specify other distributions, for example, the beta distribution. The beta distribution is a flexible distribution with only two parameters, which determine not only the first two moments but also the signs of skewness. However, it is difficult to relate the exogenous variables with moments of bidders' cost in the case of beta distributions, compared to the log-normal distributions in the main text. This also makes the interpretation of the estimated coefficients less straightforward.

Nevertheless, we tried a specification for the exponential of the linear index of exogenous variables for each parameter in the beta distribution, $\mathrm{Beta}(\alpha, \beta)$. The minimized value of the criterion function using the beta distribution is 154.92 for ultra-high voltage sites, whereas that using the log-normal distribution with a comparable specification is 71.152 (Table A.1). This suggests that a model with a beta distribution is clearly inferior to one with a log-normal distribution in terms of both interpretability and the overall goodness of fit. Therefore, all reported estimation and simulation results employ the log-normal distribution.

The next issue is variable selection, which matters especially in the specification of the load factor variable and the inclusion of the number of actual bidders (see Section 4.1). In Table A.1, we report the estimation results with and without the quadratic load factor term in the means excluding the number of actual bidders. Compared with the results in Table 5.1, we mostly observe negative and significant effects of the load factor variables and the significance of the time dummy variables. However, the goodness of fit of each dependent variable in the last two rows of Table A.1 are inferior to the corresponding values in Table 5.1, except the column providing Model 1 for the HV auctions. The key features of the specification in Table 5.1 are the inclusion of the inverse term for the load factor and the actual number of bidders, which help capture the rapidly decreasing trend in winning bids alongside the load factor and the unobserved auction-specific factor through the variance, as discussed in Section 4.1. These specifications are helpful to improve the goodness-of fit of each dependent variable (the last two rows in Tables 5.1 and A.1).

Table A.1: Alternative Model Specification

| | Ultra–High Voltage Sites | | | | | | High Voltage Sites | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Model A | | Model B | | Model C | | Model A | | Model B | | Model C | |
| | **Estimate** | **S.E.** | **Estimate** | **S.E.** | **Estimate** | **S.E.** | **Estimate** | **S.E.** | **Estimate** | **S.E.** | **Estimate** | **S.E.** |
| $\beta^{EN}$ | The mean parameter for Entrants | | | | | | | | | | | |
| Constant | 3.270 | 0.715 * | 3.138 | 0.356 * | 3.045 | 0.408 * | 3.447 | 0.206 * | 3.267 | 0.492 * | 3.240 | 0.332 * |
| Load Factor | –0.576 | 0.202 * | –0.694 | 0.356 | –0.566 | 0.133 * | –0.807 | 0.057 * | –0.791 | 0.194 * | –0.751 | 0.222 * |
| Load Factor$^2$ | | | 0.756 | 0.259 * | 1.199 | 0.166 * | | | 0.659 | 0.437 | 0.772 | 0.183 * |
| Green Contract | –0.117 | 0.403 | 0.082 | 0.099 | 0.126 | 0.334 | –0.143 | 0.062 * | 0.045 | 0.212 | 0.062 | 0.176 |
| Dummy for 2010 | –0.098 | 0.062 | 0.261 | 0.098 * | 0.227 | 0.143 | –0.032 | 0.176 | 0.243 | 0.086 * | 0.224 | 0.300 |
| Power Demand | | | | | –0.088 | 0.128 | | | | | –0.033 | 0.266 |
| $\gamma^{EN}$ | The variance parameter for Entrants | | | | | | | | | | | |
| Constant | 0.661 | 0.262 * | 0.297 | 0.154 | 0.544 | 0.100 * | 0.607 | 1.579 | 0.737 | 0.233 * | 3.325 | 0.393 * |
| Load Factor | –0.367 | 0.040 * | 0.364 | 0.084 * | –0.261 | 0.333 | –0.540 | 0.133 * | 0.329 | 0.175 | 1.077 | 0.427 * |
| Dummy for 2010 | –0.298 | 0.236 | | | | | –0.118 | 2.899 | | | | |
| Power Demand | | | | | 0.034 | 0.162 | | | | | –0.137 | 0.108 |
| $\beta^{IC}$ | The mean parameter for the Incumbent | | | | | | | | | | | |
| Constant | 2.860 | 1.189 * | 2.997 | 0.404 * | 3.108 | 0.406 * | 2.944 | 0.484 | 3.275 | 1.112 * | 3.325 | 0.393 * |
| Load Factor | –1.276 | 0.367 * | –1.361 | 0.135 * | –1.205 | 0.276 * | –1.631 | 0.495 | –1.877 | 0.442 * | –1.849 | 0.602 * |
| Load Factor$^2$ | | | –0.291 | 0.228 | –1.031 | 0.237 * | | | –0.192 | 0.312 | –0.406 | 0.139 * |
| Green Contract | –0.145 | 1.317 | 0.054 | 0.143 | –0.021 | 0.117 | 0.245 | 0.009 | 0.027 | 0.293 | 0.008 | 0.142 |
| Dummy for 2010 | 0.260 | 0.227 | –0.512 | 0.237 * | –0.407 | 0.113 * | 0.108 | 1.151 | –0.702 | 0.388 | –0.609 | 0.162 * |
| Power Demand | | | | | 0.045 | 0.351 | | | | | 0.009 | 0.243 |
| $\gamma^{IC}$ | The variance parameter for the Incumbent | | | | | | | | | | | |
| Constant | 0.171 | 0.879 | 6.162 | 1.199 * | 6.972 | 1.925 * | 0.307 | 0.079 * | 3.918 | 1.301 * | –1.981 | 0.451 * |
| Load Factor | –0.288 | 1.291 | –5.721 | 1.163 * | –6.186 | 0.843 * | -0.566 | 0.159 * | –2.791 | 1.271 * | –7.112 | 2.357 * |
| Dummy for 2010 | –0.127 | 0.934 | | | | | -0.208 | 0.204 | | | | |
| Power Demand | | | | | 0.047 | 0.217 | | | | | 5.994 | 0.993 * |
| Goodness of Fit | 43.72 (0.000) | | 63.343 (0.000) | | 71.152 (0.000) | | 29.97 (0.000) | | 48.182 (0.000) | | 128.47 (0.000) | |
| Winning Bid | 0.633 | | 0.641 | | 0.672 | | 0.836 | | 0.796 | | 0.796 | |
| Entrant Participation | 0.625 | | 0.704 | | 0.691 | | 0.684 | | 0.781 | | 0.786 | |