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An Empirical Analysis of Bidder Asymmetry in Japanese Electric Power Procurement Auctions Using Bayesian Analysis*

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Abstract

The introduction of competition has failed to reduce electricity prices in Japan, and this may be due to asymmetric costs among electricity suppliers. This paper examines whether these asymmetries exist and what is causing them, using auction data. Bayes estimator is employed to handle three unobserved variables. The result shows that despite their low market share, entrants do possess competitive advantage over incumbents. However, entrants' competitive advantage diminishes in certain types of auctions owing to some fees disproportionately imposed on entrants. Interestingly, Japanese environmental policy initially increased entrants' costs, but that effect disappeared several years after its enactment.

JEL-Classification: C11, L51, Q48, Q58

Keywords: Bidder asymmetry, Green Contract Law, Bayes estimator

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1 Introduction

The Japanese government started electricity deregulation nearly two decades ago, yet market competition has been very limited and electricity price remains expensive. New entrants represent only 2.1% of electricity retailing, and the electricity price for industry (household) was 17.9¢/kWh (26.1¢/kWh) in 2011, which was 41% (24%) and 156% (121%) higher than those in the UK and the USA, respectively (Agency for Natural Resources and Energy, 2011, 2013). In the wake of the constrained energy supplies due to the Fukushima nuclear crisis after the earthquake and tsunami in 2011, the Japanese government is revitalizing the electricity reform movement and trying to find out a way to spur new entrants into the electricity market. Several key factors suggest that electric utilities and entrants may face asymmetric costs, which could limit market competition. Therefore, this paper examines whether these asymmetries exist and what is causing them, using the data on Japanese electric power procurement auctions.

Japanese electricity deregulation is a part of the global movement toward liberalization of electricity markets started in the early 1990s. An electric utility is a typical natural monopoly and often protected by a government. It incurs a large fixed cost for creating and maintaining essential facilities, such as power plants and electric transmission networks. On the other hand, there is a very small marginal cost to provide an extra unit of electricity once necessary facilities are built. Due to these large economies of scale, an electric utility is allowed to dominate electricity service in its service territory on condition that it offers non-discriminatory service under price control. Such a natural monopoly, however, has been blamed for high electricity prices rooted in its x-efficiency. Also the enormous fixed cost which used to stand as a barrier to entry has shrunk because a small-scale thermal power plant can now generate a large amount of electricity due to innovations in electricity generation technologies. Furthermore, new power suppliers are considered increasingly important to bridge energy gaps, for an electric utility is often reluctant to take a risk of building a new power plant even if electricity demand is expected to grow. Given these situations, electricity markets have been opened to new power suppliers in many countries and regions to lower electricity prices by introducing market competitions and secure additional electricity supplies.

Different deregulation initiatives have been undertaken in different countries and regions. In the United States, the wholesale market was opened to independent power producers (IPPs) when the Public Utility Regulatory Policies Act (PURPA) was enacted in 1978. PURPA forces electric utilities to purchase electricity generated at cheaper costs by qualified IPPs. In order to bring more IPPs into the market, the Federal Energy Regulatory Commission issued Orders 888 and 889 in 1996, which promote nondiscriminatory access to transmission networks owned by electric utilities (Federal Energy Regulatory Commission, 1996a,b). Following the wholesale market deregulation, roughly half of all U.S. states undertook liberalization of electricity retail markets[1]. Currently eighteen U.S. jurisdictions deregulated their retail electricity markets[2].

Following the electricity deregulation in the United States and Europe, the Japanese government began electricity reform in the 1990s. First, the wholesale market was opened to IPPs in 1995, before which only "wholesale electricity companies" having supply capacity of two million kilowatts or above were allowed in the wholesale market[3]. Then the retail market was gradually opened to new entrants, called power producer and suppliers (PPSs). PPSs supply electricity to customers through their own generation facilities and the transmission networks owned by electric utilities. In 1999, deregulation was limited to large-scale customers contracted for 2000 kW or more of extra-high voltage power (20,000V or more), which represented 26% of total demand at that time[4]. In 2003, deregulation was expanded to middle-scale customers contracted for 500 kW or more of high voltage power (6,000V or more), and then to 50 kW or more in 2005. Further deregulation of the retail market has been suspended since then. Consequently, about 40% of the retail market, consisting of small-scale non-residential customers and all residential customers, remains excluded from deregulation (Agency for Natural Resources and Energy, 2013).

Nearly two decades of Japanese electricity reform, however, have shown decidedly limited impacts. The biggest reason is that traditional vertically integrated utilities have been kept intact. Japan is divided into ten regions and each region has been exclusively served by a single electric utility. These ten electric utilities continue to account for more than 70% of the total capacity (76.57% in 1995 and 73.17% in 2010), whereas less than 1% of the total capacity[5] is owned by new entrants (PPSs) (0.2% in 2003 and 0.71% in 2010) (Cabinet Office, 2007; Ministry of Economy, Trade and Industry, 2012). This is a sharp contrast to the situations in other deregulated markets. For example, in the United States, electric utilities' capacity shares are 28% in New York, 1% in Pennsylvania and 0.6% in Maryland in 2010 (U.S. Energy Information Administration, 2012). The dominance of Japanese electric utilities is even more remarkable in the retail market. Their market share in the deregulated retail area is 96.47% in 2012, meaning that only 3.53% belongs to PPSs (Agency for Natural Resources and Energy, 2013). Since deregulation is limited to 60% of the entire retail market, PPSs' share is actually only 2.1% in Japanese electricity retail market. On the other hand, in New York, for example, 34.8% of non-residential customers and 24.0% of residential customers are served by an alternative electric supplier as of May 2013, which together represent 25.5% of all customers and 54.2% of the total load (New York State Public Service Commission, 2013).

[1] Among these states, Arizona, Arkansas, Nevada, New Mexico and Virginia suspended deregulation after the electricity crisis in California in the early 2000s.

[2] These include seventeen states (California, Connecticut, Delaware, Illinois, Main, Maryland, Massachusetts, Michigan, Montana, New Hampshire, New Jersey, New York, Ohio, Oregon, Pennsylvania, Rhode Island, and Texas) and District of Columbia. In California, Michigan, Montana and Oregon, many residential customers are excluded from retail choice.

[3] Currently Japan Atomic Power Company and J-POWER are the only wholesale electricity companies.

[4] Deregulation in Okinawa region was limited to the customers using 20,000 kW or more of extra-high voltage power in 1999, which is now reduced to 2,000 kW.

[5] Wholesale electricity companies own the rest of the generation capacity.

Given such limited competition, it is not surprising that deregulation has not had much impact on electricity prices. The Japanese government is thus trying to find out a way to spur PPSs into the electricity market to reduce electricity prices. Cost disadvantages of PPSs, if any, can be a potential cause of their low market share. Direct cost comparison between electric utilities and PPSs is, however, impractical for several reasons. First, they use different types of power plants. While electric utilities use large-scale power plants operated by a balanced mix of oil, coal, natural gas, hydropower and nuclear, PPSs use much smaller power plants and the energy mix varies widely among PPSs. Second, there are two costs only applicable to PPSs. One is a transmission network fee to use a transmission network exclusively operated by an electric utility. The average fee is 2.03 yen/kWh for extra-high voltage and 4.15 yen/kWh[6] for high voltage (Ministry of Economy, Trade and Industry, 2012). The other is an imbalance fee imposed on PPSs as a penalty for a supply shortage. If a PPS fails to balance supply and demand every thirty minutes, an electric utility steps in to fix the imbalance. If a shortage exceeds 3%, a PPS must pay 51.73 yen/kWh in summer and 45.73 yen/kWh in other seasons[7]. Third, an environmental policy may have a larger impact on PPSs. In response to the concerns about climate changes, the Japanese government enacted what is known as green contract law in 2007. This is an environmental quality threshold regarding CO_2 emission factors and power suppliers may have to invest extra money in meeting the threshold to enter the auctions upon which green contract law applies. Heyes (2009) points out that an environmental policy tends to hit small firms disproportionately because there are substantial fixed costs associated with compliance and thus per unit regulatory compliance costs tend to be higher at smaller firms. In addition, while electric utilities own various power stations, including low-carbon nuclear power plants, PPSs often heavily rely on fossil fuels and may need to invest additional money in curbing CO_2 emissions. Finally, data availability makes any direct cost comparison between electric utilities and PPSs challenging.

To overcome these limitations, this paper focuses on the analysis of electricity procurement auctions in the public sector. The WTO Agreement on Government Procurement (GPA) covers procurements of electricity used in the public sector. Accordingly, auctions have been adopted by Japanese central and local governments and some other entities, such as national hospitals and universities, since the beginning of electricity deregulation. These auction data are relatively accessible. Also open competitive bidding is likely to reflect a bidder's true cost, which is otherwise difficult to estimate. In other words, a difference in the winning bids of electric utilities and PPSs, if any, implies a difference in their costs. Such bidder asymmetry could discourage inefficient firms from aggressively entering the auction. Therefore, in order to explore the

[6]Exchange rates were about 80 yen per USD during this time period.

[7]On the contrary, if supply exceeds demand by more than 3%, the excess electricity is obtained by an electric utility for free. Penalties are relatively cheap if an imbalance is within ±3%: a PPS pays 15.02 yen kWh for a shortage and can sell excess electricity at 10.48 yen/kWh. These fees are at Tokyo Electric Power Company in 2012. Fees vary between electric utilities.

possible causes of the PPSs' low market share, we analyze the winning bids of electric utilities and PPSs to examine the existence of bidder asymmetry. Furthermore, by looking into the factors that influence their winning bids, we explore the causes of the asymmetric costs between electric utilities and PPSs. In particular, given the growing interest in renewable energies in the aftermath of the country's nuclear power crisis, we investigate the impact of green contract law on the PPSs' winning bids.

In auction theory, it has been shown that bidder asymmetry potentially reduces competition (e.g. Myerson, 1981; Maskin and Riley, 2000; Krishna, 2002). Also, there are some empirical studies conducted on asymmetric bidders. Porter and Zona (1999) examine Ohio milk auctions and find that firm behaviors differ from each other. De Silva et al. (2003) explore differences in the bidding patterns of entrants and incumbents in road construction auctions in Oklahoma. They find that entrants bid more aggressively and win auctions with lower bids than incumbents. Estache and Iimi (2010) investigate asymmetric bidders using procurement data from official development assistance (ODA) projects. They find that entrants actually submitted aggressive bids in the presence of an incumbent.

Several studies examine Japanese electric power procurement auctions. Hattori (2010) empirically analyzes the determinants of the number of bidders. He shows that the number of bidders is negatively affected by the load factor and positively affected by the voltage level and contract demand. Hosoe and Takagi (2012) examine the effectiveness of the auctions by measuring the decline in electricity prices. They find that if PPSs participate in an auction, electricity price decreases by 0.46 yen/kWh on average. While these studies show that the participation of PPSs in auctions indeed brings down the price of electricity and that there are many factors affecting their participation decisions, it remains unclear whether bidder asymmetry exists between electric utilities and PPSs. There is an ongoing argument that transmission network and imbalance fees may be unnecessarily high and hinder entrants in auctions. However, once entering auctions, entrants actually have a much higher winning rate than incumbents as we discuss in section 2.2. Therefore, it is not clear who (electric utilities or PPSs) have cost advantage in electricity retailing, which is examined in this paper. There are also several factors that are included in this paper, but not in Hattori (2010) and Hosoe and Takagi (2012). In modeling the auction characteristics, many studies take firm effects and regional effects into considerations (e.g., Porter and Zona, 1999; De Silva et al., 2003; Estache and Iimi, 2010), whereas Hattori (2010) and Hosoe and Takagi (2012) include only regional effects. In his paper, we consider the year effect as well as firm and regional effects to control for variables that vary over time, such as technological improvements, but do not vary across firms or regions. To our knowledge, this is the first paper to include three such effects. When there are three effects, it is difficult to estimate the winning bid because three unobserved effects require triple integrals. Therefore we use Markov chain Monte Carlo (MCMC) to estimate the effect of these three factors on the winning bid. Also, we consider the impact of green contract law, which is not studied in Hattori (2010) and Hosoe and Takagi (2012).

The remainder of this paper is organized as follows. In Section 2, we explain the Japanese electric power procurement auctions and our data set. Section 3 provides an explanation of the model and Section 4 discusses the regression results. Finally, Section 5 summarizes our findings and provides some concluding remarks.

2 Japanese Electric Power Procurement Auctions

2.1 Auction Mechanism

In Japanese electric power procurement auctions, a public agency who acts as an auction organizer notifies PPSs of an upcoming auction through its website and newspapers. The information includes the contract demand (kW), the projected amount of consumption (kWh), the delivery period and the place of delivery. After the announcement, PPSs need to register for the auction several weeks before it takes place. However, PPSs can withdraw from the auction. The contracts for electricity supply are sold through first-price, sealed-bid auctions. In other words, the bidder submitting the lowest bid wins the auction if the bid is lower than the reserve price. The reserve price is the highest price that the public agency is willing to accept for the electricity contract. If the lowest bid is higher than the reserve price, the public agency holds an auction again. The application of green contract law is left to the discretion of public agencies. Also, in order to keep multiple bidders in an auction as much as possible, green contract law will not be applied if less than three bidders are expected to participate in the auction.

2.2 Data Set

Our data set consists of Japanese electric power auctions from 2005 to 2010 taken from Japan Electric Association Newspaper Division (2010). The original data include, for each auction, the auction date, the auction organizer, the place of delivery, the contract demand (kW), the projected amount of consumption (kWh), the load factor, the delivery period (days), the voltage level (high or extra-high), application or non-application of green contract law, the winning bidder, the losing bidder(s) and the winning bid (yen/kWh). A load factor is a ratio between the average and maximum usage of electricity during the contract term and calculated as $\frac{\text{the projected amount of consumption(kWh/year)}}{\text{the contract demand(kW)}\times 24\text{(hours)}\times 365\text{(days)}}$. The winning bids are converted to 2012 yen, using regional consumer price indices obtained from Statistics Japan (2014). Out of a total of 3,375 auctions conducted during the data collection period, 1,886 auctions contain the information on losing bidders, whereas the remaining auctions do not have such information. Since this paper analyzes the difference in bidding behaviors between electric utilities and PPSs, the information on losing bidders is critical to identify which and how many companies participated in each auction. Hence, we limit our analysis to the 1,886 auctions with the complete information on losing bidders. The sample means and standard deviations of the original and our data sets are reported in Table 2 in Section 3.2. Comparing the population means, we confirm that there is no statistically significant difference between these two data sets, indicating no sampling bias in our data set.

Table 1 summarizes our data set. Out of the 1,886 auctions, 1,031 auctions (55%) were won by nine electric utilities, denoted as *incumbents*, and the remaining 855 auctions (45%) were won by twelve PPSs, denoted as *entrants*[8]. The average number of bidders was 1.17 (2.29) when incumbents (entrants) won auctions. An incumbent normally participates in all auctions held in its service region, but seldom enters auctions in other regions. On the other hand, an entrant may participate in auctions in several regions, but enters only a portion of auctions. Consequently, many auctions receive only one bid, mostly from an incumbent. In our data set, there were 898 single-bidder auctions, out of which 888 auctions (99%) were incumbent-only auctions and 10 auctions (1%) were entrant-only auctions. The remaining 988 auctions had an incumbent and one or more entrants. Once entering auctions, however, entrants surprisingly outperform incumbents: entrants won 845 multi-bidder auctions (86%), whereas incumbents won only 143 (14%) of such auctions.

The average winning bids of the auctions won by incumbents and entrants were 14.65 yen/kWh and 17.69 yen/kWh, respectively. When incumbents won auctions, the average load factor was 0.47, whereas it was 0.29 when entrants won auctions. The difference in the average winning bids is partly attributed to the difference in the average load factors, since winning bids seem to be negatively correlated to load factors as shown in Figure 1. In general, electricity demand changes throughout the day. Electricity demand starts increasing in the morning, reaches a peak at noon and gradually abates, reaching the lowest point at night. A high load factor means that a supplier has to provide electricity to a customer around the clock. This is challenging to entrants, who do not have base load power plants, such as nuclear and coal-fired power plants, to produce electricity at a constant rate to meet minimum demand. Therefore, entrants face higher risks of incurring expensive imbalance fees in contracts with higher load factors and thus tend to avoid such contracts.

When we classify auctions in terms of types of the required power service, 524 auctions (28%) were for extra-high voltage power service and 1,362 auctions (72%) were for high voltage power service. Entrants won 51% of the extra-high voltage auctions and 43% of the high voltage auctions. Compared to the overall proportion of the auctions won by entrants (i.e., 45%), entrants won a larger portion of extra-high voltage

[8]Auctions have not been introduced in Okinawa region, which is the service territory of one of the ten electric utilities.

Table 1: Auction Data

	Auctions Won by Incumbents	Auctions Won by Entrants	Total
Number of Auctions	1031 (55%)	855 (45%)	1886
Average Winning Bid (yen/kWh)	14.65	17.69	16.02
Average Load Factor	0.47	0.29	0.39
Average Number of Bidders	1.17	2.99	2.00
Number of Single-bidder Auctions	888 (99%)	10 (1%)	898
Average Winning Bid (yen/kWh)	14.79	17.05	14.82
Average Load Factor	0.46	0.32	0.47
Number of Multi-bidder Auctions	143 (14%)	845 (86%)	988
Average Winning Bid (yen/kWh)	13.72	17.69	17.12
Average Load Factor	0.46	0.29	0.32
Number of Extra-high Voltage Auctions	259 (49%)	265 (51%)	524
Number of High Voltage Auctions	772 (57%)	590 (43%)	1362
Number of Green Contract Auctions	436 (55%)	362 (45%)	798
Number of Non Green Contract Auctions	595 (55%)	493 (45%)	1088

auctions and a slightly smaller portion of high voltage auctions. As mentioned in the introduction, PPSs must pay transmission network fees to incumbents to distribute electricity for customers. Since the fee for high-voltage transmission is more than twice as expensive as that for extra-high voltage transmission, high voltage auctions may be less attractive to entrants than extra-high voltage auctions.

Finally, out of 1,886 auctions, green contract law was applied to 798 auctions (42%), out of which 436 auctions (55%) were won by incumbents and 362 auctions (45%) were won by entrants. The proportion of green contract auctions won by entrants is consistent with that of the overall auctions won by entrants (i.e., 45%). This indicates that green contract law may not create an obvious hurdle for entrants to enter auctions.

3 Model

3.1 Theoretical Framework

To analyze how incumbents and PPSs behave in open competitive bidding, we employ a Bayesian approach and investigate the effect of various factors on the winning bid. Our panel data consist of nine regions and six years (2005-2010). Common unobserved variables in a panel data set are *regional effects*, which control for regional differences, and *year effects*, which control for variables that vary through time, such as improvements

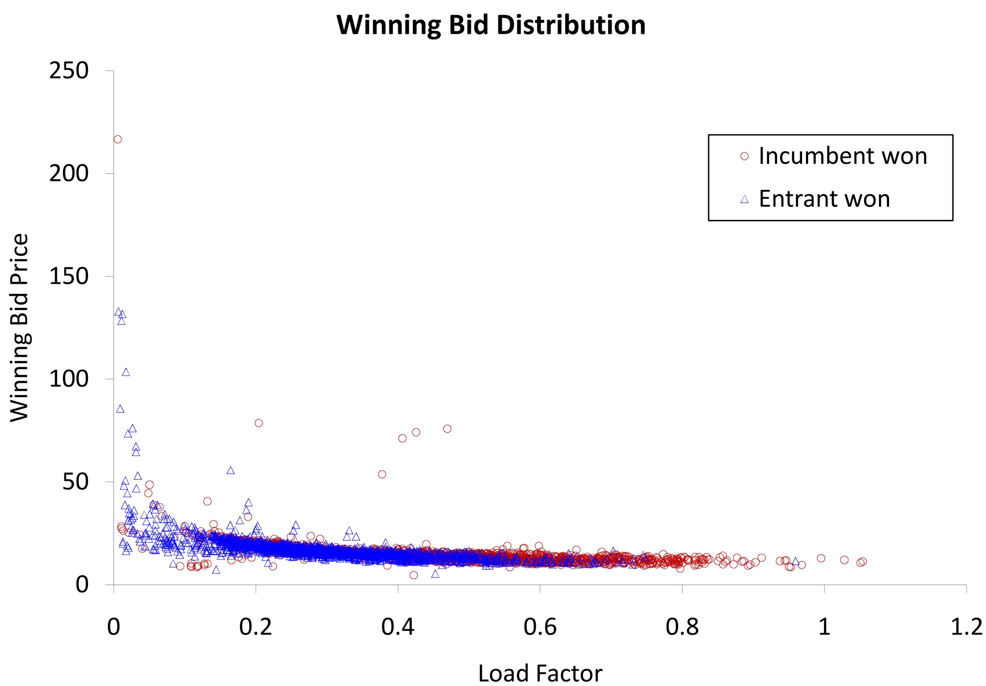

Figure 1: Load Factor and Winning Bid Distribution.

in generating electricity, but do not vary across regions. In auction data, we should also consider *firm effects*, which control for bidder heterogeneity that is not controlled by observable characteristics of bidders. For example, Porter and Zona (1999) and Jofre-Bonet and Pesendorfer (2000) include such firm effects in their models. In order to effectively handle three unobserved effects, we use a Bayesian approach which is superior to other methods in handling unobserved effects.

Unobserved effects are often handled in a fixed effect model or a random effect model. A fixed effect model assumes that unobserved effects are constant, which is a strong assumption as Lancaster (2004) states. Also, if the number of periods is small, a fixed effect model suffers an *incidental parameters problem*. According to Lancaseter (2000), Green (2000) and Clark and Linger (2013), a fixed effect model requires the estimation of a parameter for each unit, i.e., the coefficient on the the unit dummy variable. This increases the standard errors of the coefficient estimates and can substantially reduce a model's power. A random effect model can handle unobserved effects which are assumed to be random. However, applying a random effect model to our data set is challenging because it requires triple integrals for three unobserved effects.

A Bayes estimator can overcome these limitations. Lancaster (2004) suggests the use of normal distribution as a prior because unobserved effects may not be constant but similar to each other in many applied economic contexts. A Bayesian approach can also overcome the technical difficulty in taking triple integrals by using Markov chain Monte Carlo (MCMC).

3.2 Basic Model

To better understand the factors that impact winning bids, we estimate two cases: one when incumbents won auctions and the other when entrants won auctions. For both cases, the dependent variable is the winning bid (*Price*). Also we include nine independent variables. The first and second independent variables are the load factor (*Load*) and its square ($Load^2$). As shown in Figure 1, load factors affect wining bids. We include a quadratic load variable to control for a potentially nonlinear effect of the load factor on the winning bid. The third and fourth independent variables are the contract demand (kW) and the duration of the contract term (*Term*). We expect that the contract demand and duration negatively affect winning bids because firms can enjoy economies of scale. The fifth independent variable is a dummy for extra high voltage (*Voltage*). As mentioned before, entrants (PPSs) have obligation to pay transmission network fees, which are cheaper for extra-high voltage power services. Therefore, this regressor is indispensable to examine the effect of extra-high voltage on winning bids in auction. The sixth independent variable is a dummy for green contract law (*Green*). Green auctions are expected to affect entrants' winning bids because such auctions may require additional costs from entrants. The seventh independent variable is a dummy for who (an incumbent or entrant) wins the auction (*Winner*) to capture who is a strong bidder. The last independent variable is a dummy for the participation of an entrant to an auction (*Participation*). As shown in Table 1, entrants entered only half of the auctions. Some unobservable factors that affect their participation decisions could also influence the winning bids once they enter auctions. Hosoe and Takagi (2012) use Heckman's two-stage estimation to model the link between the participation decision and bid-level decision. However, their model can have large standard errors because the regressors in the first stage equation largely overlap those in the second stage equation due to the limited variety of data items in the data set. In response, the model may have low explanatory power (see Nawata, 1994). Therefore, instead of Heckman's two-stage estimation, we use the variable, *Participation*, to control for entrants' participation decisions and winning bids to proxy for bid-level decisions, given no losing bids are available. The variables are summarized in Table 2.

There are some variables which are commonly used in previous studies but not included in our model. The winning rate is often used in auction papers to control for learning effects. As discussed in Section 2.2, many observations in our original data set lack the information on losing bidders and are excluded from our analysis. This limits our ability to calculate true winning rates, and thus we exclude the winning rate from our analysis. The backlog is also commonly used in previous papers to control for the effects of capacity limits on participation decisions. We do not use backlogs obtained from our auction data to proxy entrants' capacity limits because they also sell electricity in the spot market and through contracts with private companies. Lastly, we don't include the number of bidders, which is another common variable in

Table 2: Description of Variables

Variable	Description	Mean (S.D.)	Mean (S.D.)
ln*Price*	A log of the winning bid real price (yen/kWh)	1.1904 (0.1132)	1.1837 (0.1176)
Load	The load factor	0.3730 (0.1792)	0.3885 (0.1900)
ln*kW*	A log of the contract demand (kW)	2.8775 (0.5656)	2.9552 (0.5469)
ln*Term*	A log of the length (days) of the contract term	2.6101 (0.1406)	2.6050 (0.1390)
Voltage	A dummy variable taking a value of 1 if the contract for voltage is greater than 20,000V, and 0 otherwise	0.2386 (0.4263)	0.2778 (0.4480)
Green	A dummy variable taking a value of 1 if green contract law is applied to the auction, and 0 otherwise	0.4670 (0.4990)	0.4231 (0.4940)
Participation	A dummy variable taking a value of 1 if no entrant participates in the auction, and 0 otherwise	-	0.4761 (0.4995)
Winner	A dummy variable taking a value of 1 if the incumbent wins the auction, and 0 otherwise	-	0.5467 (0.4980)
Number of observations		3,375	1,886

previous studies, in our analysis because bidders do not know who else will participate in the auction.

From the above discussion, we propose three models. First, the basic model is

$$y_i \sim N(\alpha_{j[i]} + \gamma_{t[i]} + \rho_{f[i]} + \mathbf{X}_i\beta, \sigma_y^2) \quad \text{for } i = 1, \cdots, n, \tag{3.1}$$

where

$$\begin{aligned}
&\beta \sim N(0, 10^{12}),\\
&\sigma_y^2 \sim \text{Inverse-Gamma}(10^{-3}, 10^{-3}),\\
&\alpha_{j[i]} \sim N(0, \tau_\alpha^2) \quad \text{for } j = 1, \cdots, J,\\
&\gamma_{t[i]} \sim N(0, \tau_t^2) \quad \text{for } t = 1, \cdots, T,\\
&\rho_{f[i]} \sim N(0, \tau_\rho^2) \quad \text{for } f = 1, \cdots, F,\\
&\tau_\alpha^2 \sim Uniform(0, 10^4),\\
&\tau_t^2 \sim Uniform(0, 10^4),\\
&\tau_\rho^2 \sim Uniform(0, 10^4).
\end{aligned}$$

$\mathbf{X}$ is a matrix of regressors, α is the regional effect, γ is the year effect, and ρ is the firm effect. The priors on β and σ_y^2 are assumed to be non-informative priors because we do not have any prior information. We assume that priors on unobserved effects ($\alpha_{j[i]}$, $\gamma_{t[i]}$ and $\rho_{f[i]}$) are probably similar to each other. Therefore $\alpha_{j[i]}$, $\gamma_{t[i]}$ and $\rho_{f[i]}$ have prior beliefs modeled as normal distributions. On the other hands, we do not have any prior information about their variances (τ_α^2, τ_t^2 and τ_ρ^2). Therefore we are assigning non-informative priors to τ_α^2, τ_t^2 and τ_ρ^2. The link function is

$$\begin{aligned} \ln Price_i &= \beta_0 + \beta_1 Load_i + \beta_2 (Load_i)^2 + \beta_3 \ln kW_i + \beta_4 Voltage_i + \beta_5 Green_i \\ &\quad + \beta_6 \ln Term_i + \beta_7 Winner_i + \beta_8 Participation_i + \alpha_{j[i]} + \gamma_{t[i]} + \rho_{f[i]}, \end{aligned} \tag{3.2}$$

where the variables are explained in Table 2. The log of *Price*, kW and *Term* are taken because we are interested in percentage changes in those variables.

Next, the estimated parameter values for a normal likelihood function could be greatly distorted by outliers that exist in our data (see Figure 1). Therefore, we replace the normal distribution with a t-distribution. From this discussion, the robust model is

$$y_i \sim t(\alpha_{j[i]} + \gamma_{t[i]} + \rho_{f[i]} + \mathbf{X}_i \beta, \sigma_y^2, df) \quad \text{for } i = 1, \cdots, n, \tag{3.3}$$

where

$$\begin{aligned} &\beta \sim N(0, 10^{12}), \\ &\sigma_y^2 \sim \text{Inverse-Gamma}(10^{-3}, 10^{-3}), \\ &\alpha_{j[i]} \sim N(0, \tau_\alpha^2) \quad \text{for } j = 1, \cdots, J, \\ &\gamma_{t[i]} \sim N(0, \tau_t^2) \quad \text{for } t = 1, \cdots, T, \\ &\rho_{f[i]} \sim N(0, \tau_\rho^2) \quad \text{for } f = 1, \cdots, F, \\ &\tau_\alpha^2 \sim Uniform(0, 10^4), \\ &\tau_t^2 \sim Uniform(0, 10^4), \\ &\tau_\rho^2 \sim Uniform(0, 10^4), \\ &udf \sim Uniform(0, 1), \\ &df = 1 - dfGain \times \log(1 - udf). \end{aligned}$$

The t-distribution has three parameters: the mean, the variance, and the degree of freedom. df is used as the degree of freedom parameter in the t likelihood function. According to Kruschke (2011), one way to put a prior on the degree of freedom parameter is to sample a value from a uniform distribution and transform that value into the range allowed for the degree of freedom (from 1 to infinity). *udf* is a uniform distribution to transform a value into the range allowed for the degree of freedom, and *tdfGain* is a constant that expresses the prior belief in large values of the degree of freedom. When *tdfGain* is small, the *df* values are close to one across the entire range of *udf*, which controls for outliers. We set two priors, 1 and 10, on the *tdfGain* to demonstrate that the essential conclusion from the posterior does not change. The link function remains the same as in Eq. (3.2).

Lastly, we investigate whether the result of the random effects model is close to that of the fixed effects model. If they are sufficiently close, it does not matter which model to use, according to Hausman Test. The fixed effects model is a special case of the random effects model in which unobserved effects have uniform priors. Thus, the fixed effects model is given by

$$y_i \sim t(\alpha_j + \gamma_t + \rho_f + \mathbf{X}_i\beta, \sigma_y^2, df) \quad \text{for } i = 1, \cdots, n, \tag{3.4}$$

where

$$\begin{aligned}
&\beta \sim N(0, 10^{12}),\\
&\sigma_y^2 \sim \text{Inverse-Gamma}(10^{-3}, 10^{-3}),\\
&\alpha_j \sim N(0, 10^{-5}) \quad \text{for } j = 1, \cdots, J,\\
&\gamma_t \sim N(0, 10^{-5}) \quad \text{for } t = 1, \cdots, T,\\
&\rho_f \sim N(0, 10^{-5}) \quad \text{for } f = 1, \cdots, F,\\
&udf \sim Uniform(0, 1),\\
&df = 1 - dfGain \times \log(1 - udf).
\end{aligned}$$

4 Empirical Results

4.1 Winning Bid Regression

Table 3 summarizes the regression results of the effects of various factors on the winning bid. Column (1) of Table 3 uses a normal likelihood function to estimate parameter values. Columns (2) and (3) use the t-distribution with the prior belief on *dfGain* of 10 and 1, respectively. In Bayesian inference, the most common method of assessing the goodness of fit of an estimated statistical model is the deviance information criterion (DIC). The DIC in column (1) is -5070. The DIC, however, is smaller in columns (2) and (3). Therefore column (1) is eliminated from further analysis. Next, the estimates in columns (2) and (3) are similar to each other, indicating that essential conclusions in the random effects model are not sensitive to the change in the prior specification. Also, since column (2) has a smaller DIC, column (3) is excluded from further analysis. Finally, the regression in column (4) uses a fixed effects model with the prior belief on *dfGain* of 10. The estimates in column (4) are similar to those reported in column (2), which means that the result in column (2) is not sensitive to the choice between the random and fixed effects models. Hence, we may use the results of column (2).

As expected from Figure 1, the results of the load factor (*Load*, $Load^2$) show that the load factor negatively influences the winning bid: the winning bid is estimated to decrease by 0.896% up to the turning point, *Load*=0.822 (= $0.896/(2 \times 0.545)$), when the load factor increase by 1%. The coefficients of $\ln kW$ and $\ln Term$ are both negative, meaning that the winning bid decreases as the contract amount/period increases. Firms may enjoy economies of scale and offer discounts in large contracts. 1% changes in $\ln kW$ and $\ln Term$ are associated with 1.53% and 1.44% decreases in the winning bid, respectively. The coefficient of *Voltage* is -0.0325, indicating that an auction for an extra-high power service contract pushes down the winning bid by 3.25%. The result is consistent with the structure of the transmission network fees, which are set low for extra-high voltage transmission. The coefficient of *Green* is in the ninety five percent highest density interval (HDI) going from -0.003 to 0.011 (i.e., HDI contains 0). This result means that green contract law is not likely to influence the winning bid. Also, the coefficient of *Winner* is in the ninety five percent HDI going from -0.01 to 0.02, indicating that who wins the auction is not likely to influence the winning bid.

From the regression using the auction data from 2005 and 2010, we could not find significant effects of *Winner* and *Green* on the winning bid. Since we are interested in the difference in the bidding patterns between incumbents and entrants, which is captured by *Winner*, and the impact of green contract law, which is explained by *Green*, we focus our analysis on these two variables and conduct more detailed regressions in the next two sections.

4.2 Winning Bid Regression with Load Factor Segmentation

This section explores the difference in the bidding patterns between incumbents and entrants by focusing on the load factor and the types of voltage (high or extra-high). As shown in Figure 1, the load factor negatively affects the winning bid, and we confirmed this in the regression in Section 4.1. Figure 1 also indicates that the winning bid distributions are not identical between incumbents and entrants. More specifically, Figure 2 shows that entrants won more auctions with low load factors, whereas incumbents won more auctions

Table 3: Winning Bid Regression

Dependent variable: ln*Price*

Regressor	(1)	(2)	(3)	(4)
Load	-1.15	-0.896	-0.894	-0.896
	(-1.200, -1.090)	(-0.935, -0.856)	(-0.934, -0.856)	(-0.935, -0.857)
$Load^2$	0.8	0.545	0.543	0.545
	(0.739, 0.865)	(0.503, 0.588)	(0.502, 0.585)	(0.504, 0.586)
ln*kW*	-0.0101	-0.0153	-0.0152	-0.0153
	(-0.018, -0.003)	(-0.020, -0.001)	(-0.019, -0.011)	(-0.020, -0.011)
ln*Term*	0.000018	-0.0144	-0.0127	-0.0148
	(-0.021, 0.021)	(-0.023, -0.005)	(-0.023, -0.033)	(-0.024, -0.005)
Voltage	-0.0391	-0.0325	-0.0326	-0.0326
	(-0.048, -0.030)	(-0.037, -0.028)	(-0.037, -0.028)	(-0.037, -0.028)
Green	0.00408	0.000592	0.000635	0.000839
	(-0.003, 0.011)	(-0.003, 0.004)	(-0.003, 0.004)	(-0.002, 0.004)
Participation	0.00255	0.007	0.00708	0.00694
	(-0.009, 0.014)	(0.002, 0.012)	(0.002, 0.012)	(0.002, 0.012)
Winner	0.00825	0.00556	0.00554	0.000924
	(-0.017, 0.031)	(-0.010, 0.020)	(-0.009, 0.020)	(-0.025, 0.026)
Constant	1.5	1.5	1.49	1.45
	(1.44, 1.56)	(1.46, 1.53)	(1.40, 1.54)	(1.34, 1.66)
Regional effects	Yes	Yes	Yes	Yes
Year effects	Yes	Yes	Yes	Yes
Firm effects	Yes	Yes	Yes	Yes
Number of observations	1886	1886	1886	1886
Prior belief of *dfGain*	-	10	1	10
Deviance information criterion (DIC)	-5070	-6784	-6779	-6781

These regressions are estimated from the data from 2005 to 2010. The 5th and 95th percentiles of the Gibbs samples are given in parentheses under the coefficients. The burn-in period is 500. The thinning-interval is 3. The number of chains to run is 3 times. 50001 points are in final MCMC sample. Every values of coefficients of the Gelman-Rubin convergence diagnostic are below 1.2.

with high load factors. This indicates that the bidding patterns of incumbents and entrants are different for different load factors: in auctions with low load factors ($\sim 30\%$), entrants won majority (68%) of the auctions ; in auctions with moderate load factors ($30\% \sim 45\%$), incumbents and entrants evenly won auctions; and in auctions with high load factors ($45\% \sim$), incumbents were dominant and won 81% of the auctions (see Table 4). Given these analysis, we next run regression for each of these three load factor subgroups.

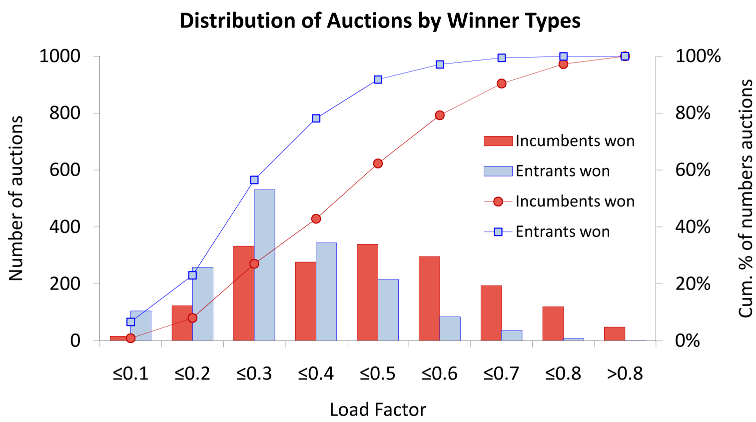

Figure 2: Winning Bid Distribution by Winner Types.

Table 4: Number of Auctions with Load Factor Segmentation

Winner	Load factor < 30%	30% ≤ Load factor < 45%	45% ≤ Load factor	Total
Entrant	480 (68%)	249(49%)	126 (19%)	855
Incumbent	228 (32%)	256 (51%)	547 (81%)	1031
Total	708	505	673	1886

When we run regression, we include the interaction term of *Winner* and *Voltage*, denoted as *Winner·Voltage*. The regression result in Section 4.1 shows that the winning bid is 3.25% lower for extra-high voltage power service than high voltage power service. This is due to the high transmission network fee associated with high voltage service. Since transmission network fees are imposed only on entrants, we expect that the types of voltage (high/extra-high) disproportionately affect the entrants' winning bids. Hence, we introduce the interaction term into the regression. Also, the square term $Load^2$ is excluded from the model. In Section 4.1, the model had the square term because load factors appear to nonlinearly affect the winning bid. Since now we divide the data into three subgroups based on the load factor, we expect the relationship between the load factor and winning bid to be linear within each subgroup. Therefore the square term is excluded from the regression. Table 5 shows the regression results.

Table 5: Winning Bid Regression with Load Factor Segmentation

Dependent variable: $\ln Price$

Regressor	Load factor < 30	$30 \leq$Load Factor< 45	$45 \leq$Load Factor
Load	-0.859	-0.422	-0.218
	(-0.911, -0.804)	(-0.473, -0.366)	(-0.238, -0.198)
$\ln kW$	-0.00852	-0.00599	-0.0264
	(-0.015, -0.002)	(-0.013, -0.001)	(-0.033, -0.020)
$\ln Term$	0.00392	-0.0191	-0.0163
	(-0.014, 0.024)	(-0.037, 0.001)	(-0.030, -0.004)
Voltage	-0.057	-0.0496	-0.0198
	(-0.069, -0.046)	(-0.058, -0.041)	(-0.031, -0.009)
Winner·Voltage	0.0419	0.0189	-0.00183
	(0.010, 0.073)	(0.007, 0.031)	(-0.014, 0.010)
Green	-0.00284	0.00379	0.00175
	(-0.009, 0.003)	(-0.001, 0.009)	(-0.003, 0.007)
Participation	0.0102	0.00863	0.00784
	(-0.003, 0.024)	(0.000, 0.017)	(0.001, 0.015)
Winner	-0.00231	0.00134	0.0042
	(-0.031, 0.025)	(-0.018, 0.019)	(-0.021, 0.031)
Constant	1.47	1.39	1.33
	(1.41, 1.52)	(1.33, 1.46)	(1.28, 1.39)
Regional effects	Yes	Yes	Yes
Year effects	Yes	Yes	Yes
Firm effects	Yes	Yes	Yes
Number of observations	708	505	673
Prior belief of *dfGain*	10	10	10

These regressions are estimated from the data from 2005 to 2010. The 5th and 95th percentiles of the Gibbs samples are given in parentheses under the coefficients. The burn-in period is 500. The thinning-interval is 3. The number of chains to run is 3 times. 50001 points are in final MCMC sample. Every values of coefficients of the Gelman-Rubin convergence diagnostic are below 1.2.

In what follows, we focus our discussion on the results of *Voltage*, *Winner*, and *Winner·Voltage* for load factors less than 30% in Table 5. The analysis can be easily expanded to the other two subgroups. The base case is *Winner*=*Voltage*=0, i.e., an entrant wins an auction for high voltage power service. The coefficient of *Winner* is in the ninety five percent HDI going from -0.031 to 0.025, meaning that the winning bid is not likely to be affected by the winner type (incumbent/entrant). Therefore we could conclude that incumbents and entrants are equally efficient in bidding in high voltage auctions. Next, the coefficient of *Voltage* is -0.057 and is statistically significant. This means that when an entrant wins an auction for extra-high voltage power service, the winning bid decreases by 5.7% compared to the base case. On the other hand, the coefficient of *Winner·Voltage* is 0.0419. Along with the coefficients of *Winner* and *Voltage*, the result implies that when an incumbent wins an auction for extra-high voltage power service (i.e., *Winner*=*Voltage*=1), the winning bid decreases by 1.51% (=4.19 + 0 − 5.7) compared to the base case. Since the winning bid is lower when an entrant wins an auction than an incumbent does, we could conclude that entrants have cost advantage in extra-high voltage power service. In other words, entrants are likely to be the strong bidder in extra-high voltage auctions.

Table 6 summarizes the results in all three subcategories. It shows the differences in the winning bids in various types of auctions, expressed as the percent changes compared to the base case. In auctions for high voltage power service, there is no difference in the winning bids regardless of who wins the auction. This implies that there is no difference in the costs between incumbents and entrants if high voltage power service is involved. On the other hand, in auctions for extra-high voltage power service, the winning bid is lower when an entrant wins the auction. Furthermore, the lower the load factor, the bigger is the difference in the winning bids between incumbents and entrants. The difference disappears when a load factor exceeds 45%. From these results, we may conclude that entrants' costs are cheaper than incumbents' costs in extra-high voltage power service, but the cost advantage diminishes as the load factor increases.

Table 6: Percent Change in Winning Bid Compared to the Base Case

Voltage	Winner	Load factor < 30	$30 \leq$Load Factor< 45	$45 \leq$Load Factor
High	Entrant (Base Case)	-	-	-
	Incumbent	0	0	0
Extra-high	Entrant	-5.7%	-4.96%	-1.98%
	Incumbent	-1.51%	-3.07%	-1.98%

4.3 Effects of Green Contract Law

In this section, we investigate the impact of green contract law on the winning bid by limiting our analysis to *entrants*. The regression result in Section 4.1 shows that it is quite likely that green contract law did not influence the winning bids in the auctions held between 2005 and 2010. There are two potential reasons for this insignificant result. First, when green contract law was enacted in 2007, firms made investments to reduce CO_2 emissions and meet the environmental quality threshold. Since these investments are often one-time costs, the impact of green contract law on the winning bids may have faded away over time. Second, green contract law disproportionately impacts entrants because unlike incumbents, entrants have no low-carbon nuclear power plants and often heavily rely on fossil fuels. Therefore, green contract law puts a heavier burden on entrants, which, however, may not be detectable when incumbents and entrants are analyzed all together. In order to address the two possible causes of the previous insignificant results regarding green contract law, we eliminate the auctions won by incumbents, who are little affected by the law. Also, in order to see whether the impact of green contract law changed over time, we run regressions for the auctions held between 2005 and 2007 and the auctions held in 2010. Green contract was enacted in 2007, but some public entities, such as the Ministry of the Environment, started applying the law to their auctions before 2007. Therefore, the former group (2005-2007) includes the early green auctions. The latter (2010), on the other hand, contains the latest green auctions in our data set.

The results are summarized in Table 7. The result for the auctions held between 2005 and 2007 shows that the coefficient of *Green* is 0.0101 and statistically significant. That is, the winning bid increases by 1.01% if green contract law is applied. This indicates that the winning bids in early green auctions were indeed affected by the law. On the other hand, the result for the auctions in 2010 shows that the coefficient of *Green* is in the ninety five percent HDI going from -0.009 to 0.010 (i.e., HDI contains 0). This implies that several years after its enactment, green contract law no longer influences the winning bids in green auctions. Therefore, we may conclude that the impact of green contract law on the winning bids faded away over time.

5 Conclusion

The introduction of competition has failed to reduce electricity prices in Japan, and this may be due to asymmetric costs among electricity suppliers. We examine whether these asymmetries exist and what is causing them, using auction data. Given the very limited market share of the entrants (2.1%), we expected to find incumbents' cost advantage over entrants. Surprisingly, however, entrants do possess a competitive advantage in many cases despite some compliance costs that disproportionately hit entrants. In particular, we find that the environmental policy has only a temporal impact on entrants' costs. This is an encouraging result for the ongoing energy reform in Japan. As a technical contribution, we use a Bayesian analysis to include three unobserved effects, which are otherwise difficult to include due to triple integrals required in the analysis. Also, our estimation method is robust because a Bysesain analysis can handle outliers using t-distribution which is robust against outliers. The main findings of this paper are summarized below.

First, if it were not for transmission network fees, entrants could be more cost efficient than incumbents in all types of auctions. A transmission network fee is more than twice as expensive for high voltage power service than extra-high voltage power service. This inevitably increases entrants' costs of high voltage power service. Nevertheless, our result shows that there is no difference in the winning bids between entrants and incumbents in high-voltage power service, implying that entrants' costs are comparable to incumbents'

Table 7: Entrant Winning Bid Regression: 2005-2007 and 2010

Dependent variable: $\ln Price$

Regressor	2005-2007	2010
Load	-1.1	-0.902
	(-1.200, -1.00)	(-1.050, -0.758)
$Load^2$	0.842	0.762
	(0.716, 0.971)	(0.570, 0.957)
$\ln kW$	-0.0419	-0.0128
	(-0.053, -0.031)	(-0.026, 0.001)
$\ln Term$	0.0113	-0.0462
	(-0.026, 0.060)	(-0.092, 0.020)
Voltage	-0.0366	-0.0459
	(-0.046, -0.027)	(-0.061, -0.031)
Green	0.0101	0.000841
	(0.003, 0.017)	(-0.009, 0.010)
Constant	1.55	1.57
	(1.4, 1.65)	(1.42, 1.74)
Regional effects	Yes	Yes
Year effects	No	No
Firm effects	Yes	Yes
Number of observations	311	201
Prior belief of $dfGain$	10	10

These regressions are estimated from the data from 2005 to 2010. The 5th and 95th percentiles of the Gibbs samples are given in parentheses under the coefficients. The burn-in period is 500. The thinning-interval is 3. The number of chains to run is 3 times. 50001 points are in final MCMC sample. Every values of coefficients of the Gelman-Rubin convergence diagnostic are below 1.2.

costs. In addition, we find that entrants have cost advantage over incumbents if extra-high voltage power service is considered. These results together indicate that in some circumstances entrants possess competitive advantage over incumbents, which, however, is lessened by transmission network fees.

Second, imbalance fees reduce entrants' ability to outperform incumbents, especially in auctions for contracts with high load factors. Imbalance fees are the expensive penalties for creating supply shortages. Since balancing electricity supply and demand is challenging for entrants who do not have flexible generating capacities (e.g., gas and hydro power plants), imbalance fees drive up their costs significantly. Also, our result shows that imbalance fees become relatively more expensive as the load factor increases because electricity price is negatively correlated to the load factor. Accordingly, the entrants' cost advantage over the incumbents in extra-high voltage power service diminishes as the load factor increases.

Finally, compliance with green contract law initially increased entrants' costs but does not create a longlasting hindrance for their entry to market. There is a general concern that an environmental policy may obstruct entry of new firms into a market because per unit compliance costs are larger at smaller firms. Indeed, green contract law disproportionately hits entrants, who have no low-carbon nuclear power plant and often heavily rely on fossil fuels. However, our result shows that green contract law increased entrants' winning bids slightly when it was enacted in 2007 and that the effect disappeared in 2010. That is, green contract law requires initial investments from entrants, but they can absorb the costs over time. It is even less likely that entrants suffer disproportionately from green contract law in the last few years, since incumbents have not been able to use nuclear power plants in the aftermath of the Fukushima nuclear crisis. How the suspension of nuclear power plants and increasing dependency on fossil fuels have changed incumbents' bids in electricity procurement auctions remains as future research.

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