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Abstract

This paper investigates how an environmental policy disproportionately hit smaller companies by analyzing the impact of green contract law on new entrant electricity retailers in Japanese electric power procurement auctions. The endogenous switching regression model is employed to account for selection bias. The results show that green contract law lowers entrant participation in the auction by 9.9% and increases the winning bid by 1.2% once entrants enter the auction. On the other hand, the effect of green contract law on the winning bid is not statistically significant if only incumbents participate in the auction. Various other factors are also analyzed to explore the causes of the limited competition in Japanese retail electricity market.

Keywords: Green Contract Law, Procurement Auction, Endogenous Switching Regression Model.

JEL classification codes: C34, L51, Q48, Q58

I. Introduction

For nearly twenty years, the electricity sector in Japan has been undergoing reforms aiming at securing stable supplies of electricity, expanding competitive retail energy options, and suppressing electricity prices by increasing market competition. Historically, Japan was divided into ten regions and each region has been exclusively served by a single electric utility. In 1995, the wholesale market was first opened to independent power producers (IPPs). Then, the deregulation of the retail market started in 1999, and new entrants, called power producer and suppliers (PPSs), were allowed to enter the market. PPSs supply electricity to customers through their own generation facilities and the transmission networks owned by electric utilities. In 1999, the deregulation was limited to large-scale customers contracted for 2000 kW or more of extra-high voltage power. In 2003, it was expanded to middle-scale customers contracted for 500 kW or more of high voltage power, and then to 50 kW or more in 2005. With the deregulation of retail electricity market, public entities have gradually adopted electric power procurement auctions since 2006.

Despite more than a decade of electricity reforms, however, Japan has not achieved its intended goals. The market competition is still limited: new entrants (PPSs) represented only 0.71% of the total capacity in 2010 and 2.1% of electricity retail in 2012 (Ministry of Economy, Trade and Industry, 2012a, Agency for Natural Resources and Energy, 2013b). Also, electricity prices remain expensive. In 2011, the electricity price for industry (household) was 17.9¢/kWh (26.1¢/kWh) in Japan, which was 41% (24%) and 156% (121%) higher than those in the UK and the USA, respectively (Agency for Natural Resources and Energy, 2013a). The monopoly by vertically integrated electric utilities has been blamed for the high electricity prices. Thus how to increase the participation of new entrants has become a key in the electricity reforms.

While bringing more entrants into the market is desirable to increase competition, it may bring in a new environmental issue. Japan ratified the Kyoto Protocol on global warming in 2002 and agreed to reduce its carbon emissions during the Protocol's first period (2008-2012) by 6% compared to its1990 emission level. While electric utilities own many power plants operated by a balanced mix of oil, coal, natural gas, hydropower and nuclear power, entrants sometimes heavily rely on fossil fuels to generate electricity. Consequently, the Japanese government enacted what is known as green contract law in 2007. Green contract law is an environmental quality threshold regarding CO_2 emission factors. A supplier may have to invest extra money in meeting the threshold to make a contract with a public entity if green contract law is applied. There is also a comprehensive movement toward the green energy revolution after Japan's earthquake and tsunami in 2011. The Japanese government approved the revitalization strategy to solve issues confronting the country after the disaster. One of the major projects for revitalization is called "Green," which is designed to realize innovative energy and ecological environment. In the wake of the Fukushima Daiichi nuclear crisis after the earthquake, Japanese electricity prices have been on the rise in recent years as a result of increasing reliance on fossil fuels. A rise in oil prices can push up Japanese electricity prices even more. Hence, the Japanese government is working to strengthen the renewable energy field in order to reduce dependence on nuclear power and foreign oil. Under these circumstances, entrants are gradually shifting to renewable energy.

Given the growing interest in PPSs in the midst of Japan's electricity reforms, this paper explores the effects of environmental policies on entrants. Specifically, we investigate electric power procurement auctions in the public sector and examine the following points: (1) whether green contract law lowers entrants' participation in auctions; and (2) whether green contract law raises the entrants' winning bids. On one hand, the government encourages more entrants to enter the market to suppress electricity prices by increasing competition. On the other hand, entrants' participation in the electricity market is controlled by green contract law in response to the Kyoto Protocol. In the same sense that environmental policies may stunt economic growth in developing countries, environmental policies may affect small companies the most. For example, Heyes (2009) points out that an environmental policy tends to hit small firms more severely 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, entrants often heavily rely on fossil fuels and may need to invest additional money in curbing CO_2 emissions. Therefore, we expect that entrants are disproportionately affected by green contract law, which may lower entrants' participation and push up their bids in electric power procurement auctions. If this is the case, some measures need to be taken to support the market entry of new entrants, who are expected to play an important role to invigorate the renewable energy industry, to achieve the two conflicting goals, lowering electricity prices and increasing green compliance.

In addition to the impact of green contract law on entrants, we also consider two other possible barriers for entrants. One is a transmission network fee only applicable to entrants. Since transmission networks are operated by electric utilities, entrants must pay the fees to electric utilities to supply electricity for customers. The average fee is 2.03 yen/kWh[1] for extra-high voltage and 4.15 yen/kWh for high voltage (Ministry of Economy, Trade and Industry, 2012b). The other is an imbalance fee imposed on entrants as a penalty for a supply shortage. In order to prevent a blackout, entrants are required to adjust the balance between electricity supply and demand to a tolerance of three percent every thirty minutes. If an entrant fails, an electric

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

utility steps in to fix the imbalance. If the shortage exceeds 3%, the entrant must pay 51.73 yen/kWh in summer and 45.73 yen/kWh in other seasons[2]. Under these circumstances, entrants have focused on particular auctions where they can make profits.

Several studies investigate the effect of Japanese electric power auctions on electricity prices. To our knowledge, Hattori and Saegusa (2010) is the only study which examines the effects of green contract law on entrants. Using the ordinary least squares (OLS) regression, they show that green contract law lowers the number of bidders by 32% and increases the winning bid by 3.1%. One limitation of Hattori and Saegusa (2010) is that although they show the impacts of green contract law on all bidders, they do not examine whether the law disproportionately affects entrants. Another limitation is that they do not take selection bias into consideration. However, some unobservable factors which affect entrants' participation decisions could also influence the winning bids once they enter auctions. Therefore, we employ the endogenous switching regression model to consider selection bias. Hosoe and Takagi (2012) also use the endogenous switching regression model, though they do not include green contract law in their model. They show that electric power procurement auctions drove down electricity prices by 0.48 yen/kWh on average. Hattori (2010) examines the determinants of the number of bidders and concludes that entrants are willing to bid for extra-high voltage contracts but refrain from bidding for contracts with high load factors. Green contract, however, is not considered in the analysis.

The remainder of this paper is organized as follows: we explain the Japanese electric power procurement auctions in section 2; section 3 describes our data set; section 4 provides an

[2] 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.

explanation of the model; Section 5 discusses the regression results; and finally section 6 provides some concluding remarks.

II. Japanese Electric Power Procurement Auctions

A. Auction mechanism

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, after the deregulation of the electricity retail market. In Japanese electric power procurement auctions, a public agency, who acts as an auction organizer, notifies entrants (PPSs) of an upcoming auction through its website and newspapers. The information includes the contract demand, the projected amount of consumption, the delivery period, and the place of delivery. After the announcement, entrants need to register for the auction several weeks before it takes place, but they can withdraw from the auction later. 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 seller 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.

B. Green contract law

There has been a concern that carbon emissions may increase as more entrants enter the market because many entrants have only thermal power stations and rely heavily on fossil fuels to generate electricity. On the other hand, electric utilities, denoted as *incumbents*, have mixed generation portfolios, including low-carbon nuclear power, and can reduce carbon emissions from electricity generation more than entrants can. In response to this concern and the compliance with the Kyoto Protocol, the Japanese government enacted green contract law in 2007, which is an environmental quality threshold regarding CO_2 emission factors. **Table 1** presents an example scoring system for the threshold. If a supplier gets a grade of more than 70 on this scoring system, this company can participate in the auction. If a supplier's score is below 70, the government excludes it from the auction. The application of green contract law is left to the discretion of public agencies.

Table 1: Example of Scoring System for Environmental Quality Threshold (Kanto Area)

Element	Range	Point
CO2 Emission Factor during the Last Year ($kg\text{-}CO^2/kWh$)	Less than 0.350	70
	0.350 to 0.375	65
	0.375 to 0.400	60
	0.400 to 0.425	55
	0.425 to 0.450	50
	0.475 to 0.500	45
	0.500 to 0.525	35
	0.525 to 0.550	30
	0.550 to 0.575	25
	Greater than 0.575	20
Utilization of Unused Energy as a Percentage of its Supply during the Last Year	Greater than 1.35%	15
	0.675% to 1.35%	10
	Up to 0.675%	5
	None	0
Introduction of Renewable Energy during the Last Year	Greater than 1.50%	15
	0.75% to 1.50%	10
	Up to 0.75%	5
	None	0
Planned Transfer of Green Certificates as a Percentage of Consumption	5.0%	10
	2.5%	5
	None	0
Providing customers with energy saving tips	Yes	5
	No	0

Source: Ministry of the Environment.

III. Auction Data

Our data set consists of Japanese electric power procurement auctions from 2005 to 2010 taken from the 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, so this shows the anticipated consistency of demand. The winning bids are converted to real values, using regional consumer price indices obtained from Statistics Japan (2014). Also, the West Texas intermediate (WTI) monthly prices are obtained from Union Pacific (2014) and converted to real Japanese yen using the exchange rates from U.S. dollar to Japanese yen and regional consumer price indices (Forex Forum Global-View, 2014, 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. In our analysis, information on losing bidders is critical to identifying whether any entrants participated in the auction. Hence, we limit our analysis to the 1,886 auctions with the complete information on losing bidders. **Table 2** describes the variables of interest in our data set. It also reports the sample means and standard deviations of any observable variables in the original data set (3375 observations) and the one used in our analysis (1886 observations). Comparing two population means, we confirm that there is no statistically significant difference between the two data sets, indicating no sampling bias in our data set.

Table 2: Description of Variables

Variables	Description	Mean (S.D.) No. of Obs. 3375	Mean (S.D.) No. of Obs. 1886
Entrant	The dummy variable taking a value of 1 if entrants participate in the auction, and 0 if not.	-	0.529 (0.499)
Price	The winning bid real price (yen/kWh) in the auction	16.088 (7.365)	16.024 (8.136)
Green	The dummy variable taking a value of 1 if the green contract law is applied to the auction, and 0 if not.	0.467 (0.499)	0.423 (0.494)
ln*kW*	Log of the contract demand (kW)	2.877 (0.566)	2.955 (0.547)
ln*Term*	Log of the length (days) of the contract term	2610 (0.141)	2.605 (0.139)
Load	The load factor*	0.373 (0.179)	0.386 (0.190)
Voltage	The dummy variable taking a value of 1 if the contract for voltage is greater than 20,000V, and 0 if not.	0.239 (0.426)	0.278 (0.448)
ln*WTI*	Log of the West Texas intermediate monthly real price (yen/barrel)	-	3.859 (0.132)
Number	The number of bidders participating in the auction	-	1.996 (1.199)

The total number of observations is 1886.

*The load factor is the ratio between the average and maximum usage of electricity during the contract term. It is calculated as the required amount per year divided by the required capacity:

$$\frac{\text{Amount of electricity to be supplied (kWh/year)}}{\text{Maximum power (kW)}\times 24\text{ (hours)}\times 365\text{ (days)}}.$$

Figure 1 shows the trend in green auctions. The proportion of green auctions has been between 44% and 61% since the enactment of green contract law in 2007. The winning rate of the entrants in non-green auctions remains around 40% to 60%. On the other hand, their winning rate in green auctions is more variable: it was lower than that in non-green auctions in 2007 and 2008, but higher in 2009 and 2010. Hence, it is not clear from the winning rates whether green contract law has affected entrants' performance in electric power procurement auctions. A selection bias can be one possible reason for this inconsistency. Out of the 1886 auctions, 1031auctions were won by nine incumbents and the remaining 855 auctions were won by twelve entrants (**Table 3**). 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. In our data set, there were 889 auctions with no entrants, i.e., auctions with only an incumbent. The remaining 997 auctions had an incumbent and one or more entrants. Once entering auctions, entrants notably outperform incumbents: entrants won 855 out of 889 auctions with a winning rate of 86%. Also, **Figure 2** shows that winning bids seem to be negatively correlated to load factors and that entrants tend to target auctions with low load factors. Unlike electric utilities, entrants do not have base load power plants, such as nuclear and coal-fired power plants, which 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. Under this situation, entrants seem to only participate in likely lucrative auctions with high probabilities of winning. In other words, entrants' decisions as to which auctions are worth to participation seems to be affected by selection bias, which may disguise entrants' true winning rates in (non-)green auctions. Therefore, we employ endogenous switching regression models to allow for the possible selection bias.

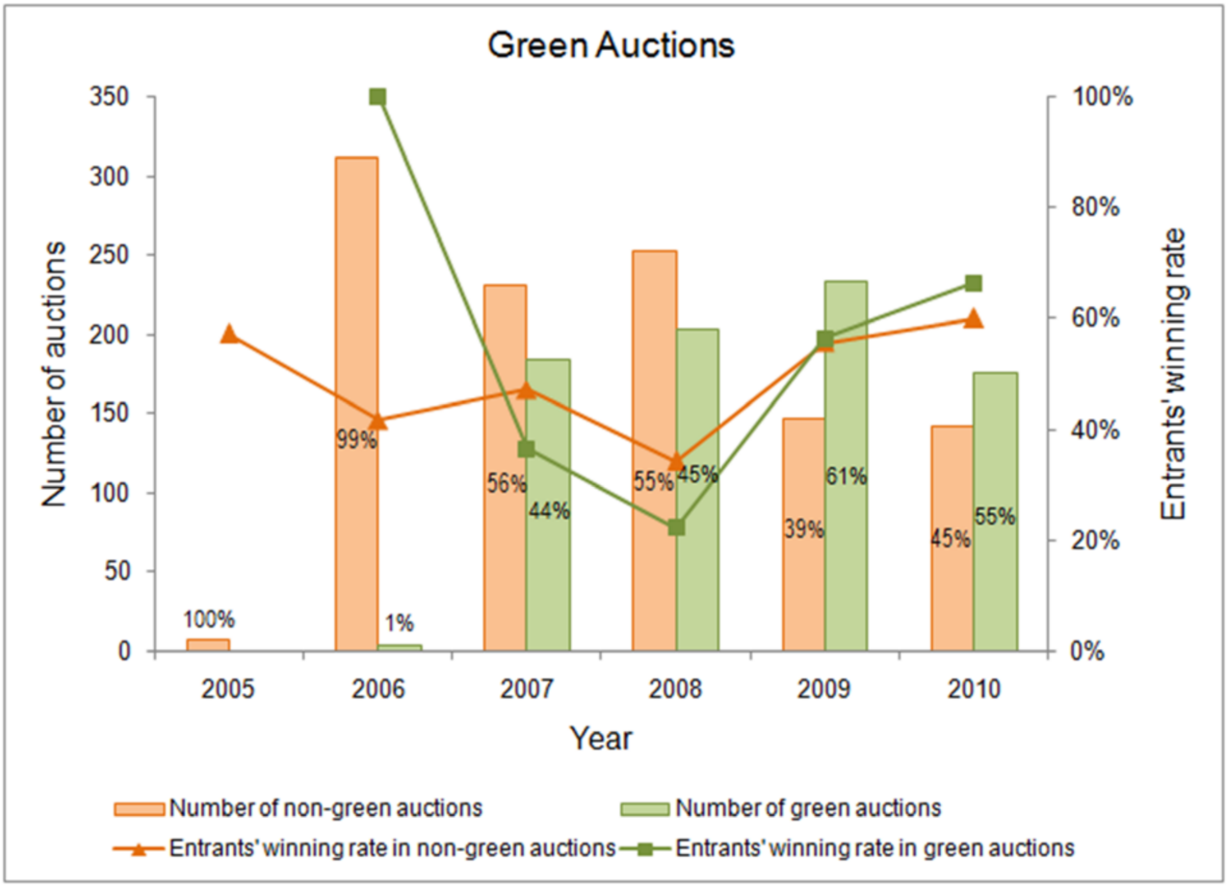

Figure 1: Trends of Green Auction and Entrants' Winning Rate

Table 3: Auction Data

	Auctions Won by Incumbents	Auctions Won by Entrants	Total
Auctions without entrants	889 (100%)	-	889
Auctions with entrant	142(14%)	855(86%)	997
Total	1031 (55%)	855 (45%)	1886

Winning rates are in the parenthesis.

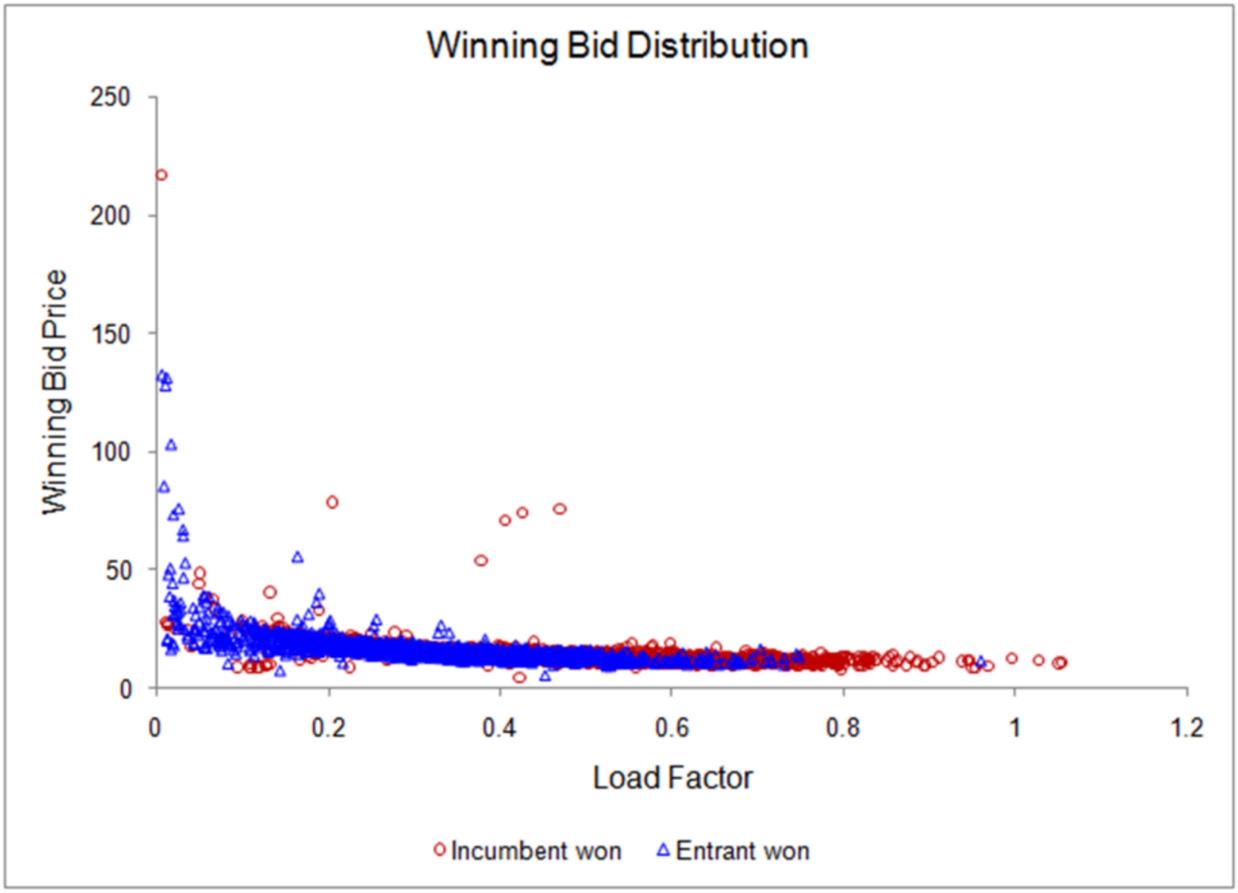

Figure 2: Winning Bid Distribution

IV. Model

A. Theoretical framework

The endogenous switching regression model is employed to analyze the effect of green contract law on entrants as well as the effects of various other factors on the entrants' decision to participate in the auction and the winning bids (for the endogenous switching regression model, see, for example, Maddala, 1983, and Lokshin and Sajaia, 2004). In Japanese electric power procurement auctions, incumbents participate in almost all auctions held in their service territories[3]. On the other hand, entrants enter an auction only if the auction is expected to be profitable. Therefore, entrants' bids are endogenous to their decisions to participate in the auction. In other words, some unobservable factors that affect entrants' decisions on whether or not to participate in the auction could also influence the winning bid once they enter the auction. Neglecting this effect is likely to give a false picture of the differences in the winning bids between the auctions with and without entrants. These reasons warrant estimating distinct regressions, instead of a single regression, for the two auction groups.

The first step in the endogenous switching regression model is to determine the factors influencing entrants' decisions to participate in the auction based on a probit function. A selection equation is specified as

$$D_i = 0 \ \text{ if } \boldsymbol{\gamma}\mathbf{Z}_i + v_i < 0, \qquad (1)$$

$$D_i = 1 \ \text{ if } \boldsymbol{\gamma}\mathbf{Z}_i + v_i \geq 0, \qquad (2)$$

where D_i is a latent variable that expresses entrants' participation in auction i. That is, this dummy variable takes a value of one if entrants bid for the electricity contract and a value of zero if they do not. $\mathbf{Z}_i$ is a vector of characteristics that influence entrants' decisions to participate in the auction, $\boldsymbol{\gamma}$ is a vector of parameters, and v_i is the error term.

The second step in the endogenous switching regression model is to define outcome equations which separate the winning bids of the auctions with entrants and those without entrants. Outcome equations are expressed as

$$\text{Regime 1:} \quad Y_{0i} = \alpha_0 + \boldsymbol{\beta}_0\mathbf{X}_{0i} + u_{0i} \quad \text{if } D_i = 0 \text{ (auctions without entrants)}, \qquad (3)$$

$$\text{Regime 2:} \quad Y_{1i} = \alpha_1 + \boldsymbol{\beta}_1\mathbf{X}_{1i} + u_{1i} \quad \text{if } D_i = 1 \text{ (auctions with entrants)}, \qquad (4)$$

[3] Incumbents participated in all but 10 of the 1886 auctions in our data set.

where $\mathbf{X}_{0i}$ and $\mathbf{X}_{1i}$ are the vectors of characteristics affecting the winning bids Y_{0i} and Y_{1i}, respectively, $\boldsymbol{\beta}_0$ and $\boldsymbol{\beta}_1$ are the vectors of parameters, and u_{0i} and u_{1i} are the error terms. Also, u_{0i}, u_{1i} and v_i have a trivariate normal distribution, with mean vector zero and a covariance matrix

$$\varphi = \begin{bmatrix} \sigma_v^2 & \sigma_{0v} & \sigma_{1v} \\ \sigma_{0v} & \sigma_0^2 & \sigma_{01} \\ \sigma_{1v} & \sigma_{01} & \sigma_1^2 \end{bmatrix}, \tag{5}$$

where σ_v^2 is a variance of the error term in the selection equations (1)-(2), σ_0^2 and σ_1^2 are the variances of the error terms in outcome equations (3)-(4), σ_{0v} is a covariance of v_i and u_{0i}, and σ_{1v} is a covariance of v_i and u_{1i}. We assume σ_v^2 =1.

Since we cannot observe Y_{0i} if $D_i = 1$ and Y_{1i} if $D_i = 0$, we need to write these outcomes in a selection equation format. Taking expectations of the outcome equations[4], we can find the expected winning bid prices for the auctions without entrants as

$$\begin{aligned} E(Y_{0i}|D_i = 0) &= E(Y_{0i}|\boldsymbol{\gamma}\mathbf{Z}_i + v_i < 0) = E(Y_{0i}|v_i < -\boldsymbol{\gamma}\mathbf{Z}_i) \\ &= \alpha_0 + \boldsymbol{\beta}_0\mathbf{X}_{0i} + E(u_{0i}|v_i > \boldsymbol{\gamma}\mathbf{Z}_i) \\ &= \alpha_0 + \boldsymbol{\beta}_0\mathbf{X}_{0i} - \sigma_{0v}\left[\frac{\phi(\boldsymbol{\gamma}\mathbf{Z}_i)}{1-\Phi(\boldsymbol{\gamma}\mathbf{Z}_i)}\right], \end{aligned} \tag{6}$$

where $\Phi(\cdot)$ and $\phi(\cdot)$ are the cumulative distribution function and probability density function of the standard normal distribution, respectively. Similarly, the expected winning bid for the auctions with entrants is

$$\begin{aligned} E(Y_{1i}|D_i = 1) &= E(Y_{1i}|\boldsymbol{\gamma}\mathbf{Z}_i + v_i \geq 0) = E(Y_1|v_i \geq -\boldsymbol{\gamma}\mathbf{Z}_i) \\ &= \alpha_1 + \boldsymbol{\beta}_1\mathbf{X}_{1i} + E(u_{1i}|v_i \leq \boldsymbol{\gamma}\mathbf{Z}_i) \\ &= \alpha_1 + \boldsymbol{\beta}_1\mathbf{X}_{1i} + \sigma_{1v}\left[\frac{\phi(\boldsymbol{\gamma}\mathbf{Z}_i)}{\Phi(\boldsymbol{\gamma}\mathbf{Z}_i)}\right]. \end{aligned} \tag{7}$$

[4] To derive $E(y|x)$, we need the following fact about the normal distribution: if $z \sim Normal(0,1)$, then , for any constant c, $E(z|z > c) = \frac{\phi(c)}{1-\Phi(c)}$.

The system consisting of equations (1)-(7) is called an endogenous switching model. To solve this endogenous switching model, we substitute the first stage probit model into the second stage regression model (the two-step estimator). However, standard errors in the two-step estimator are in general large (Cameron and Trivedi, 2009). This is 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 two-step estimator suffers from collinearity in the second stage (Nawata, 1994). The maximum likelihood estimation is an alternative to the two-stage approach (Hoshino, 2009) to overcome low explanatory power of the models. Letting $\alpha_j + \boldsymbol{\beta}_j \mathbf{X}_j \equiv \boldsymbol{\beta}_j \mathbf{X}_j$, j = 0,1, for simplicity, the log likelihood for this model is

$$logL = \sum_{D=1} \left[\log\{\Phi(\eta_1)\} - \frac{1}{2}\{\log(2\pi\sigma_{1v}) - \left(\frac{\boldsymbol{Y}-\boldsymbol{\beta}_1\mathbf{X}_1}{\sigma_1}\right))^2\} \right]$$

$$+ \sum_{D=0} \left[\log\{\Phi(\eta_0)\} - \frac{1}{2}\{\log(2\pi\sigma_{0v}) - \left(\frac{\boldsymbol{Y}-\boldsymbol{\beta}_0\mathbf{X}_0}{\sigma_0}\right))^2\} \right], \qquad (8)$$

where

$$\eta_1 = \frac{\boldsymbol{\gamma Z}+(\boldsymbol{Y}-\boldsymbol{\beta}_1\mathbf{X}_1)\sigma_{1v}/\sigma_1^2}{\sqrt{1-\rho_1^2}} \text{ and } \eta_0 = \frac{\boldsymbol{\gamma Z}+(\boldsymbol{Y}-\boldsymbol{\beta}_0\mathbf{X}_0)\sigma_{0v}/\sigma_0^2}{\sqrt{1-\rho_0^2}}.$$

Note that $\rho_{jv} = \frac{\sigma_{jv}}{\sigma_j}$ for j = 0, 1. To derive robust results, we employ both estimations and compare the result of the winning bid price regression (the second stage) with the two-step estimator to that with the maximum likelihood estimator.

B. Selection model

The selection model is a probit regression model which examines the entrants' decisions to participate in the auction. The dependent variable is the dummy for entrant participation (*Entrant*). We include seven independent variables. The first independent variable is the dummy for green contract law (*Green*). Entrants could incur additional costs of compliance to participate in green auctions. Therefore, this regressor is indispensable to examine the effect of green contact law on the entrants' decisions to participate in green auctions. The second and third independent variables are the contract demand (*kW*) and the length of a contract term in days (*Term*), which may both positively affect entrant participation due to economies of scale. The fourth and fifth independent variables are the load factor (*Load*) and its square ($Load^2$). We postulate that a high load factor decreases entrant participation. A high load factor means that a supplier has to provide electricity to a customer around the clock. This may be a handicap for entrants because they often do not have base load power plants. The square term is included to capture a conceivably non-linear effect of the load factor. The sixth independent variable is the dummy for extra-high voltage power service (*Voltage*). As mentioned in the introduction, entrants are obligated to pay transmission network fees, which are cheaper for extra-high voltage transmission than high voltage transmission. Therefore, entrants may have bigger incentives to enter auctions for extra-high voltage power service. The last independent variable is the West Texas intermediate monthly price (*WTI*). As a high crude oil price is likely to increase the cost of generating electricity, we expect that the WTI price negatively impacts entrant participation. In addition, a time trend (*Year*) is adopted to control for energy-efficient improvements in generating electricity that vary over time. Also, since Japan is divided into ten regions and each region is exclusively served by a single incumbent, a vector of regional dummy variables (**Region**) is included to allow for regional differences.

There are two variables commonly used in previous studies but not included in our model (e.g., Porter and Zona, 1999, De Silva et al., 2003, and Estache and Iimi, 2010). First, the winning rate is often used in auction papers to control for learning effects. However, 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 meaningful winning rates. Second, the backlog is also commonly used to account for the effects of capacity limits on participation decisions. As entrants also sell electricity through other channels (e.g., spot market and contracts with private companies), the backlogs obtained from our auction data may not reflect their true capacity limits. For these reasons, the winning rate and backlog are not adopted in our model.

The model we use for the first stage is then given as

$$\begin{aligned}\Pr\,(Entrant = 1\,|\mathbf{Z} = Green, \ln kWh, \ln Term, Load, Load^2, Type, \ln WTI, Year, \mathbf{Region}) \\ = \Phi(\alpha_1 + \beta_{1,1}Green + \beta_{1,2}\ln kWh + \beta_{1,3}\ln Term + \beta_{1,4}Load \\ +\beta_{1,5}Load^2 + \beta_{1,6}Type + \beta_{1,7}\ln WTI + \beta_{1,8}Year + \boldsymbol{\beta}_{1,9}\mathbf{Region}), \quad (9)\end{aligned}$$

where the variables are explained in **Table 2**. ***Z*** is a vector of characteristics that have effects on entrant participation. The logs of *kW*, *Term* and *WTI* are taken because we are interested in percentage changes in those variables.

C. Outcome equations

We estimate outcome equations to better understand the factors that impact the winning bid. There are two outcome equations, one for the auctions without entrants and the other for the auctions with entrants. For both equations, the dependent variable is the winning bid (*Price*). In addition to the variables in the selection model, the outcome equation has one more independent variable, the number of bidders participating in the auction (*Number*). Many researchers argue that the winning bid decreases as the number of bidders increases (e.g., De Silva et al, 2003, Klemperer, 2004, and Hattori, 2010). It is thus reasonable to add this independent variable to outcome equations.

Then, the second stage models are

$$E(\ln Price|D_i = 0) = \alpha_0 + \boldsymbol{\beta}_0\mathbf{X}_{0i} = \alpha_0 + \beta_{0,1}Green + \beta_{0,2}\ln kWh + \beta_{0,3}\ln Term + \beta_{0,4}Load$$
$$+\beta_{0,5}Load^2 \ + \beta_{0,6}Type \ + \beta_{0,7}\ln WTI + \beta_{0,8}Year + \beta_{0,9}Number$$
$$+\boldsymbol{\beta}_{0,10}\mathbf{Region} - \sigma_{0v}\left[\frac{\phi(\gamma Z_i)}{\Phi(\gamma Z_i)}\right], \qquad \text{(for auctions without entrants),} \qquad (10)$$

$$E(\ln Price|D_i = 1) = \alpha_1 + \boldsymbol{\beta}_1\mathbf{X}_{1i} + \alpha_1 + \beta_{1,1}Green + \beta_{1,2}\ln kWh + \beta_{1,3}\ln Term + \beta_{1,4}Load$$
$$+\beta_{1,5}Load^2 \ + \beta_{1,6}Type + \beta_{1,7}\ln WTI + \beta_{1,8}Year + \beta_{1,9}Number$$
$$+\boldsymbol{\beta}_{1,10}\mathbf{Region} + \sigma_{1v}\left[\frac{\phi(\gamma Z_i)}{1-\Phi(\gamma Z_i)}\right], \qquad \text{(for auctions with entrants),} \qquad (11)$$

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

In order to estimate the maximum likelihood estimation, **Z** in equation (9) and **X** in equations (10)-(11) are substituted into equation (8). Then we find the values of parameters that maximize equation (8) given our data.

V. Empirical Results

A. Entrant participation

The regression results of the selection model (a probit model) are presented in **Table 5**. Since a probit model is nonlinear, a marginal effect at the sample mean of each regressor is then computed in **Table 6**. These results show the effects of various factors on the probability of entrant participation. Green auctions (*Green*) are estimated to decrease the probability of entrant participation by 9.9%. The result is consistent with our hypothesis that green contract law hampers entrant participation. A 1% increase in contract demand (*kW*) is estimated to increase the probability of entrant participation by 21.5%, whereas a contract term (ln*Term*) is not statistically significant at the 5% level. This implies that strong economies of scale exist in highvolume contracts, but not in long-term contracts. When a load factor (*Load*) increases by 1%, the probability of entrant participation is estimated to decrease by 0.69%. As we expected, a high load factor discourages entrants from participating in auctions. Auctions for extra-high voltage power service (*Voltage*) are estimated to increase the probability of entrant participation by 6.6%. A cheaper transmission network fee for extra-high voltage transmission indeed encourages entrants to enter auctions. A 1% increase in the WTI price (ln*WTI*) is estimated to decrease the probability of entrant participation by 36.0%. This result indicates that entrants' operation is very susceptible to crude oil price changes. Finally, a time trend (*Year*) exists, and the probability of entrant participation is estimated to increase by 3.6% each year.

Table 5: Entrant Participation Regression

Dependent variable: *Entrant* = 1 if entrants participate in the auctions, 0 if not Regressor	
Green	−0.369**
	(0.080)
ln*kW*	0.799**
	(0.089)
ln*Term*	0.387
	(0.279)
Load	−2.595**
	(0.892)
Load^2	−2.622**
	(1.046)
Voltage	0.247**
	(0.109)
ln*WTI*	−1.339**
	(0.270)
Year	0.133**
	(0.029)
Constant	2.204**
	(1.261)
Regional Effects	Yes
Log likelihood Value	−899.191
Pseudo R-squared	0.311

These regressions were estimated using the data from 2005 to 2010. The number of observations is *n*=1886. Standard errors are given in parentheses under the coefficients. The individual coefficient is statically significant at 5% level (**) or 10% level (*). The probit regression was estimated by maximum likelihood.

Table 6: Estimated Marginal Effects of Entrant Participation Regression

Regressor	
Green	-0.099^{**}
	(0.021)
ln*kW*	0.215^{**}
	(0.023)
ln*Term*	0.104
	(0.075)
Load	-0.698^{**}
	(0.238)
$Load^2$	-0.705^{**}
	(0.281)
Voltage	0.066^{**}
	(0.029)
ln*WTI*	-0.360^{**}
	(0.071)
Year	0.036^{**}
	(0.008)

These regressions were estimated using the data from 2005 to 2010. The number of observations is n=1886. Standard errors are given in parentheses under the coefficients. The individual coefficient is statically significant at 5% level (**) or 10% level (*).

B. Winning bid prices

Table 7 and **Table 8** summarize the results of the outcome equations, i.e., the effects of various factors on the winning bid, using the two-step estimator and the maximum likelihood estimator, respectively. Columns (1) and (2) in **Table 7** and **Table 8** report the results of the auctions with and without entrants, respectively.

Coefficient estimations in the two- step estimator are similar to those in the maximum likelihood estimator. However, as Nawata (1994) points out, standard errors in the two-step estimator in **Table 7** are larger than those of the maximum likelihood estimator in **Table 8**. Accordingly, the time trend (*Year*) is not statistically significant in **Table 7**, but statistically significant at the 10 % level in **Table 8**. Therefore, we focus on the results from the maximum likelihood estimator in **Table 8**.

Overall, all variables, except for the length of the contract term (*Term*), have some effects on the winning bids. Also the magnitudes of their effects increase when entrants enter the auction most likely due to the increased competition. Next we explain the result of each variable. The coefficient of *Green* is 0.012 and significant at the 5% level in the auctions with entrants, whereas it is not statistically significant at the 5% level in the auctions without entrants. That is, green contract law is likely to increase the winning bid by 1.2% if entrants enter the auction, but it may not change the winning bid if no entrant enters the auction. The result is consistent with the previous studies that show the positive impact of green contract law on the winning bid (e.g., Hattori and Saegusa, 2010). But we further show that the costs of compliance disproportionately hit the entrants. While a 1% increase in the contract demand (*kW*) is associated at the 5% level of significance with a 4.1% decrease in the winning bids when entrants enter the auction, the contract demand is not statistically significant at the 5% level when no entrant enters the auction. This may imply that the size of each contract does matter for entrants, who are much smaller than incumbents, to create economies of scale. Regarding the length of the contract term (*Term*), the result is not statistically significant at the 5% level, indicating again that a longer contract does not create economies of scale and thus does not influence the winning bid. The results of the load factor (*Load*, $Load^2$) show that the winning bid is estimated to decrease by 1.472% up to the turning point, *Load* = 0.54 (=1.472/(2*1.366)), when the load factor increases by 1% in the auctions with entrants. Similarly, a 1% increase in the load factor is estimated to bring down the winning bid by 0.933% until the turning point, *Load* = 0.82 (=0.933/(2*0.571)), in the auctions without entrants. These results are consistent with the winning bid distributions in **Figure 2**, which shows that there seems to be a non-linear (negative) correlation between the winning bid and load factor. The entrants tend to focus on the auctions with low load factors, where the winning bid is more sensitive to the load factor. The coefficients of *Voltage* are −0.049 and −0.028 in the auctions with and without entrants, respectively. This means that the winning bid for extra-high voltage power service decreases by 4.9% if entrants are in the auction and by 2.8% if no entrant is in the auction, compared to the winning bid for the high voltage power service. In general, extra-high voltage power service is cheaper than high voltage service. In addition, a cheaper transmission network fee for extra-high voltage transmission is attributable to the further decrease in the winning bid when entrants enter the auction. A 1% increase in WTI crude oil price (ln*WTI*) is estimated to reduce the winning bid by 4% if entrants participate in the auction, and 8% if no entrant participates in the auction. Unlike the other variables, the crude oil price has a diminishing impact on the winning bid if entrants enter the auction. In the previous section, we find that an entrant's decision to participate in an auction is very sensitive to the WTI price. We presume that the WTI price has a limited impact on the bids of those entrants which actually enter the auction because a high WTI price sifts out those entrants which heavily rely on oil beforehand. The coefficients of the time trend (*Year*) are 0.003 and 0.004 in auctions with and without entrants, respectively. That is, each year the winning bids increase by 0.3% and 0.4% in auctions with and without entrants, respectively. Although we expected that technological improvements could lower the winning bids over time, they in fact slightly push up the winning bids. One probable cause for this positive time trend is that the recent shift to renewable energy technologies may be driving up the winning bids. Finally, having one more entrant in the auction (*Number*) is estimated to reduce the winning bid by 1.1%, which agrees with auction theory (e.g., Klemperer, 2004). On the other hand, *Number* is not statistically significant at the

5% level in the auctions with no entrant because the number of bidders is always one in such auctions.

Table 7: Winning Bid Price Regression (The two-step estimator)

Dependent variable: ln*Price*		
Regression model: Heckit		
Regressor	(1)	(2)
Green	0.019**	0.008
	(0.006)	(0.005)
ln*kW*	−0.061**	−0.011
	(0.011)	(0.007)
ln*Term*	−0.020	−0.003
	(0.018)	(0.013)
Load	−1.475**	−0.898**
	(0.050)	(0.052)
$Load^2$	1.537**	0.562**
	(0.100)	(0.043)
Voltage	−0.053**	−0.029**
	(0.007)	(0.006)
ln*WTI*	−0.0133	−0.075**
	(0.020)	(0.016)
Year	0.0003	0.003
	(0.002)	(0.002)
Number	−0.011**	0.010
	(0.002)	(0.056)
Constant	1.874**	1.713**
	(0.082)	(0.088)
Regional Effects	Yes	Yes
Hazard rate for column (1)	−0.091**	−0.015**
Inverse Mills Ratio for column (2)	(0.022)	(0.014)
Adjusted R-squared	0.737	0.689
Number of observation	997	889

Column (1) reports the results of the auctions with entrants, and column (2) reports the results of the auctions without entrants. The regressions are estimated with the data from 2005 to 2010. Standard errors are given in parentheses under the coefficients. The individual coefficient is statically significant at the 5% (**) level or 10% level (*).

Table 8: Winning Bid Price Regression (Maximum Likelihood Estimation)

Dependent variable: ln*Price*		
Regression model: Heckit		
Regressor	(1)	(2)
Green	0.012**	0.007
	(0.005)	(0.005)
ln*kW*	−0.041**	−0.010
	(0.007)	(0.005)
ln*Term*	−0.012	0.001
	(0.018)	(0.006)
Load	−1.472**	−0.933**
	(0.050)	(0.044)
$Load^2$	1.366**	0.571**
	(0.072)	(0.042)
Voltage	−0.049**	−0.028**
	(0.007)	(0.006)
lnWTI	−0.040**	−0.080**
	(0.017)	(0.014)
Year	0.003*	0.004**
	(0.001)	(0.002)
Number	−0.011**	0.010
	(0.002)	(0.056)
Constant	1.848**	1.730**
	(0.083)	(0.084)
Regional Effects	Yes	Yes
Log likelihood Value	437.680	417.781
Number of observation	997	889

Column (1) reports the results of the auctions with entrants, and column (2) reports the results of the auctions without entrants. The regressions are estimated with the data from 2005 to 2010. Standard errors are given in parentheses under the coefficients. The individual coefficient is statically significant at the 5% (**) level or 10% level (*).

V. Conclusion

There has been a growing expectation for new electric power suppliers to bring increased market competition, yet the market share of such new entrant electricity retailers has only reached 2% after two decades of electricity reforms. This paper investigates various factors which might hit entrants disproportionately and thus limit market competitions. In particular, we aim at green contract law, which is an environmental quality threshold electricity retailers must meet to supply electricity to public entities. In recent years, the Japanese government has endeavored to push the energy sector toward increased use of green energy. As shown in the environmental policy literature, these environmental policies often disproportionately hit small companies, the market entrants that regulators had previously sought, due to higher unit compliance costs. We employ the endogenous switching regression model and show that green contract law reduces entrant participation in electric power procurement auctions and that it indeed affects entrants' bids disproportionately once they enter the auction. To be concrete, green contract law lowers entrant participation in the auction by 9.9% and increases the winning bid by 1.2% once entrants enter the auction. The effect of green contract law on the winning bid is not statistically significant if only incumbents participate in the auction. Our results suggest that the government should subsidize entrants to support their shift to renewable energy as they strive to remain competitive in the retail electricity market.

The analysis also finds various other factors which hamper entrant participation in auctions and affect their bids disproportionately once they enter the auction. There is an ongoing argument over the fairness of the transmission network fees and imbalance fees, both of which are imposed only on entrants. We show that both fees clearly obstruct entrant participation in auctions and push up their bids once they enter the auction. High electricity prices have been another concern resulting from low market competitions. Our results show that a 1% increase in the contract demand (kW) increases entrant participation and decreases the winning bid by 4.1%. This implies that public entities can induce lower bids by aggregating small contracts. Also, we find a positive time trend in the winning bids. Normally we expect that technological improvements will bring electricity prices down over time. On the contrary, our data shows that the winning bid increases by 0.3% to 0.4% each year, perhaps indicating that the shift to renewable energy technologies are driving up electricity prices.

One limitation of this paper is that our data is restricted to the time period before the Fukushima Daiichi nuclear crisis. Most nuclear power plants have been suspended since the nuclear crisis. In response, the proportion of nuclear power in Japan's energy mix dropped from 28.6% in 2010 to 1.7% in 2012 (The Federation of Electric Power Companies of Japan, 2013). Furthermore, the proportion of the cost of fuel to the total cost of electricity generation increased from 30.8% in 2008 to 41.7% in 2012 due to the increasing fossil fuel prices (Agency for Natural Resources and Energy, 2013c). 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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