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Impact of Environmental Regulation and the 2011 Earthquake on the Japanese Electricity Industry

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Abstract

Environmental regulations may erode competition owing to additional costs of compliance. To investigate the impact of such regulations in the Japanese electricity market, we analyze the effects of the environmental quality threshold set for public sector procurement. Using data on electricity procurement auctions from 2005 to 2012, we employ an endogenous switching regression model. We show that the environmental quality threshold lowers the participation of new power suppliers in auctions but does not increase their winning bids. In fact, compliance with the quality threshold has made new power suppliers competitive in green auctions. By contrast, electricity utilities have suffered increased compliance costs since the Great East Japan Earthquake in 2011 owing to the shutdown of nuclear power plants and increased reliance on fossil fuels.

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1 Introduction

An electricity utility is a typical natural monopoly and is often protected by the government of the country in which it operates. The utility incurs a large fixed cost for creating and maintaining essential facilities, such as power plants and electricity transmission networks. On the other hand, there is a very small marginal cost to provide an extra unit of electricity once the necessary facilities have been built. Owing to these large economies of scale, an electricity utility is allowed to dominate electricity services in its territory on condition that it offers nondiscriminatory service under price controls. Such a natural monopoly, however, has been blamed for high electricity prices rooted in x-efficiency. In addition, the enormous fixed cost that used to stand as a barrier to entry has shrunk because small-scale thermal power plants can now generate large amounts of electricity owing to innovations in electricity generation technologies. Given this situation, since the early 1990s, electricity markets in many countries and regions have been opened to new power suppliers in order to lower electricity prices by the introduction of market competition and to secure additional electricity supplies.

Following the global movement toward the liberalization of electricity markets, the Japanese government started electricity deregulation more than two decades ago, yet it has shown limited impacts on the electricity industry. In fact, new power suppliers, which we call *entrants* hereafter, represent less than 1% of the total electricity-generating capacity and 2.1% of electricity retailing. In addition, Japanese electricity prices have remained high compared to other developed countries. For example, Japan's industrial (residential) electricity price is 45% (28%) and 190% (133%) higher than those in the UK and US, respectively (Agency for Natural Resources and Energy, 2014). Furthermore, Japan has suffered from electricity shortages and corresponding power price increases since the Great East Japan Earthquake in 2011. Accordingly, the Japanese government is under pressure to revisit electricity deregulation to attract more market entrants, who are considered increasingly important to bridge energy gaps and stabilize electricity prices.

Given this situation, there is a growing need to clarify what is preventing new entrants in the market and how this potentially affects electricity prices. Previous studies show that it is generally difficult to enhance competition in retail electricity markets (e.g., Joskow and Tirole, 2006; Von Dehr Fehr and Hansen, 2010; Creti, Pouyet and Sanin, 2013). In addition, the Japanese retail electricity market has several obvious institutional barriers that can be blamed for the low participation of new power suppliers. One such barrier is transmission network fees applied to entrants to use transmission networks exclusively operated by electricity utilities, which we call *incumbents* hereafter. Since transmission network fees are set higher for the transmission of high voltage power than those for the transmission of extra-high voltage power[1], high

[1] For example, the fees were 2.03 yen/kilowatt hour (kWh) for extra-high voltage service and 4.15 yen/kWh for high voltage service in 2012 (Ministry of Economy, Trade and Industry, 2012).

voltage power supply is less attractive to entrants (Hattori, 2010). In addition, expensive fees imposed on entrants as a penalty for supply shortages hinder new companies from entering the market[2].

In this study, we focus particularly on the impact of environmental policies, which might affect the entry of new power suppliers but have been ignored largely by previous studies. In response to concerns about climate change, the Japanese government enacted what is known as the green contract law in 2007. This is an environmental quality threshold regarding CO_2 emission factors. As Heyes (2009) points out, an environmental policy can hit small firms disproportionately because per unit regulatory compliance costs will be higher at smaller firms if there are substantial fixed costs associated with compliance. If this is the case, the green contract law may lower entrants' competitiveness, reduce market competition, and potentially raise electricity prices. Indeed, unlike incumbents that own various power stations, including extremely low-carbon nuclear power plants, entrants tend to rely heavily on fossil fuels, implying high compliance costs. On the other hand, however, entrants' thermal generators are newer than those of incumbents, indicating lower CO_2 emissions and compliance costs for entrants. Therefore, it is not clear whether the green contract law has disproportionately adverse effects on entrants. At a more macro level, there is a rich body of literature on the impact of environmental policies on the competitiveness of a country, among which Porter (1991) and Porter and van der Linde (1995), together known as the Porter Hypothesis, stand out. The Porter Hypothesis states that strict, well-designed environmental regulations can trigger innovation that partially or more than fully offsets the costs of compliance. If the hypothesis holds for the green contract law, complying with the law may make entrants competitive against incumbents, increase market competition, and possibly lower electricity prices. However, many studies that have tested the Porter Hypothesis only provide conflicting results, probably because outcomes depend highly on the context and methodologies. For example, Jaffe, Peterson and Portney (1995) review previous studies and find either small or statistically insignificant effects of environmental regulations on competitiveness. Lanoie, Patry and Lajeunesse (2008) examine productivity growth in Quebec's manufacturing sector and find that the impact of environmental regulations on productivity is contemporaneously negative but becomes positive a few years later. This indicates the importance of capturing the dynamic impact of the green contract law in our analysis.

Another important consideration is the effect of the green contract law on electricity prices. Although it is important to curb the country's CO_2 emissions, the green contract law can raise electricity prices to a greater or lesser degree if the compliance costs are sufficiently high. Furthermore, it is feared that comprehensive advancement towards the green energy revolution after the 2011 earthquake would cause a rise in electricity

[2] If an entrant fails to balance supply and demand every 30 minutes, an incumbent steps in to fix the imbalance. For example, if a shortage exceeds 3%, an entrant must pay 51.73 yen/kWh in summer and 45.73 yen/kWh in other seasons. On the contrary, if supply exceeds demand by more than 3%, the excess electricity is obtained by an incumbent for free. Penalties are relatively low if an imbalance is within $\pm 3\%$: an entrant pays 15.02 yen/kWh for shortages and can sell excess electricity at 10.48 yen/kWh. These fees are for Tokyo Electric Power Company in 2012, and fees vary among incumbents.

prices. Energy shortages became an acute problem after the earthquake when all of Japan's nuclear power plants came to complete standstills. Since then, the government has been revitalizing electricity reform to spur more entrants into the electricity markets in order to increase supplies and stabilize prices. Moreover, the government approved revitalization strategies to solve various issues confronting the country after the earthquake, one of which is called "Green" and is designed to realize an innovative energy and ecological environment. Consequently, there is a growing trend toward sustainable energy among entrants, such as solar and wind power. However, since electricity prices have been on the rise already as a result of increased reliance on fossil fuels among incumbents, the government needs to carefully control the movement toward sustainable energy, which is usually expensive, and the expansion of the scope of the green contract law to suppress further increases in electricity prices. Hence, in this study, we examine the impacts of the green contract law on electricity prices as well as the market entry of new power suppliers.

To investigate potentially asymmetric impacts of the green contract law on entrants and incumbents, we analyze Japanese electricity procurement auctions in the public sector. The Government Procurement Agreement of the World Trade Organization covers the procurement of electricity used in the public sector. Consequently, since the beginning of electricity deregulation, auctions have been adopted by Japanese central and local governments as well as some other entities, such as national hospitals and universities. These auction data are relatively accessible. In addition, open competitive bidding is likely to reflect a bidder's true cost, which is otherwise difficult to estimate. In other words, differences, if any, in the winning bids of entrants and incumbents imply differences in the costs of entrants and incumbents. Furthermore, we examine possible changes in the costs of entrants and incumbents after the earthquake by analyzing electricity procurement auctions before and after the earthquake.

In auction theory, it has been shown that bidder asymmetry potentially reduces competition (e.g. Myerson, 1981; Maskin and Riley, 2000; Krishna, 2009). In addition, there are some empirical studies conducted on asymmetric bidders based on a reduced form. Porter and Zona (1999) examine Ohio milk auctions and find that behavior differs by firm. De Silva, Dunne and Kosmopoulou (2003) explore differences in the bidding patterns of entrants and incumbents in road construction auctions in Oklahoma. They find that entrants bid more aggressively than incumbents and win auctions with lower bids. Estache and Iimi (2010) investigate asymmetric bidders using procurement data from official development assistance projects. They find that entrants actually submitted aggressive bids in the presence of incumbents. An important empirical issue in estimating a reduced form is the endogeneity of the number of bidders, which is usually solved by using instrument variable estimators.

Several studies examine Japanese electricity procurement auctions. Hattori (2010) empirically analyzes the determinants of the number of bidders from 2005 to 2008. He shows that the number of bidders is affected negatively by the load factor[3] and is affected positively by the voltage level (high or extra-high) and contract demand. Hosoe and Takagi (2012) examine the effectiveness of the auctions by measuring the decline in electricity prices in 2005. Using the endogenous switching regression model to solve the endogeneity of the number of bidders, they show that electricity procurement auctions reduced the electricity price by 0.46 yen/kilowatt hours (kWh) on average. One limitation of Hattori (2010) and Hosoe and Takagi (2012) is that they use data from only 2005 to 2008. Consequently, they do not study the impacts of the green contract law nor the Great East Japan Earthquake on the Japanese retail electricity market. To fill the gap, we investigate the effect of the green contract law before and after the earthquake based on the approach used in Hosoe and Takagi (2012).

The remainder of this paper is organized as follows. We explain Japanese electricity procurement auctions and the green contract law in section 2. Section 3 describes our data set. Our models are explained in section 4. Regression results are provided in section 5. We discuss some policy implications in section 6. Finally, section 7 summarizes our findings.

2 Background

2.1 Japanese Electricity Market and Deregulation

The Japanese government began electricity reform in the 1990s. First, the wholesale market was opened to independent power producers (IPPs) in 1995, before which only wholesale electricity companies with supply capacity of 2,000 megawatts or more were allowed entry to the wholesale market[4]. Then, the retail market was opened gradually to entrants, known as power producers and suppliers (PPSs). PPSs either own generating facilities or purchase electricity from IPPs, private generators, and the Japan Electric Power Exchange (JEPX), the wholesale electricity exchange. In 2000, deregulation was limited to large-scale customers contracted for 2,000 kilowatts (kW) or more of extra-high voltage power (20,000 volts (V) or more), which represented 26% of the total demand at that time[5]. In 2003, deregulation was expanded to mid-scale customers contracted for 500 kW or more of high voltage power (6,000 V 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 nonresidential customers and all residential customers, continues to be excluded from deregulation.

[3]A load factor is the ratio between the average and maximum usage of electricity during the contract term. It is calculated as: $\frac{\text{Amount of electricity to be supplied (kWh/year)}}{\text{Maximum power (kW)} \times 24\text{(hours)} \times 365\text{(days)}}$. A load factor shows the anticipated consistency of demand.

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

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

However, nearly 2 decades of Japanese electricity reform have shown relatively limited impacts on electricity markets. The biggest reason is that traditional vertically-integrated incumbents have been kept intact. Historically, Japan was divided into 10 regions, each of which was served exclusively by a single incumbent. These 10 incumbents continue to account for more than 70% of the total capacity, whereas less than 1% of the total capacity is owned by PPSs and the rest is owned by wholesale electricity companies (Cabinet Office, 2007). This is in sharp contrast to other deregulated markets. For example, in the US, incumbents' capacity shares were 28% in New York, 1% in Pennsylvania, and 0.6% in Maryland in 2010 (U.S. Energy Information Administration, 2012). The dominance of incumbents is even more remarkable in the Japanese electricity retail market. Their market share in the deregulated retail area was 96.47% in 2012, meaning that only 3.53% belonged to PPSs (Agency for Natural Resources and Energy, 2013). Since deregulation is limited to 60% of the entire retail market, the share of PPSs is actually only 2.1% in the Japanese electricity retail market. On the other hand, in New York, for example, in May 2013, 34.8% of nonresidential customers and 24% of residential customers were served by entrants, which together represent 25.5% of all customers and 54.2% of the total load (New York State Public Service Commission, 2013)[6]. Thus, how to increase entrant participation has become a key concern in Japanese electricity reform.

2.2 Auction Mechanism

The Japanese electricity procurement auctions are reverse auctions, in which sellers compete in auctions to win contracts from buyers. Sellers are entrants (i.e., PPSs) and incumbents (i.e., electricity utilities) while buyers are central/local governments and other public institutes. A public agency (e.g., a municipal/ward office), which acts as an auction organizer, notifies entrants and incumbents of an upcoming auction through its website and newspapers. The information includes the contract demand, projected amount of consumption, delivery period, and place of delivery. After the announcement, entrants need to register for the auction but they can withdraw from the auction before it takes place. On the contrary, incumbents always enter auctions held in their respective service regions with a few exceptions (e.g., the pandemonium and acute electricity shortage after the earthquake). A contract for electricity supply is sold through a first-price sealed-bid auction. That is, a seller submitting the lowest bid wins a contract if the bid is lower than a preset reserve price. A reserve price is the highest price that a buyer is willing to accept for the contract. If the lowest bid is higher than the reserve price, the public agency holds another auction.

[6] The data do not include the Long Island Power Authority, small regulated utilities, or those municipalities or other entities that are supplied power through long-term contracts with the New York Power Authority (New York State Public Service Commission, 2013).

2.3 Green Contract Law

A concern developed that carbon emissions might increase as more entrants enter the market. While incumbents had mixed generation portfolios, including low-carbon nuclear power, most entrants had only thermal power stations, and consequently, relied heavily on fossil fuels to generate electricity. In addition, Japan ratified the Kyoto Protocol in 2002, an international climate change agreement that binds signatories to emission reduction targets, and had to reduce greenhouse gas emissions by 6% below the 1990 level by 2012. In response to these concerns, the Japanese government in 2007 enacted the green contract law, which establishes an environmental quality threshold. The green contract law stipulates the basic policy regarding CO_2 emission factors and promotes its application to all contracts in the public sector. However, the application of the green contract law remains arbitrary, and central and local governments and other public institutions may adopt different thresholds at their own discretion. Table 1 presents an example scoring system for a threshold. CO_2 emission factors are the primary requirement, although points can be earned for other efforts, such as introducing renewable energy and transferring green certificates to buyers. If a seller obtains a grade of more than 70 in the scoring system, it can participate in a green auction. If not, the seller is excluded from the auction.

[Table 1 about here.]

3 Data

Our dataset consists of Japanese electricity procurement auctions from December 2005 to March 2012 taken from Japan Electric Association Newspaper Division (2010). The original data include, for each auction, the auction date, auction organizer, place of delivery, contract demand (kW), projected amount of consumption (kWh), load factor, delivery period (days), voltage level (high or extra-high), application or nonapplication of green contract law, winning bidder, losing bidder(s), and winning bid (yen/kWh). In addition, daily spot prices at JEPX are obtained from Japan Electric Power Exchange (2014), and monthly average prices of imported coal are obtained from Trade Statistics of Japan (2014). Winning bids, spot prices, and coal prices are converted to real values using regional consumer price indexes obtained from Statistics Japan (2014).

Out of a total of 4,863 auctions conducted during the data collection period, 2,457 auctions contain the information on losing bidders and winning bids, whereas the remaining auctions do not have such information. In our analysis, winning bids are essential and information on losing bidders is vital to identifying whether any entrants participated in the auction. Hence, we limit our analysis to the 2,457 auctions with the complete information on losing bidders. Table 2 describes the variables of interest in our dataset.

[Table 2 about here.]

Figure 1 shows the trend in green auctions, that is, the auctions to which the green contract law is applied. The proportion of green auctions has been 44–61% since the enactment of the green contract law in 2007. The winning rate of entrants in nongreen auctions remains around 40–60%. On the other hand, their winning rate in green auctions is more variable: it was lower than the rate in nongreen auctions in 2007 and 2008, but higher in other years. Hence, it is not clear from the winning rates whether the green contract law has adverse impacts on entrants' costs.

[Figure 1 about here.]

Our data show a potential selection bias among entrants. An incumbent normally participates in all auctions held in its service region, but seldom enters auctions held in the service regions of other incumbents. On the other hand, an entrant may participate in auctions in several service regions but enters only a portion of auctions. In our dataset, there were 1,033 auctions (42%) without any entrants, that is, only an incumbent in the service region participated in the auction (Table 3), and the remaining 1,424 auctions (58%) had an incumbent and one or more entrants. Hereafter, we refer to the former as *single-bidder auctions* and to the latter as *multiple-bidder auctions*. Furthermore, entrants notably outperform incumbents once entering auctions: entrants won 1,239 out of 1,424 auctions with a winning rate of 87% (Table 3). This indicates that entrants focus on specific auctions to raise winning rates.

[Table 3 about here.]

The selection bias can be explained partially by load factors. Figure 2 shows that winning bids are correlated negatively to load factors and that entrants tend to target auctions with low load factors. Unlike electricity utilities, entrants do not have baseload power plants, such as nuclear and coal-fired power plants, which produce electricity at a constant rate to meet minimum demand. Entrants, therefore, face higher risks of incurring expensive imbalance fees in contracts with high load factors. Consequently, entrants are more likely to participate in auctions for low load-factor contracts.

[Figure 2 about here.]

4 Model

4.1 Theoretical Framework

Entrants' decisions as to which auctions are worth participating in seem to be affected by selection bias, which may disguise entrants' true winning rates in (non)green auctions. Unlike incumbents, entrants enter an auction only if the auction is expected to be profitable. Entrants' bids are, therefore, endogenous to their decisions to participate in the auction. In other words, some unobservable factors that affect entrants' decisions on whether 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 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 (with and without entrants). Accordingly, we employ endogenous switching regression models to allow for the possible selection bias and analyze the effects of the green contract law as well as various other factors on entrants' decisions to participate in auctions and winning bids. For the endogenous switching regression model, see, for example, Maddala (1986) and Lokshin and Sajaia (2004).

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

$$D_i = \begin{cases} 0 & \text{if } \boldsymbol{\gamma}\boldsymbol{Z}_i + v_i < 0, \\ 1 & \text{if } \boldsymbol{\gamma}\boldsymbol{Z}_i + v_i \geq 0, \end{cases} \tag{4.1}$$

where D_i is a latent variable that expresses entrants' participation in auction i, that is, it takes a value of one if entrants enter auction i, and zero if not; $\boldsymbol{Z}_i$ is a vector of characteristics that influence entrants' decisions to participate in the auction; $\boldsymbol{\gamma}_i$ 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 that separate the winning bids in multiple-bidder auctions from those in single-bidder auctions. Outcome equations are expressed as

$$\begin{cases} Y_{0i} = \alpha_0 + \boldsymbol{\beta}_0 \boldsymbol{X}_{0i} + u_{0i} & \text{if } D_i = 0 \text{ (single-bidder auctions)}, \\ Y_{1i} = \alpha_1 + \boldsymbol{\beta}_1 \boldsymbol{X}_{1i} + u_{1i} & \text{if } D_i = 1 \text{ (multiple-bidder auctions)}, \end{cases} \tag{4.2}$$

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

$$\varphi = \begin{bmatrix} \sigma_v^2 & \sigma_{0v} & \sigma_{1v} \\ \sigma_{0v} & \sigma_0^2 & \sigma_{01} \\ \sigma_{1v} & \sigma_{01} & \sigma_1^2 \end{bmatrix}, \tag{4.3}$$

where σ_v^2 is a variance of the error term in the selection equation (4.1); σ_0^2 and σ_1^2 are variances of the error terms in the outcome equation (4.2); σ_{0v} is a covariance of v_i and u_{0i}; and σ_{1v} is a covariance of v_i and u_{1i}.

Since we cannot observe Y_{0i} if $D_i = 1$ and Y_{1i} if $Di = 0$, we need to write these outcomes in a selection equation format. Taking expectations of the outcome equations[7], we can find the expected winning bid in single-bidder auctions as

$$\begin{aligned} E(Y_{0i}|D_i = 0) &= E(Y_{0i}|\boldsymbol{\gamma}\boldsymbol{Z}_i + v_i < 0) = E(Y_{0i}|v_i < -\boldsymbol{\gamma}\boldsymbol{Z}_i) \\ &= \alpha_0 + \boldsymbol{\beta}_0\boldsymbol{X}_{0i} + E(u_{0i}|v_i > \boldsymbol{\gamma}\boldsymbol{Z}_i) \\ &= \alpha_0 + \boldsymbol{\beta}_0\boldsymbol{X}_{0i} - \sigma_{0v}\left[\frac{\phi(\boldsymbol{\gamma}\boldsymbol{Z}_i)}{1-\Phi(\boldsymbol{\gamma}\boldsymbol{Z}_i)}\right] + u_{0i}, \end{aligned} \tag{4.4}$$

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 in multiple-bidder auctions is

$$\begin{aligned} E(Y_{1i}|D_i = 1) &= E(Y_{1i}|\boldsymbol{\gamma}\boldsymbol{Z}_i + v_i \geq 0) = E(Y_{1i}|v_i \geq -\boldsymbol{\gamma}\boldsymbol{Z}_i) \\ &= \alpha_1 + \boldsymbol{\beta}_1\boldsymbol{X}_{1i} + E(u_{1i}|v_i \geq \boldsymbol{\gamma}\boldsymbol{Z}_i) \\ &= \alpha_1 + \boldsymbol{\beta}_1\boldsymbol{X}_{1i} + \sigma_{1v}\left[\frac{\phi(\boldsymbol{\gamma}\boldsymbol{Z}_i)}{\Phi(\boldsymbol{\gamma}\boldsymbol{Z}_i)}\right] + u_{1i}. \end{aligned} \tag{4.5}$$

The system consisting of equations (4.1)-(4.5) is called an endogenous switching model. To solve this model, we substitute the first-stage probit model into the second-stage regression model (the two-step estimator).

4.2 Selection Model (First Stage)

The selection model is a probit regression model that examines entrants' decisions to participate in auctions. The dependent variable is the dummy for entrant participation (*Entrant*). We include eight independent variables, the first of which is the dummy for the application of the 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 variable is the contract demand (*Usage*) (kWh/year), which may affect entrant participation positively owing to economies of scale. The third independent variable is the load factor (*Loadfactor*). 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 baseload power plants. The fourth independent variable is an inverse of the load factor ($\frac{1}{Loafactor}$), which

[7] 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, $E(z|z > c) = \frac{\phi(c)}{1-\Phi(c)}$.

is included to capture a conceivably nonlinear effect of the load factor shown in Figure 2. In the endogenous switching model, all of the second-stage regressors should be a strict subset of the first-stage regressors because excluding some of the second-stage regressors can lead to inconsistency (Wooldredge, 2010). This is why an inverse of the load factor is included in the first-stage regressors. The fifth independent variable is the dummy for extra-high voltage power service (*Extrahigh*). 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 greater incentives to enter auctions for extra-high voltage power service. The sixth independent variable is the wholesale electricity price (*JEPX*). As many entrants rely on the wholesale market as their major supply source, we expect that wholesale prices adversely affect entrant participation. The seventh independent variable is the coal price (*Coal*), which may affect entrant participation negatively. Coal and natural gas together account for about 55% of electricity generation in Japan. Since both show similar price trends, only the coal price is included in our analysis. Finally, the eighth independent variable is the dummy for the Great East Japan Earthquake that occurred on March 11, 2011 (*Earthquake*), and is expected to capture changes, such as supply shortages, in the electricity industry in the aftermath of the earthquake. In addition to these independent variables, a vector of year dummy variables (*Year*) is adopted to control for energy-efficient improvements in generating electricity that vary over time. In addition, since Japan is divided into 10 regions, each of which is served exclusively by a single incumbent, a vector of regional dummy variables (*Region*) is included to allow for regional differences[8].

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; Estache and Iimi, 2010). First, a winning rate of each bidder is used often in auction studies to control for learning effects. However, many observations in our original dataset lack the information on losing bidders, that is, a buyer does not reveal losing bidders. This limits our ability to calculate a meaningful winning rate for each entrant. Second, backlogs are used commonly to account for the effects of capacity limits on participation decisions. As entrants sell electricity through other channels (e.g., the wholesale market and contracts with private companies), the backlogs obtained from our auction data may not reflect their true capacity limits. For these reasons, winning rates and backlogs are not adopted in our model.

Standard errors in a two-step estimator are large, in general. This is because the regressors in the first-stage equation largely overlap those in the second-stage equation owing to the limited variety of data items in the dataset. In response, the two-step estimator suffers from collinearity in the second stage (Nawata, 1994). For robust identification, it is recommended that exclusion restrictions be imposed (Cameron and Trivedi,

[8]Okinawa, one of the 10 regions, is excluded from our analysis because electricity procurement auctions have not been introduced in the region.

2009). Our selection equation includes a variable, *Exante*, which is a dummy variable taking a value of one if a contract requires less than 2,000 kW of high voltage (less than 20,000 V) power, and zero if not. At the start of the retail market deregulation in 1999, entrants were allowed to sell electricity only to large-scale customers with more than 2,000 kW of extra-high voltage (more than 20,000 V) power. When auctions were introduced in 2005, further deregulation took place and buyers of less than 2,000 kW of high voltage power joined auctions. If entrants are eager to expand their markets, these new buyers may be attractive, and thus, a participation rate of entrants in these auctions might be higher than that in auctions with more than 2,000 kW of extra-high voltage power. Therefore, using this variable, exclusion restrictions are imposed in our models.

Then, the model we use for the first stage is given as

$$
\begin{aligned}
&\Pr(Entrant{=}1|\boldsymbol{Z}{=}Green, \ln Usage, Loadfactor, Etrahigh, \ln JEPX, \ln Coal, Earthquake, Exante, \boldsymbol{Year}, \boldsymbol{Region}) \\
&= \phi(\alpha_1 + \beta_{1,1}Green + \beta_{1,2}\ln Usage + \beta_{1,3}Loadfactor + \beta_{1,4}\frac{1}{Loadfactor} \\
&+ \beta_{1,5}Extrahigh + \beta_{1,6}\ln JEPX + \beta_{1,7}\ln Coal + \beta_{1,8}Earthquake \\
&+ \beta_{1,9}Exante + \beta_{1,10}\boldsymbol{Year} + \beta_{1,11}\boldsymbol{Region}. \qquad (4.6)
\end{aligned}
$$

The variables are explained in Table 2. The logs of *Usage*, *JEPX*, and *Coal* are taken because we are interested in percentage changes in those variables.

4.3 Outcome Equations (Second Stage)

We estimate outcome equations to understand the factors that affect winning bids better. There are two outcome equations, one for single-bidder auctions and the other for multiple-bidder auctions. For both equations, the dependent variable is the winning bid (*Price*). Then, the second-stage models are

(For single-bidder auctions)

$$
\begin{aligned}
E(\ln Price_{it}|D_{it}=0) =& \alpha_0 + \beta_0\boldsymbol{X}_{0i} \\
=& \alpha_0 + \beta_{0,1}Green_{it} + \beta_{0,2}\ln Usage_{it} + \beta_{0,3}Loadfactor_{it} + \beta_{0,4}\frac{1}{Loadfactor} \\
&+ \beta_{0,5}Extrahigh_{it} + \beta_{0,6}\ln JEPX_{it} + \beta_{0,7}\ln Coal_{it} + \beta_{0,8}Earthquake_{it} \\
&+ \beta_{0,9}\boldsymbol{Year}_{jt} + \beta_{0,10}\boldsymbol{Region}_{kt} - \sigma_{0v}\left[\frac{\phi(\gamma Z_{it})}{\Phi(\gamma Z_{it})}\right] + u_{0it}, \qquad (4.7)
\end{aligned}
$$

(For multiple-bidder auctions)

$$
\begin{aligned}
E(\ln Price_{it}|D_{it}=1) =& \alpha_1 + \beta_1 \boldsymbol{X}_{1i} \\
=& \alpha_1 + \beta_{1,1} Green_{it} + \beta_{1,2} \ln Usage_{it} + \beta_{1,3} Loadfactor_{it} + \beta_{1,4} \frac{1}{Loadfactor} \\
& + \beta_{1,5} Extrahigh_{it} + \beta_{1,6} \ln JEPX_{it} + \beta_{1,7} \ln Coal_{it} + \beta_{1,8} Earthquake_{it} \\
& + \beta_{1,9} \boldsymbol{Year}_{jt} + \beta_{1,10} \boldsymbol{Region}_{kt} - \sigma_{1v} \left[\frac{\phi(\gamma Z_{it})}{1-\Phi(\gamma Z_{it})} \right] + u_{1it},
\end{aligned} \tag{4.8}
$$

where the variables are explained in Table 2. The logs of *Price*, *Usage*, *JEPX*, and *Coal* are taken because we are interested in percentage changes in those variables.

5 Empirical Results

5.1 Entrant Participation

The regression results of the selection model (probit model, first stage) are presented in Table 4. Since a probit model is nonlinear, a marginal effect at the sample mean of each regressor is computed in Table 5. Each column in Table 4 reports a different regression. Column (1) in Table 4 presents the results for ordinary least squares (OLS) regression and columns (2) and (3) in Table 4 present results for probit regression with and without exclusion restrictions. Our analysis uses a dataset with eight years and nine regions, and controls the regional and year effects. Therefore, our model is an extension of the difference in difference (DD) estimator of multiple periods. Although DD has an assumption of common trend, which is a very strong assumption, our model relaxes the assumption by adding an interaction term between regional dummies and time trend (Besley and Burgess, 2004). This result is represented in column (4) in Table 4.

[Table 4 about here.]

[Table 5 about here.]

In Tables 4 and 5, the coefficient on green auctions (*Green*) is statistically significant in columns (2), (3), and (4), but not in column (1). As is known, the linearity that makes OLS regression easy to use is its major flaw because it is not always reasonable to assume that probability is linear in regressors. Thus, column (1) is excluded from our analysis. Since the estimated coefficients on *Green* do not vary much in columns (2) and (3), we can conclude that the regression result is not sensitive to exclusion restrictions (column (2)) or regional-specific trends (column (4)). Hence, in what follows, we use column (2) as the base specification.

The effects of various factors on the probability of entrant participation are shown in column (2) in Table 5. Green auctions (*Green*) are estimated to decrease the probability of entrant participation by 3.2%. This result is consistent with our hypothesis that the green contract law hampers entrant participation. Expected usage ($\ln Usage$) positively affects entrant participation, implying that strong economies of scale exist in high-volume contracts. As expected, a high load factor ($Loadfactor$) significantly discourages entrants from participating in auctions. Auctions for extra-high voltage power service ($Extrahigh$) moderately increase the probability of entrant participation, affirming that cheaper transmission network fees for extra-high voltage transmission encourage entrants to enter auctions. Coal prices ($\ln Coal$) have a remarkably large negative impact on entrant participation. Finally, the inverse of load factor ($\frac{1}{Loadfactor}$), wholesale prices ($\ln JEPX$), and the earthquake ($Earthquake$) have little impact on entrant participation.

5.2 Winning Bids

Tables 6 and 7 summarize the results of the outcome equations (second stage), that is, the effects of various factors on winning bids, in multiple-bidder auctions and single-bidder auctions, respectively. Column (1) in each table presents the result of OLS regression. As in Tables 4 and 5, column (2) is the result without exclusion restrictions and is used as the base specification. We impose exclusion restrictions in column (3), and add an interaction term between regional dummies and time trend in column (4) to confirm the robustness of the result in column (2), that is, coefficients of *Green* do not vary significantly between the two regressions. In addition, since the hazard rates are not statistically significant at the 5% levels in Table 6, multiple-bidder auctions do not have selection bias, and thus, the results in columns (1) and (2) in Table 6 are similar. On the other hand, the inverse Mills ratios are statistically significant at the 5% level in Table 7, indicating selection bias in single-bidder auctions. Therefore, the endogenous switching regression model is appropriate in our dataset.

[Table 6 about here.]

[Table 7 about here.]

The results in column (2) in each of Tables 6 and 7 show that overall, all variables have some effects on the winning bids. In addition, the magnitudes of their effects are larger in multiple-bidder auctions (Table 6) than in single-bidder auctions (Table 7), most probably owing to increased competition. Furthermore, a comparison of the coefficients of *Green* in the two tables reveals an asymmetric impact of the green contract law on entrants and incumbents. While winning bids do not increase in multiple-bidder green auctions, that is, green auctions with an entrant(s) and incumbent (Table 6), they do increase in single-bidder green auctions, that is, green auctions with only an incumbent (Table 7). Given that entrants won 87% of the auctions they entered (Table 3), the result suggests that the green contract law certainly pushes up incumbents' bids but may not raise entrants' bids. This is contrary to previous research (e.g., Heyes, 2009) that environmental policies can affect small companies disproportionately owing to higher per unit regulatory compliance costs. However, it is not clear from our analysis whether the higher winning bids in single-bidder green auctions are a result of an increase in incumbents' costs (i.e., compliance costs) or a result of incumbents' grabby behavior to take advantage of no competition. This is examined further in Subsection 5.4. The expected usage ($\ln Usage$) negatively affects the winning bid, and the impact is larger in multiple-bidder auctions. This may imply that the size of each contract does matter for entrants, which are much smaller than incumbents, to create economies of scale. Load factors ($Loadfactor$, $\frac{1}{Loadfactor}$) have significant negative impacts on winning bids, especially in multiple-bidder auctions. As shown in Figure 2, there is a nonlinear negative correlation between winning bids and load factors. Indeed, entrants tend to focus on the auctions with low load factors, where winning bids are more sensitive to load factors. Winning bids decrease in auctions for extra-high voltage power service ($Extrahigh$). In general, extra-high voltage power service is cheaper than high voltage service. In addition, cheaper transmission network fees for extra-high voltage transmission are attributable to the further decrease in winning bids in multiple-bidder auctions. Wholesale electricity prices ($\ln JEPX$) positively affect winning bids in single-bidder auctions but not in multiple-bidder auctions. This is a surprising result because some entrants do not own their electricity-generating facilities and are considered to be more dependent on the wholesale market than incumbents are. The effect of wholesale electricity prices on entrants' winning bids is examined further in Subsection 5.4. Coal prices ($\ln Coal$) have significant positive impacts on winning bids. Finally, the earthquake has positive impacts on winning bids only in multiple-bidder auctions. This result indicates that the earthquake has affected the operations of entrants and incumbents differently, which is investigated in more detail in Subsection 5.4.

5.3 Entrants' Winning Rates

The analysis in Subsection 5.2 shows that the green contract law does not raise entrants' winning bids. This may imply that the impact of the green contract law is not large enough to affect entrants' competitiveness. To investigate this point, this subsection examines entrants' winning rates.

Table 8 shows the regression results of entrants' winning rates after enactment of the green contract law (2007–2012) compared to those before enactment (2005–2006). Columns (1), (2), and (3) present the results of a probit model, probit marginal effect, and probit marginal effect of treatment on the treated (ETT), respectively (for ETT, see, for example, Angrist and Evans (1998)). In all regression results, the coefficients of *Green* are statistically insignificant. That is, the green contract law does not affect entrants' winning rates, indicating that, indeed, the green contract has no impact on entrants' competitiveness.

In addition, the coefficients of year variables reveal a possible dynamic effect of the green contract law, as pointed out in Lanoie, Patry and Lajeunesse (2008). In all regressions, the coefficients of year variables are negative in 2007 and 2008 but are positive after 2009. This may indicate that the compliance with the law made entrants' operations environmentally efficient and competitive against incumbents over time, as stated in the Porter Hypothesis.

[Table 8 about here.]

5.4 Breaks after the Earthquake

The Japanese government has shut down all nuclear power stations since the earthquake in 2011. Previously, nuclear energy provided about 30% of electricity in Japan. The Japanese government required that each nuclear plant should stop operating for a periodic inspection every 12–24 months. When the earthquake occurred, nuclear power plants in Fukushima were damaged and shut down immediately. The other nuclear power plants did not suffer any direct damage, but those that were under periodic inspections during the earthquake have not resumed operation ever since owing to safety concerns. For the same reason, all the other nuclear power plants were shut down after undergoing periodic inspections.

The earthquake clearly produced a break in the time-series behavior of winning bids, at least in multiple-bidder auctions, because the coefficient of *Earthquake* in Table 6 is positive. In addition, incumbents probably have been affected by the earthquake, and yet, the impacts are not evident in our previous analysis (Table 7). To examine the details of the impacts of the earthquake, the whole sample is divided into two periods, before and after the earthquake, and the corresponding regression results are shown in Tables 9 and 10. We use the same base specification used in column (2) in each of Tables 6 and 7.

[Table 9 about here.]

[Table 10 about here.]

First, we discuss the regression results for multiple-bidder auctions in column (1) in each of Tables 9 and 10. As shown in Table 6, winning bids in multiple-bidder auctions are affected positively by the occurrence of the earthquake. The increase in winning bids after the earthquake may be attributable to entrants' increased reliance on the wholesale market after the earthquake. While the coefficient of $\ln JEPX$ is insignificant before the earthquake, it is positive and large after the earthquake. Amid a shortfall of electricity supply by incumbents after the earthquake, entrants who want to expand their market but do not own electricity-generating facilities may rely more on the wholesale market.

Next, we examine the regression results for single-bidder auctions in column (2) in each of Tables 9 and 10. The previous analysis shows that the green contract law has a positive impact on winning bids in single-bidder auctions when the whole sample is examined (Table 7). In reality, however, the green contract law affects winning bids in single-bidder auctions only after the earthquake (Tables 9 and 10). This can be explained by the expansion and reopening of fossil fuel plants to cope with electricity supply shortages in the wake of the earthquake and shutdowns of nuclear power plants. In addition, it is found that wholesale electricity prices ($\ln JEPX$) affect incumbents' winning bids only after the earthquake. Moreover, they have negative impacts on winning bids, that is, higher wholesale prices decrease winning bids. This is counterintuitive and may suggest that the wholesale market did not function well after the earthquake. Indeed, the Japanese government stepped in and limited market transactions during acute power shortages after the earthquake. TEPCO, an incumbent in the Tokyo region, lost about one third of its electricity-generating capacity right after the earthquake. As mentioned in the introduction, incumbents own transmission networks and monitor all transactions, including JEPX transactions, to balance the supply of electricity on the networks. Since TEPCO was very busy filling the huge energy gap by implementing rolling blackouts immediately after the earthquake, the Japanese government temporarily suspended JEPX transactions to lighten the burden imposed on TEPCO. On the other hand, TEPCO requested all power suppliers (entrants and private power-generating companies) to operate at their maximum capacity and purchased all surplus electricity, which was then sold to entrants that could not secure enough electricity owing to wholesale market suspension at lower than wholesale market prices. This unusual situation might have caused the counterintuitive result in our analysis.

6 Policy Implications

Given the ongoing shortfall of electricity supply and rising electricity prices, the Japanese government is trying to attract more entrants to the market to secure additional supply and stabilize prices. The rationale for this is a common notion that increased competition induces price reduction. To see if this is the case in electricity procurement auctions, we now examine the differences in winning bids between multiple-bidder and single-bidder auctions.

An estimate of the average treatment effect (ATT) of entrant participation can be obtained from the following equation, based on estimating the endogenous switching regression model:

$$E(Y_1 - Y_0|D=1) = \{E(X|D=1\}^t(\beta_1 - \beta_0) + (\sigma_{1v} - \sigma_{0v})E\left(\frac{\phi(\gamma \boldsymbol{Z}_i)}{\Phi(\gamma \boldsymbol{Z}_i)}|D=1\right), \tag{6.1}$$

where Y_1 represents winning bids in multiple-bidder auctions, Y_0 represents winning bids in single-bidder auctions, X denotes a n(number of observation) $\times$ k(number of regressors) matrix of vector regressors, and β_1 and β_0 are coefficients of regressors. To obtain the ATT, we first estimate β_1, β_0, σ_{1v}, σ_{0v} and $\boldsymbol{\gamma}$ by the endogenous switching regression model; then, we plug these estimators and sample means of X and $\boldsymbol{Z}$ into equation (4.3). It is found that winning bids become 0.424 yen/kWh cheaper in multiple-bidder auctions than in single-bidder auctions. Thus, it is confirmed that increased competition certainly induces price reduction in the electricity procurement auctions, which is consistent with the auction theory (Klemperer, 2004).

Under increasing international pressure to reduce carbon emissions, the Japanese government enacted the green contract law in 2007 in response to the concern that carbon emissions might increase as more new power suppliers enter the market. Using the CO_2 emission factors obtained from Ministry of the Environment (2013), we perform a regression analysis to examine whether the green contract law has achieved its original goal of reducing carbon emissions. The independent variable is *Green* and the dependent variable is the CO_2 emission factor (metric tons per kWh) of the auction winner multiplied by the expected usage (*Usage*). The result shows that when the green contract law is applied, CO_2 emissions decrease by 821.151 metric tons per auction[9]. Thus, it is found that indeed, the green contract law can reduce CO_2 emissions.

As pointed out in the introduction, there is a possibility that the green contract law, which prevents high-carbon suppliers from entering the market to curb the country's CO_2 emissions, may conflict with electricity deregulation to increase competition and lower electricity prices. Our analysis shows that the green contract law reduces entrant participation by 3.2% (Table 5) but does not affect their winning bids (Table 6). In addition, although entrants suffered low winning rates in the first few years of enactment of the green contract law, they retrieved the original level of winning rates thereafter, implying increased efficiency of entrants' operations owing to compliance with the green contract law. On the contrary, incumbents' winning bids are affected positively by the green contract law after the earthquake (Table 10). Hence, we can say that the green contract law does not conflict with the government's effort to lower electricity prices as long as enough competition is maintained.

Overall, the results are encouraging to the government, although one concern exists. Our analysis of earthquake impacts reveals that the shutdown of nuclear power plants has affected incumbents' operating costs significantly, which results in higher winning bids, especially in green auctions. Our analysis may provide one piece of supporting evidence for the ongoing discussions about how and when to reinstate nuclear power capacity.

[9]The standard error is 361.486. The coefficient is statistically significant at the 5% level.

7 Conclusion

Expectations have been growing that new electricity suppliers would bring increased market competition; however, the market share of such new entrants in the electricity retail market has reached only 2% after 2 decades of electricity reforms. This study investigates various factors that might affect entrants disproportionately, and thus, limit market competition. In particular, we focus on the green contract law, which is an environmental quality threshold that electricity retailers must meet in order 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 some studies on environmental policies, such environmental policies might hit small companies disproportionately owing to higher unit compliance costs. On the other hand, other studies provide supporting evidence for the Porter Hypothesis, which states that stringent, well-designed environmental regulations can trigger innovation that may offset the costs of compliance. We employ an endogenous switching regression model to show how the green contract law affects entrant participation and winning bids in Japanese electricity procurement auctions. Next, we summarize our findings.

First, it is found that the green contract law lowers entrants' participation rates in auctions by 3.2%. Second, however, the green contract law does not increase winning bids. Together with the first result, this implies that the green contract law imposes disproportionately large compliance costs on some, but not all, entrants and effectively eliminates these high-carbon entrants from auctions. For those entrants that enter auctions, however, required compliance costs are minimal, probably because they already own carbon-efficient electricity-generating facilities. Therefore, there is no difference between green and nongreen auctions in entrants' winning bids. Third, in fact, compliance with the green contract law helped entrants enhance their operations, which was sufficient to offset the compliance costs in a few years after enactment of the law. Fourth, the green contract law did not affect incumbents' winning bids before the earthquake but started raising them by 3% after the earthquake. This is due to increased reliance on fossil fuels following the shutdown of nuclear power plants. Finally, introducing competition can reduce winning bids by 0.434 yen/kWh. Overall, our analysis shows that as long as sufficient competition is maintained, green auctions can curb CO_2 emissions by eliminating high-carbon suppliers from auctions without raising winning bids. As incumbents' bids have increased since the earthquake, it has become even more important to bring more entrants into the market in order to hold back the increase in electricity prices.

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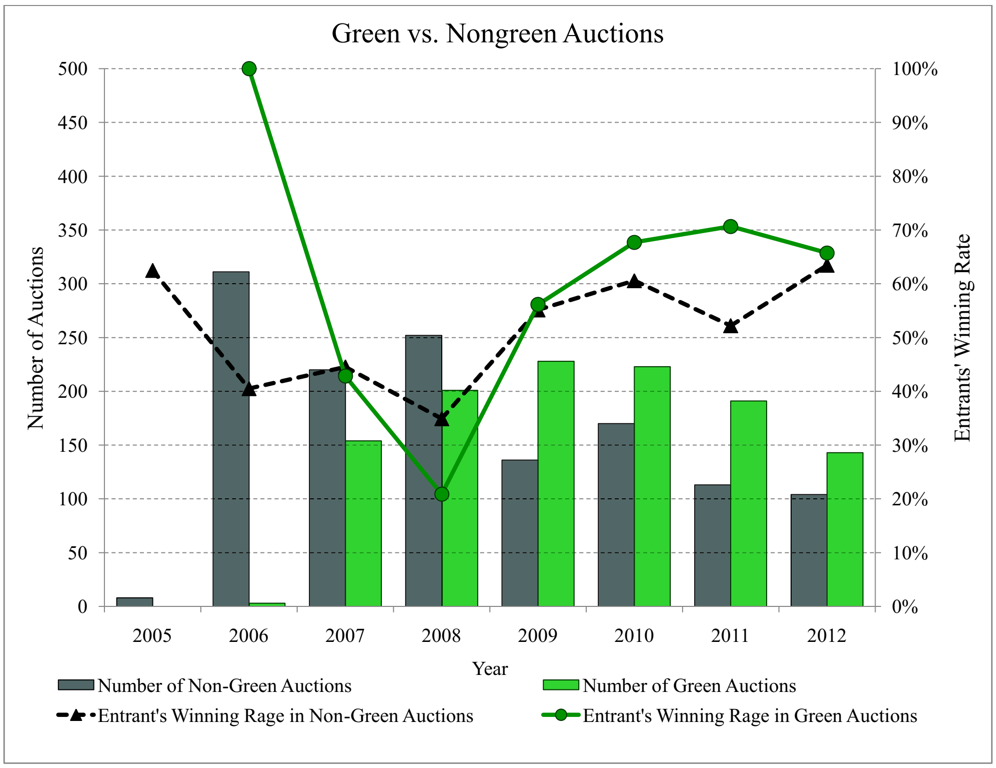

Figure 1: Entrants' Winning Rates in Green/Nongreen Auctions

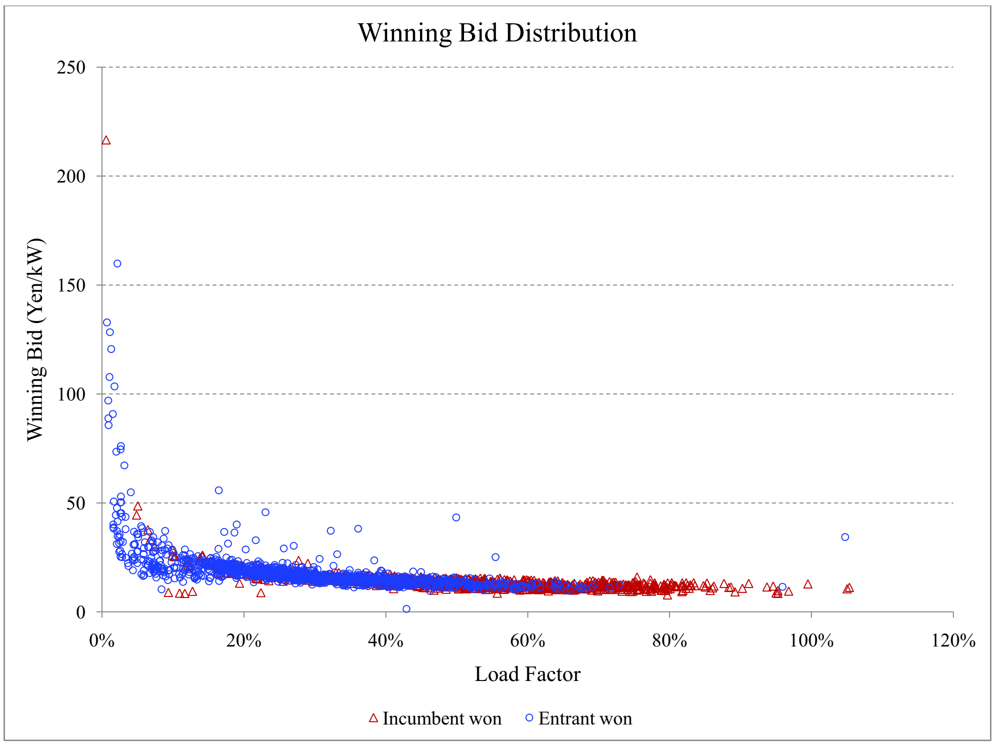

Figure 2: Load Factor and Winning Bid Distribution

Table 1: Example Scoring System for Environmental Quality Threshold

Element	Range	Point
CO_2 emission factor during the last year (kg-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
	0.450 to 0.475	45
	0.475 to 0.500	40
	0.500 to 0.525	35
	0.525 to 0.550	30
	greater than 0.550	25
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 relative to the benchmark during the last year	greater than 100%	15
	80% to 100%	5
Planned transfer of green certificates as a percentage of consumption	5.0%	10
	2.5%	5
	None	0

Source: Ministry of the Environment.

Table 2: Description of Variables

Variable	Description	Mean (S.D.)
Entrant	Dummy variable taking value 1 if entrants participate, and 0 if not	0.580 (0.494)
Price	Real winning bid (yen/kWh)	16.606 (9.287)
Green	Dummy variable taking value 1 if the green contract law is applied, and 0 if not	0.465 (0.499)
$\ln Usage$	Log of expected usage (kWh/year)	14.884 (1.390)
Loadfactor	Load factor	0.382 (0.190)
Extrahigh	Dummy variable taking value 1 if contract is greater than 20,000 V, and 0 if not	0.310 (0.463)
JEPX	Log of monthly real wholesale market price (yen/kWh)	11.087 (4.311)
Earthquake	Dummy variable taking value 1 for auctions held after the Great East Japan Earthquake, and 0 otherwise	0.134 (0.341)
Coal	Log of monthly real imported coal price	10.322 (1.792)

The total number of observations is 2,457.

Table 3: Auction Data

	Auctions Won by Entrants	Auctions Won by Incumbents	Total
Multiple-bidder Auctions	1,239 (87.0%)	185 (13.0%)	1,424 (58.0%)
Single-bidder Auctions	-	1,033 (100%)	1,033 (42.0%)
Total	1,239 (50.4%)	1,218 (49.6%)	2,457

Table 4: Entrant Participation Regression

Dependent variable: *Entrant*

	(1) OLS	(2) W/O Exclusion Restrictions	(3) W/ Exclusion Restrictions	(4) Extended DD
Green	-0.013	-0.130*	-0.120*	-0.184**
	(0.018)	(0.070)	(0.070)	(0.073)
$\ln Usage$	0.083**	0.275**	0.311**	0.279**
	(0.011)	(0.047)	(0.048)	(0.049)
Loadfactor	-1.570**	-6.090**	-6.230**	-6.290**
	(0.056)	(0.364)	(0.361)	(0.397)
$1/Loadfactor$	-0.002*	-0.001	-0.0001	-0.0006
	(0.001)	(0.006)	(0.006)	(0.006)
Extrahigh	0.070**	0.474**	0.767**	0.456**
	(0.023)	(0.100)	(0.144)	(0.102)
$\ln JEPX$	-0.037	-0.130	-0.162	-0.116
	(0.037)	(0.144)	(0.144)	(0.152)
$\ln Coal$	-0.261**	-1.050**	-1.054**	0.238
	(0.066)	(0.250)	(0.249)	(0.397)
Earthquake	-0.031	-0.188	-0.181	-0.369**
	(0.043)	(0.164)	(0.165)	(0.167)
Exante	-	-	0.405**	-
			(0.145)	
Constant	0.466**	0.526	-0.257	-2.167**
	(0.229)	(0.866)	(0.912)	(1.188)
Regional Effects	Yes	Yes	Yes	Yes
Year Effects	Yes	Yes	Yes	Yes
Reginal Trends	No	No	No	Yes
Observations	2,455	2,455	2,455	2,455
Adjusted R^2	0.381	0.352	0.354	0.368

Heteroskedasticity-robust standard errors are given in parentheses under the coefficients. The individual coefficient is statistically significant at the 5% (**) or 10% (*) level. The probit regression was estimated by maximum likelihood.

Table 5: Estimated Marginal Effects of Entrant Participation Regression

Dependent variable: *Entrant*

	(1) OLS	(2)W/O Exclusion Restrictions	(3) W/ Exclusion Restrictions	(4) Extended DD
Green	-0.013	-0.032*	-0.030*	-0.045**
	(0.018)	(0.017)	(0.017)	(0.017)
ln*Usage*	0.083**	0.069**	0.077**	0.068**
	(0.011)	(0.011)	(0.011)	(0.011)
Loadfactor	-1.570**	-1.517**	-1.547**	-1.533**
	(0.056)	(0.062)	(0.061)	(0.065)
1/*Loadfactor*	-0.002*	-0.0003	-0.0003	-0.0002
	(0.001)	(0.001)	(0.001)	(0.001)
Extrahigh	0.070**	0.118**	0.190**	0.111**
	(0.023)	(0.025)	(0.036)	(0.025)
ln*JEPX*	-0.037	-0.032	-0.040	-0.028
	(0.037)	(0.036)	(0.036)	(0.037)
ln*Coal*	-0.261**	-0.261**	-0.262**	0.058
	(0.066)	(0.061)	(0.062)	(0.097)
Earthquake	-0.031	-0.047	-0.045	-0.090**
	(0.043)	(0.041)	(0.041)	(0.041)
Exante	-	-	0.101**	-
			(0.036)	

Delta Method standard errors are given in parentheses under the coefficients. The individual coefficient is statically significant at the 5% (**) or 10% (*) level.

Table 6: Winning Bid Regression in Multiple-Bidder Auctions

Dependent variable: $\ln Price$

	(1) OLS	(2) W/O Exclusion Restrictions	(3) W/ Exclusion Restrictions	(4) Extended DD
Green	0.010	0.009	0.010	0.015
	(0.009)	(0.009)	(0.010)	(0.009)
$\ln Usage$	-0.044	-0.044**	-0.045**	-0.050**
	(0.010)	(0.008)	(0.008)	(0.008)
Loadfactor	-0.584**	-0.583**	-0.550**	-0.513**
	(0.160)	(0.160)	(0.138)	(0.169)
$1/Loadfactor$	0.017**	0.017**	0.017**	0.017**
	(0.001)	(0.001)	(0.001)	(0.001)
Extrahigh	-0.073**	-0.074**	-0.075**	-0.073**
	(0.020)	(0.020)	(0.020)	(0.021)
$\ln JEPX$	0.019	0.020	0.019	0.026
	(0.018)	(0.018)	(0.018)	(0.018)
$\ln Coal$	0.147**	0.147**	0.153**	0.031
	(0.041)	(0.041)	(0.038)	(0.043)
Earthquake	0.078**	0.078**	0.080**	0.094**
	(0.020)	(0.020)	(0.021)	(0.021)
Constant	3.043**	2.651**	3.056**	3.408**
	(0.117)	(0.086)	(0.101)	(0.193)
Regional Effects	Yes	Yes	Yes	Yes
Year Effects	Yes	Yes	Yes	Yes
Reginal Trends	No	No	No	Yes
Observations with Entrants	1,422	1,422	1,422	1,422
Hazard Rate	-	-0.022	-0.032	-0.039
		(0.077)	(0.073)	(0.086)

Heteroskedasticity-robust standard errors are given in parentheses under the coefficients. The individual coefficient is statically statistically significant at the 5% (**) or 10% (*) level.

Table 7: Winning Bid Regression in Single-Bidder Auctions

Dependent variable: ln*Price*

	(1) OLS	(2) W/O Exclusion Restrictions	(3) W/ Exclusion Restrictions	(4) Extended DD
Green	0.012**	0.012**	0.012**	0.015**
	(0.006)	(0.006)	(0.006)	(0.006)
ln*Usage*	-0.025**	-0.025**	-0.024**	-0.023**
	(0.004)	(0.004)	(0.004)	(0.004)
Loadfactor	-0.406**	-0.406**	-0.432**	-0.406**
	(0.068)	(0.068)	(0.065)	(0.076)
1/*Loadfactor*	0.027**	0.027**	0.027**	0.027**
	(0.002)	(0.002)	(0.002)	(0.003)
Extrahigh	-0.065**	-0.065**	-0.062**	-0.064**
	(0.011)	(0.011)	(0.011)	(0.011)
ln*JEPX*	-0.031**	-0.031**	-0.031**	-0.045**
	(0.011)	(0.118)	(0.011)	(0.014)
ln*Coal*	0.189**	0.189**	0.182**	0.083**
	(0.024)	(0.024)	(0.024)	(0.038)
Earthquake	-0.003	-0.003	-0.005	0.012
	(0.014)	(0.014)	(0.014)	(0.015)
Constant	2.652**	2.651**	2.670**	2.940**
	(0.086)	(0.086)	(0.014)	(0.120)
Regional Effects	Yes	Yes	Yes	Yes
Year Effects	Yes	Yes	Yes	Yes
Reginal Trends	No	No	No	Yes
Observations with Entrants	1,029	1,029	1,029	1,029
Inverse Mills Ratio	-	-0.062**	-0.051**	-0.062**
		(0.022)	(0.021)	(0.023)

Heterosledasticity-robust standard errors are given in parentheses under the coefficients. The individual coefficient is statically statistically significant at the 5% (**) or 10% (*) level.

Table 8: Entrant Winning Rates

Dependent Variable: A dummy variable taking value 1 if an entrant won the auction, and 0 if not.

Regressor	(1) Probit	(2) Marginal Effect	(3) Marginal Effect of Treatment on the Treated
Green	-0.124	-0.019	-0.020
	(0.119)	(0.018)	(0.025)
$\ln Usage$	-0.336**	-0.052**	-0.054**
	(0.079)	(0.120)	(0.013)
Loadfactor	-4.346**	-0.672**	-0.704**
	(0.516)	(0.075)	(0.085)
Extrahigh	0.534**	0.083**	0.087**
	(0.150)	(0.023)	(0.025)
$\ln JEPX$	-0.217	-0.036	-0.035
	(0.270)	(0.042)	(0.044)
$\ln Coal$	0.626	0.097	0.101
	(0.404)	(0.062)	(0.065)
Constant	6.392**	-	-
	(0.148)		
2007	-0.358**	-0.055**	-0.058**
	(0.148)	(0.228)	(0.023)
2008	-0.780**	-0.121**	-0.126**
	(0.218)	(0.023)	(0.035)
2009	-0.111	-0.017	-0.018
	(0.226)	(0.035)	(0.037)
2010	0.107	0.017	0.017
	(0.200)	(0.031)	(0.032)
2011	-0.148	-0.023	-0.024
	(0.208)	(0.321)	(0.033)
2012	0.142	0.022	0.023
	(0.299)	(0.046)	(0.049)
Regional Effect	Yes	Yes	Yes
Observations	1,352	1,352	1,352
Pseudo R2	0.297	-	-

In column(1), Heteroskedasticity-robust standard errors are given in parentheses under the coefficients. In columns (2) and (3), Delta Method standard errors are given in parentheses under the coefficients. The individual coefficient is statically significant at the 5% (**) or 10% level (*).

Table 9: Winning Bid Regression Before Earthquake

Dependent Variable: ln$Price$

Regressor	(1) Multiple-Bidder	(2) Single-Bidder
Green	-0.010	0.016
	(0.011)	(0.010)
ln$Usage$	-0.048**	-0.045**
	(0.014)	(0.010)
Loadfactor	-0.422**	-0.148**
	(0.187)	(0.117)
1/*Loadfactor*	0.018**	0.027**
	(0.001)	(0.002)
Voltage	-0.120**	-0.069**
	(0.016)	(0.013)
ln$JEPX$	0.017	0.004
	(0.025)	(0.019)
ln$Coal$	0.204**	0.174**
	(0.038)	(0.027)
Constant	3.126**	2.821**
	(0.106)	(0.078)
Observations without Entrants	1,207	1,207
Hazard Rate/Inverse Mills Ratio	-0.082**	-0.303**
	(0.069)	(0.047)

The other control variables are the same as those in Tables 6 and 7. All regressions include fixed effects. Heteroskedasticity-robust Standard errors are given in parentheses under the coefficients. individual coefficient is statically significant at the 5% (**) or 10% level (*). The difference between the coefficients before and after the earthquake is statistically significant at the 5% level.

Table 10: Winning Bid Regression After Earthquake

Dependent Variable: ln*Price*

Regressor	(1) Multiple-Bidder Auctions	(2) Single-Bidder Auctions
Green	0.023	0.030**
	(0.030)	(0.011)
ln*Usage*	-0.054**	-0.012**
	(0.022)	(0.009)
Loadfactor	-0.805**	-0.263**
	(0.555)	(0.100)
1/*Loadfactor*	0.016**	0.159**
	(0.003)	(0.037)
Extrahigh	0.117**	-0.013
	(0.047)	(0.023)
ln*JEPX*	0.148**	-0.014**
	(0.067)	(0.023)
ln*Coal*	0.059	-0.080
	(0.096)	(0.056)
Constant	3.290**	2.862**
	(0.291)	(0.233)
Observations without Entrants	215	114
Hazard Rate/Inverse Mills Ratio	-0.053	0.101**
	(0.057)	(0.037)

The other control variables are the same as those in Tables 6 and 7. All regressions include fixed effects. Heteroskedasticity-robust standard errors are given in parentheses under the coefficients. Individual coefficients are statically significant at the 5% (**) or 10% level (*). The difference between the coefficients before and after the earthquake is statistically significant at the 5% level.