Dynamic and Strategic Behavior in Hydropower-Dominated Electricity Markets: Empirical Evidence for Colombia

Por: Jorge Balat, Juan E. Carranza, Juan D. Martin

Borradores de ECONOMÍA

Núm. 886
2015

BANCO DE LA REPÚBLICA COLOMBIA

Bogotá - Colombia - Bogotá - Colombia - Bogotá - Colombia - Bogotá - Colombia - Bogotá - Colombia - Bogotá - Colombia

Dynamic and Strategic Behavior in Hydropower-Dominated Electricity Markets: Empirical Evidence for Colombia*

Jorge Balat†
Juan E. Carranza ‡
Juan D. Martin§

Abstract

In this paper we formulate a dynamic multi-unit auction model to characterize bidding behavior in hydro power dominated electricity markets. Our model implies that, in order to maximize expected profits, hydro producers will submit bid prices above its marginal production costs that account for the intertemporal opportunity cost of water and the expected strategic effects of bids on rivals' behavior. We test the predictions of our model against data of the Colombian electricity market, where hydro producers hold 63% of total installed capacity, and find evidence consistent with both dynamic and strategic behavior.

Keywords: Dynamic auction model; Bidding behavior; Market power; Electricity markets.
JEL Classification: L25, D22, D44.

---

*This study is the result of a work for the *Centro de Estudios sobre Economía Industrial e Internacional* (CEEII) of Banco de la República in Cali, Colombia. We are thankful to Álvaro Riascos, José Morán, Daniel Osorio, Luis Fernando Melo, seminar participants at Banco de la República-Bogotá, and the research staff of the CEEII for helpful discussions and excellent insights. Date of this draft: May19, 2015.

†Johns Hopkins University and Banco de la República. Email: jorge.balat@jhu.edu
‡Banco de la República. Email: jcarraro@banrep.gov.co
§Icesi University and Banco de la República. Email: jdmartin@icesi.edu.co

1 Introduction

Many electricity markets around the world work as multi-unit auctions where generators submit day-ahead supply schedules that are then used by the market operator who defines the daily generation dispatch. These market designs are intended to bring enough competition so that firms' bid prices are near to the competitive levels.

The literature on electricity markets suggest, however, that this does not necessarily hold. The most important finding in these studies is the presence of inefficient pricing, primarily associated with the exercise of market power and strategic behavior. Green and Newbery (1992) and Green (1996), von der Fehr and Harbord (1993), Wolfram (1998) and Crawford, Crespo, and Tauchen (2007) find evidence for both strategic behavior and significant price-cost markups in the British electricity market. At the same time, Borenstein and Bushnell (1999) show that the extent to which generation firms are able to exercise market power in the Californian market is higher during high demand periods. Similar results are obtained for the Spanish market by Ciarreta and Espinosa (2010) who show that the exercise of market power is associated with large multi-plant firms.

In many countries, such as Argentina, Brazil, Colombia and Chile, the generation of electricity is dominated by hydropower plants. In such cases inefficiencies may be even larger due to the presence of additional dynamic incentives. Although this technology allows for virtually zero variable production costs, the possibility to store energy allows firms to switch generation from one period to another of higher expected payoffs implying an intertemporal opportunity cost. Thus, non-trivial dynamic incentives arise because a firm operating such technology will account for the effect that its decisions for current production have on its future profits. Stacchetti (1999), Garcia, Reitzes, and Stacchetti (2001), and Garcia, Campos, and Reitzes (2005) are, to our knowledge, the only works that explicitly model the dynamic aspects of hydro generation. A common finding in these studies is that, as water becomes scarce, hydro producers have incentives to increase bid prices in order to withhold generation and achieve higher future payoffs. These authors show that such behavior may result in higher prices and inefficient outcomes.

We propose a dynamic multi-unit auction model to characterize bidding behavior in hydro power dominated electricity markets. The model builds on the works by Hortacsu and Puller (2008) who model the Texas electricity market as a share auction, and Balat (2014) who follows the specification of Jofre-Bonet and Pesendorfer (2003) for dynamic auction models. In equilibrium, when the intertemporal opportunity cost of water is sufficiently high, hydro generators will submit bids above its marginal production costs to postpone production and to set the market price that maximizes its expected profits. We derive explicit predictions regarding the relationships between bidding strategies and the state variables. In particular, we find that, for a given firm, equilibrium bids are nonincreasing functions of current own stock, rivals' stock, expected future own stock and expected future rivals' stock.

We then test the predictions of our model using data of the Colombian electricity market. In this industry, hydroelectric generation is the dominant technology with more than 63% of the system installed capacity, 95% of which belongs to plants that use dams. Generation is determined at each point in time by a uniform-price, multi-unit auction where producers submit day-ahead supply schedules on an hourly-period basis that are then used by a market operator who defines daily generation dispatches. We focus on the 2001–2008 period when the auction format was practically unchanged. During this time, the market was dominated by three large generation companies that own more than 56% of the total production capacity and almost 70% of the total water storage capacity. The database consists on detailed information of daily bid prices, water stocks and inflows at bidder level, as well as other market variables.

Our econometric approach is based on a regression analysis of equilibrium bids, current water stocks and future inflows. The analysis is divided in two major parts. In the first part of our analysis we define a linear equation where a given generator's equilibrium bid will depend on its own and rivals' current stock. The dynamic component of the model is incorporated by including future realizations of river flows as a signal for future stock values. In the second part, we define different subsets of bidders that we believe behave closer to our dynamic benchmark. Hence, we redefine our equilibrium bid equation and estimate it for different definitions of "optimal bidders".

The empirical evidence supports the existence of both dynamic and strategic behavior of hydro producers. A given firm's bid price is negatively correlated with its own current aggregate stock. Given its own stock, each firm will, on average, bid less aggressively if the aggregate stock of the firm's rivals is relatively low. At the same time, higher bid prices are associated with low expected inflows. A given bidder will submit higher bid prices when expecting low inflows for its rivals' dams. We also find evidence supporting the hypothesis that bidding behavior of the different sets of "optimal bidders" is closer with our notion of dynamic profit maximization. Our findings are robust to different specifications, different definitions of future inflows and different sets of optimal bidders.

The paper is structured as follows. In section 2 we briefly discuss some of the empirical literature on electricity markets. Section 3 presents a dynamic multi-unit auction model of bidding behavior from which we obtain explicit predictions regarding the relationships between equilibrium bids and future water stocks. In section 4 we present a description of the structural characteristics, auction rules and the database of the Colombian electricity market used in this paper. Section 5 presents the methodology and regression estimates of our empirical analysis. Section 7 concludes.

2 Literature Review

In this section we summarize some of the previous studies that address the problems of producers' incentives, market power and the dynamic component of hydro generation in wholesale electricity markets.

The work of Green and Newbery (1992), and later Green (1996), evaluates the competition of producers in the recently deregulated electricity market of England and Wales. Assuming elastic demand and smooth supply functions, they apply the optimal supply function with demand uncertainty approach discussed in Klemperer and Meyer (1989) to observed cost and bid data. Both articles find evidence of market power. The authors conclude that lower markups are achievable by increasing the number of suppliers in the market.

In its seminal paper, von der Fehr and Harbord (1993) instead propose a static sealed-bid multi-unit auction model arguing that in most wholesale electricity markets retail demand is actually inelastic and firms' bids are step-supply schedules. They assume homogeneous costs across firms and generation units. The model suggests that, for levels of demand sufficiently high, producers have more incentives to submit higher prices as their probability to be dispatched increases.

Borenstein and Bushnell (1999) use a notion of Cournot equilibrium and historical cost data to simulate the Californian electricity market after deregulation. Their findings agree with previous works in that high demand periods allow firms to exercise market power. Another an important result of their contribution is the role of hydroelectric production in determining the severity of market power.

The more recent work by Crawford et al. (2007) extends the model of von der Fehr and Harbord (1993) allowing for heterogeneous costs across firms' different generating units. They introduce a notion of *Bid Function Equilibria* with pure-strategy asymmetric bidding. Their model predicts that a single firm bids strategically to set the market clearing price while the remaining firms bid their costs. They find empirical evidence supporting this theory for the British spot market between 1993 and 1995.

The empirical works by Wolfram (1998 and 1999) analyze the determinants of producers' markups in the England and Wales electricity market. The first article is based on a uniform-price multi-unit auction model where bid shading is more likely to occur for the last dispatched units. Using markup estimates, the author finds that strategic bid increases are also associated with larger production capacity shares. The second article is based on a duopoly model and on direct measures of marginal cost and price-cost margins. The author finds that bid prices are not as high as predicted by most theoretical models. She suggests that regulatory constraints and long-term financial contracts are possible explanations for these results.

Similar to von der Fehr and Harbord (1993) and Wolfram (1998), Ciarreta and Espinosa (2010) show that the exercise of market power is particularly associated with large firms owning several generating units. Their empirical approach is based on the notion that smaller firms owning a unique generating unit will bid lower prices than larger multi-unit firms with similar characteristics.

The authors find evidence for significant exercise market power in the Spanish wholesale electricity market and conclude that if larger firms had bid as their smaller counterparts, market prices would have been substantially lower.

The empirical works by Wolak (2000, 2003 and 2007) analyze the effect of forward contracting in the producers' bidding strategies in the National Electricity Market in Australia. On one hand, the model developed in Wolak (2000) is based on the notion of *best-response price* strategies. The model suggests that firms with a positive quantity of energy sold in hedge contracts should submit lower bid prices than they would with a neutral or short contract position. On the other hand, Wolak (2003 and 2007) tests if firms bidding behavior is also consistent with an alternative model of expected profit maximization. In both of these two works the estimated marginal cost functions support an expected profit maximization behavior.

Hortacsu and Puller (2008) also analyze the effect of forward contracting. The article uses a multi-unit auction model to characterize producers' bidding behavior in a Bayesian-Nash equilibrium. In this model, firms are assumed to maximize expected profits under uncertainty of demand. Contract positions are assumed to influence the producers' bidding strategies as private signals. The authors use bids and costs data of the Texas electricity balancing market, to compare actual bidding behavior to their theoretical benchmarks. They find that, while large firms performed close to the static profit maximization behavior, smaller firms' significantly deviate from their benchmark.

A recent paper by Reguant (2014) investigates the effect of thermal producers' start-up costs in bidding behavior. The paper extends the multi-unit auction estimation techniques to a setting of complex bids in which firms declare cost complementarities over time. The author finds that start-up costs play an important role in a dynamic setting as they limit the ability of firms to change production over time, exacerbating fluctuations in market prices.

Though some of the above studies recognize the role of water storage in markets dominated by hydro power and some even mention its dynamic component, they do not explicitly model these features. Stacchetti (1999), Garcia, Reitzes, and Stacchetti (2001), and Garcia, Campos, and Reitzes (2005) are, to our knowledge, the only works that explicitly model the dynamic aspects of hydro generation. A common finding in these studies is that, when electricity is storable with constrained capacity, hydro generators face an intertemporal opportunity cost. Under this setting, hydro generators have incentives to withhold generation in order to save energy and achieve higher profits in future periods. Stacchetti (1999) presents a stylized dynamic model that incorporates the main rules and technical characteristics of the Colombian spot market in 1997. The author uses an artificial variable to account for the opportunity cost of water assuming that each dominant firm bids a unique price for all its plants. The model suggests that, under low stocks of water, hydro generators have stronger incentives to bid higher prices, specially during peak hours.

Garcia et al. (2001) formalize this notion through a two-period duopoly model where hydro generators engage in a dynamic Bertrand competition. Assuming that water replenishing is governed by a first-order Markov stochastic process, these authors characterize a Markov Perfect Equilibrium where players bid conditional on their stock of water at the beginning of each period. Garcia et al. (2005) extend this model to more general oligopoly model. Both articles find that the bidding strategies will depend on the probability that a given firm can reach a future state of significant market power due to the depletion of its rivals' water reserves.

The most recent paper by Vegard Hansen (2009), on the other hand, propose a two-period model with stochastic inflows. The model suggests that the opportunity cost faced by hydro producers depends on the distribution of both demand and water inflow, as well as on the shape of the demand. In particular, the author finds that market prices tend to be higher when demand is convex or when the volatility of inflows is relatively high.

Recent findings for the Colombian electricity market include those of Garcia and Arbeláez (2002), Espinosa and Riascos (2010), and de Castro, Oren, Riascos, and Bernal (2014). Garcia and Arbeláez (2002) construct a dynamic Cournot model for Colombian wholesale electricity market. This model is used to simulate the effect of possible mergers. The authors find that, in presence of market power, energy withholding results in substantially higher spot prices. Espinosa and Riascos (2010) propose a model where optimal bidding behavior is characterized by a Bayesian game based on the results of de Castro and Riascos (2009). They find evidence for substantial gains in efficiency in the Vickrey auction compared to the actual uniform auction. On the other hand, de Castro et al. (2014) evaluate the impact of the transition form self-commitment to centralized-commitment defined by Resolution CREG 051. The authors conclude that, although there is an improvement in productive efficiency, most gains were apportioned by producers through higher markups.

Our approach is different from previous work in that we incorporate the dynamic problem of hydro producers in a multi-unit auction model. We adopt a Markov-perfect equilibrium concept that enables us characterize the dynamic behavior of generation firms in a hydropower dominated electricity market. Under this setting, hydro producers submit the bid schedules that maximize their expected discounted profits conditional on the current stock of its own and rivals' dams as well as on its expectations about its own and rivals' future inflows. In particular, we find that equilibrium bids are nonincreasing functions of the water stocks and expected inflows. These implications are supported by empirical evidence obtained from data of the Colombian electricity market.

3 An Auction Model of Hydro Generation

In this section we present a dynamic uniform-price auction model for electricity wholesale markets where hydropower is a dominant technology. Our model is based on the static Bayes-Nash equilibrium proposed in Hortacsu and Puller (2008) for the Texas electricity market and the specification of dynamic auction models of Balat (2014) and Jofre-Bonet and Pesendorfer (2003) . We first present the static version of the auction model to understand the basic strategic behavior and then extend it to a dynamic setting in the following Section.

3.1 A standard static model

We model competition in an electricity auction based on the Bayesian-Nash equilibrium characterized in Hortacsu and Puller (2008). This model follows the "share auction" formulation of Wilson (1979). In the model, firms choose bid functions to maximize expected profits under uncertainty coming from two sources. First, total demand for electricity is determined by random events such as weather shocks, so it is stochastic from the perspective of the bidder at the time of bidding. Second, firms cannot predict the equilibrium bids of their competitors with certainty because each firm possesses private information regarding their own marginal costs.

Consider a multi-unit auction model with independent private values (IPV) (conditionally symmetric). There are N hydropower generation firms whose production costs at time t are denoted by $\{C_{it}(q; s_{it}), i = 1, \ldots, N\}$, where s_{it} is a private signal distributed $F(s_{it})$. The stock of water of firm i at the beginning of each period t is denoted by w_{it}, and is assumed to be of common knowledge. We also assume zero costs of storing water which is equivalent to assume that spilling water is allowed and costless. Demand is defined as the sum of a deterministic price-elastic component and a stochastic constant term, $\tilde{D}_t(p) = D_t(p) + \varepsilon_t$.

In each time period t, each firm simultaneously submits a supply schedule, $S_{it}(p, s_{it}, \mathbf{w}_t)$, conditional on its private signal and the water stock vector, $\mathbf{w}_t \equiv (w_{1t}, \ldots, w_{Nt})$. As in Hortacsu and Puller (2008), we restrict $S_{it}(p, s_{it}, \mathbf{w}_t)$ to be continuously differentiable, with bounded derivatives. Observe also that $\partial S_{it}(p, s_{it}, \mathbf{w}_t)/\partial w_{it} \geq 0$ is a natural assumption since an increase in w_i should not imply a reduction in i's optimal output, but a reduction in w_i does restricts the firm's set of production possibilities implying, when the restriction is binding, a reduction in i's optimal output.

Now let p_t^c be the market clearing price that satisfies

$$\sum_{i=1}^{N} S_{it}(p_t^c, s_{it}, \mathbf{w}_t) = \tilde{D}_t(p_t^c)\,. \tag{1}$$

Due to the uniform price setting, each firm gets paid $S_{it}(p_t^c, s_{it})p_t^c$. Hence, firm i's *ex post* profit, upon the realization of the market clearing price, p_t^c, is

$$\pi_{it} = S_{it}(p_t^c, s_{it}, \mathbf{w}_t)p_t^c - C_{it}(S_{it}(p_t^c, s_{it}, \mathbf{w}_t)\,; s_{it})\,. \tag{2}$$

The most important source of uncertainty in the profit equation above is p_t^c. In a strategic equilibrium, the uncertainty in p_t^c, from the perspective of firm i, comes from two factors: the uncertainty in market demand, $\tilde{D}_t$, and the unobserved components of i's competitors' profit maximization problems, that is, their marginal cost signals, s_{-it}.

Following Wilson (1979), in the Bayes-Nash equilibrium of the game firms' strategies are of the form $S_{it}(p, s_{it}, \mathbf{w}_t)$. Thus, as in Hortacsu and Puller (2008) we define a probability measure over the realizations of p_t^c, conditional on firm i's private information, s_{it}, the observed stocks, $\mathbf{w}_t$, and the fact that firm i submits the supply schedule, $\hat{S}_{it}(p)$, while its rivals are playing their equilibrium bidding strategies, $\left\{S_{jt}(p, s_{jt}, \mathbf{w}_t),\ j \in -i\right\}$,

$$H_{it}\Big(p, \hat{S}_{it}(p); s_{it}, \mathbf{w}_t\Big) \equiv \Pr\left(p_t^c \leq p \mid s_{it}, \mathbf{w}_t, \hat{S}_{it}(p)\right). \tag{3}$$

Using the market clearing condition (1), we can rewrite this probability distribution as

$$\begin{aligned} H_{it}\Big(p, \hat{S}_{it}(p); s_{it}, \mathbf{w}_t\Big) &= \Pr\left(\sum_{j\in -i}^{N} S_{jt}(p, s_{jt}, \mathbf{w}_t) + \hat{S}_{it}(p) \geq \tilde{D}_t(p) \;\middle|\; s_{jt}, \mathbf{w}_t, \hat{S}_{it}(p)\right) \\ &= \int_{s_{jt}\times\varepsilon_t} \mathbf{1}\left\{\sum_{j\in -i}^{N} S_{jt}(p, s_{jt}, \mathbf{w}_t) + \hat{S}_{it}(p) \geq \tilde{D}_t(p)\right\} dF\left(s_{jt}, \varepsilon_t \mid s_{it}, \mathbf{w}_t\right). \end{aligned} \tag{4}$$

Assuming risk-neutrality, we can now rewrite the bidder's expected payoff maximization problem

$$\max_{\hat{S}_{it}(p)} \int_{\underline{p}}^{\bar{p}} \left[p\hat{S}_{it}(p) - C_{it}\Big(\hat{S}_{it}(p); s_{it}\Big)\right] dH_{it}\Big(p, \hat{S}_{it}(p); s_{it}, \mathbf{w}_t\Big), \tag{5}$$

where the expectation is taken over all possible realizations of the market clearing price, weighted by the probability density, $dH_{it}(\cdot)$. Following Hortacsu and Puller (2008), we derive the following Euler-Lagrange necessary condition for the (pointwise) optimality of the supply schedule $S_{it}^*(p)$

$$p = C_{it}'(S_{it}^*(p); s_{it}) + S_{it}^*(p)\frac{H_S\left(p, S_{it}^*(p); s_{it}, \mathbf{w}_t\right)}{H_p\left(p, S_{it}^*(p); s_{it}, \mathbf{w}_t\right)}, \tag{6}$$

where

$$H_S(p, S_{it}^*(p); s_{it}, \mathbf{w}_t) \equiv \frac{\partial}{\partial S_{it}} \Pr\left(p_t^c \leq p \mid s_{it}, \mathbf{w}_t, S_{it}^*(p)\right),$$

$$H_p(p, S_{it}^*(p); s_{it}, \mathbf{w}_t) \equiv \frac{\partial}{\partial p} \Pr\left(p_t^c \leq p \mid s_{it}, \mathbf{w}_t, S_{it}^*(p)\right).$$

Hence, in the static equilibrium, each firm i's bid price will be equal to the marginal production cost plus a markup term. Hortacsu and Puller (2008) interpret $H_p\Big(p, S_{it}^*(p); s_{it}, \mathbf{w}_t\Big)$ as the "density" of the market clearing price conditional on firm i's bid schedule $S_{it}^*(p)$, and $H_S\Big(p, S_{it}^*(p); s_{it}, \mathbf{w}_t\Big)$ as term that captures i's "market power". Intuitively, (6) shows that in the multi-unit auction setting bidders trade off between bidding a price sufficiently high that results in a higher market clearing price, and bidding a lower price in order to increase its own probability of being dispatched (see von der Fehr and Harbord (1993)). Thus, for a firm with significant market power the first effect will dominate the second and it will be optimal for that firm to bid over its marginal cost.

We highlight two relevant implications from the first order condition in (6). The most relevant implication is that, since H_p and H_S are both nonnegative, bid prices will never be less than the marginal production costs. The other relevant implication is that the extend to which firm i is able to exercise market power is restricted by strategic interactions. These occurs because the distribution of the market clearing price, and thus H_p and H_S, depends on the strategies of i's rivals. Intuitively, an increase in the supply of firm i's rivals will imply a drop in i's probability of being dispatched, keeping other things equal. Therefore, by the Bayes-Nash structure of the equilibrium, firm i's best response will be to reduce its markup.

3.2 Dynamic model

The formulation and notation of the dynamic model follow from the previous section. Time is discrete with an infinite horizon, $t = 1, 2, \ldots$. We assume that future demand is not known to the firms at time t, but the distribution function $F_\varepsilon(\cdot)$ is common knowledge.

Let the vector $\mathbf{z}$ (with support Z) indicate the amount of electricity each firm has to produce as a result of the auction outcome. Water inflows to the dam are realized after the auction ends and is denoted by δ_i. We assume δ_i follows a first-order Markov process $F_\delta(\delta_{it} \mid \delta_{it-1})$. Now, let W denote the support of $\mathbf{w}$. Then, the transition function of the firms' state variable $\boldsymbol{\omega} : W \times Z \times \Delta \to W$ is a deterministic function of the state variables, the auction outcome, and the realized inflows. This function updates the water stock of each of the firms as follows. The i-th component of the transition function is given by

$$\omega_i(\mathbf{w}, \mathbf{z}) = w_i - z_i + \delta_i. \tag{7}$$

where $z_i = S_i(p)$ when the price p satisfies market clearing condition

$$S_i(p) = \tilde{D}(p) - \sum_{j \in -i} S_j(p). \tag{8}$$

Bidders discount the future with a common discount factor $\beta \in (0, 1)$. The discount factor is constant over time and known to the econometrician and to all bidders.

Conditional independence of demand, marginal cost, and inflows realizations is a crucial assumption that allows us to adopt a Markovian dynamic decision process. We consider a Markov-perfect equilibrium concept (and restrict to symmetric strategies). This means that the equilibrium strategies do not depend on time. Let $S_i(p, s_{it}, \mathbf{w}_t, \delta_{it})$ be i's strategy.

Since the outcome of the auction affects not only current profits but also the firm's water stock, firms choose their bids in order to maximize the expected discounted value of future profits. Therefore, the discounted sum of future expected payoffs for bidder i can be written in value function form as (dropping the t subscript)

$$\begin{aligned} M_i\left(s_i, \mathbf{w}, \delta_i, S_{-i}\right) = \max_{\hat{S}_i(p)} \Bigg\{ \int_{\underline{p}}^{\bar{p}} \bigg[\left(p\hat{S}_i(p) - C_i\left(\hat{S}_i(p); s_i\right)\right) + \beta E_{s_i', \mathbf{w}', \delta_i'} \left[M_i\left(s_i', \mathbf{w}', \delta_i', S'_{-i}\right)\right] \bigg] \\ \times dH\left(p, \hat{S}_i(p); s_i, \mathbf{w}\right) \Bigg\}. \end{aligned} \tag{9}$$

It is convenient to write the maximization problem at the beginning of a period, prior to the realization of the private signal and prior to the realization of the demand. Therefore, we define the *ex ante* value function as

$$V_i(\mathbf{w}, S_{-i}) = E_{s_i', \mathbf{w}', \delta_i'} \left[M_i \left(s_i, \mathbf{w}, \delta_i, S_{-i} \right) \right]. \tag{10}$$

Due to the Markov structure of the problem, equation (10) can be written recursively as follows, dropping the dependence on rivals' bidding strategies for notational simplicity,

$$\begin{aligned} V_i(\mathbf{w}) = E_{s_i', \mathbf{w}', \delta_i', z} \Bigg[\max_{\hat{S}_i(p)} \Bigg\{ \int_{\underline{p}}^{\bar{p}} \Big[\left(p\hat{S}_i(p) - C_i \left(\hat{S}_i(p); s_i \right) \right) + \beta V_i \left(\omega \Big(\mathbf{w}, \hat{S}_i(p) \Big) \right) \Big] \\ \times dH \left(p, \hat{S}_i(p); s_i, \mathbf{w} \right) \Bigg\} \Bigg]. \end{aligned} \tag{11}$$

Therefore, the Euler-Lagrange necessary condition when strategy is optimal $S_i^*(p)$ in the dynamic equilibrium is given by[1]

$$p = C'(S_i^*(p); s_i) + \Theta(p, S_i^*(p); s_i, \mathbf{w}) + \beta \left(\Psi_i(\omega(\mathbf{w}, S_i^*(p))) - \sum_{j \in -i} \Psi_j(\omega(\mathbf{w}, S_i^*(p))) \right), \tag{12}$$

where

$$\Theta(p, S_{it}^*(p); s_{it}, \mathbf{w}_t) \equiv S_{it}^*(p) \frac{H_S \left(p, S_{it}^*(p); s_{it}, \mathbf{w}_t \right)}{H_p \left(p, S_{it}^*(p); s_{it}, \mathbf{w}_t \right)}$$

$$\Psi_j(\omega(\mathbf{w}, S_i^*(p))) \equiv \frac{\partial}{\partial \omega_j} V_i(\omega(\mathbf{w}, S_i^*(p))).$$

Hence, in the dynamic equilibrium, the price will have an extra markup term that incorporates the dynamic behavior of the firm. Notice that Ψ_i can be interpreted as the "shift" in firm i's discounted sum of future expected payoffs due to a change in its expected future stock, ω_i. Analogously, the sum of Ψ_j represents the total shift in the sum of i's future expected payoffs due to a variation in the expected future stock of each one of i's competitors $j \in -i$. Hence, this dynamic markup term can be interpreted as firm i's intertemporal opportunity cost of water.

[1] See Appendix A for a proof.

Observe also that Ψ_i is nonngeative because, holding the market price and the current stock constant, an increase in ω_i weakly increases i's sum of future expected payoffs. At the same time, Ψ_j is nonpositive because, holding everything else constant, a decline in the future water stock of i's rivals weakly increases the probability for i to be dispatched in future periods and thus its future expected payoffs. Consequently, as in the static model, the equilibrium price of the dynamic model is never below the production marginal cost of the firm. The intuition is as follows: assume, for example, that the stock of water for future periods is expected to be low. Knowing this, firm i is willing to produce a positive quantity only if the market price is sufficiently high to compensate the discounted future payoffs that the firm is giving up by producing $S^*_{it}(p)$.

3.3 Predictions

Equation (12) suggests that hydro producers will have incentives to withhold generation and increase the market clearing price if the following condition holds:

$$\frac{\partial}{\partial S^*_i(p)}\left(\Psi_i(\omega(\mathbf{w}, S^*_i(p))) - \sum_{j\in -i}\Psi_j(\omega(\mathbf{w}, S^*_i(p)))\right) > 0.$$

That is, firms will postpone generation if slightly increasing its current output also increases the total value of future production that firm i expects to achieve by producing exactly $S^*_i(p)$. Observe also that, since the dynamic term in (12) depends on $\mathbf{w}$, firm i's incentives to increase its bid price would also depend on its rivals' actions.

We can sharpen the predictions of the model if we make a cuople of additional assumptions. First, assume that firm i's opportunity cost of current production is a nonincreasing function of its own current stock and own future inflows:

$$\frac{\partial}{\partial w_i}\left(\Psi_i(\omega(\mathbf{w}, S^*_i(p))) - \sum_{j\in -i}\Psi_j(\omega(\mathbf{w}, S^*_i(p)))\right) \leq 0 \tag{13}$$

$$\frac{\partial}{\partial \delta_i}\left(\Psi_i(\omega(\mathbf{w}, S^*_i(p))) - \sum_{j\in -i}\Psi_j(\omega(\mathbf{w}, S^*_i(p)))\right) \leq 0 \tag{14}$$

The intuition behind this assumption is that, an increase in either firm i's current stock or future inflows, implies as well an increase in its own future stock. This means that, for a given level of current output, firm i is able to achieve higher levels of future output. There is thus a decline in firm i's opportunity cost because, for any future realization of the market clearing price, the total value of future production that firm i gives up by keeping its current output constant is lower. For the converse case, observe that when either firm i's stock or expected inflow is relatively low, any positive level of current output implies less water for future production. Therefore, for any future realization of the market price, the total value of future production that firm i gives up by keeping its current output constant increases.

The second assumption is that firm i's opportunity cost of current production is a nonincreasing function of its rivals' current stock and its rivals' future inflows. In other words, assume that for any $j \neq i$

$$\frac{\partial}{\partial w_j}\left(\Psi_i(\omega(\mathbf{w}, S_i^*(p))) - \sum_{j \in -i} \Psi_j(\omega(\mathbf{w}, S_i^*(p)))\right) \leq 0 \tag{15}$$

$$\frac{\partial}{\partial \delta_j}\left(\Psi_i(\omega(\mathbf{w}, S_i^*(p))) - \sum_{j \in -i} \Psi_j(\omega(\mathbf{w}, S_i^*(p)))\right) \leq 0 \tag{16}$$

Following the same argument we used in our previous assumption, an increase in firm j's either current stock or future inflows, implies an increase in j's future stock. This means that, for a given level of current output, j is able to achieve higher levels of future production. Other things equal, this reduces the probability that the market clears at higher prices in the future. Thus, the expected sum of future payoffs that firm i can achieve from withholding production in the current period declines. Conversely, holding everything else constant, a decline in j's current stock or future inflows implies an increase in the probability of achieving future states of higher market prices. Therefore, firm i's cost of current output will increase for any given state of its own and expected inflows.

With these assumptions in mind, we thus summarize the following testable predictions of our model

1. *Firm i's equilibrium bid prices are nonincreasing in its current own water stock*. From assumption (13), we have that a decline in w_{it} implies a greater opportunity cost for firm i. According to first-order condition (12), i's best response will be to withhold current production by increasing the price it bids for any level of output. Therefore, $\partial p/\partial w_{it} \leq 0$.

2. *Firm i's equilibrium bid prices are nonincreasing in its own expected inflows*: From assumption (14), *ex ante* lower expected inflows for its own dams implies a higher opportunity cost of current production for firm i. Then, bidder i's best response will be to increase its equilibrium bid price whether to save water for future production or to set a market price sufficiently high that compensates the expected value of withholding that i gives up by increasing its current output. Therefore, $\partial p/\partial \delta_{it} \leq 0$.

3. *Firm i's equilibrium bid prices are nonincreasing in its rivals' water stock*: Because of strategic symmetry, prediction 1 implies that bidder $j \neq i$ will submit a lower equilibrium bid price when its current stock is relatively high. Also, from assumption (15), there is a decline in firm i's opportunity cost of current production. Also, other things equal, this implies a lower probability for i to be dispatched in current period. Consequently, i's best response will be to bid lower prices. In other words, $\partial p/\partial w_{jt} \leq 0$.

4. *Firm i's equilibrium bid prices are nonincreasing in its rivals' expected inflows*: By the same logic of predictions 2 and 3, if bidder $j \neq i$ expects its inflows to be relatively low, that bidder's best will be to increase its equilibrium bid price. Other things constant, this will imply an increase in the probability of i to be dispatched. Hence, i's best response will be to increase its own bid as well. Therefore, $\partial p/\partial \delta_{jt} \leq 0$.

Below we empirically test these four predictions using detailed auction data of the Colombian electricity market.

4 The Colombian Electricity Market

In this section we present a brief description of the electricity market in Colombia and the auction data used for our empirical analysis. We focus on the wholesale market, called the *Mercado de Energía Mayorista* (MEM), where the price and quantity of produced electricity are defined (see Carranza, Riascos, and Morán (2014) for a detailed description).

The wholesale electricity market in Colombia was established in 1994 when generation and trade were deregulated. The MEM is a centralized market interconnected through the *Sistema Interconectado Nactional* (SIN), a country-wide network. The main transactions in this market involve four types of agents. Generators and retailers are the only active agents of the MEM. Generators produce the electricity that is sold in the MEM. Retailers buy that electricity to sell it to the final consumer. The other two agents, transmitters and distributors, are completely owned by the State. Competition in transmission and distribution activities is possible only in projects for the expansion of the network.

Trade and operation in MEM are coordinated by the *Centro Nacional de Despacho* (CND), the market operator. The CND is responsible for the planning, supervision and control of the integrated operation of generation resources and the transmission connectivity of the SIN. A subsidary of the CND, the *Administrador del Sistema de Intercambios Comerciales* (ASIC), administrates all monetary transactions made by the active agents of the MEM. Since 2005, both ASIC and CND are administrated by XM, a subsidiary of *Interconexión Eléctrica S.A.* (ISA). Finally, all transactions are monitored by the *Comisión de Regulación de Energía y Gas* (CREG), the regulatory agency.

The MEM consists of two separated markets: the forward market and the spot[2] market. Most electricity is traded in the forward market through bilateral contracts between generators and retailers. However, the role of the forward market is merely a financial one. All production decisions are centralized by the CND and defined in the spot market.

Procurement in the spot market occurs through a multi-unit uniform-price auction where gen-

[2]This is rather a day-ahead market since, as we describe in following sections, the energy price is calculated a day after real-time production. Nevertheless, as in de Castro et al. (2014), we will follow the usual practice in Colombia and refer to this market and its price as "spot market" and "spot price", respectively.

erators submit supply schedules to satisfy load demand in an hourly-period basis. The bidding structure and the definition of the market price (spot price) differ across three different periods since 1995. For our empirical analysis we focus on the 2001–2008 period when the auction format was practically unchanged.

4.1 Productive structure

Generation technology is primarily hydroelectric (hydro) and themoelectric (thermal). During the sample period, the dominant production technology was hydro with more than 63% of the total installed capacity of the SIN (see Figure 2). More than 95% of hydro capacity was operated by plants that use dams, while the reminder 5% belonged to run-of-river plants. Thermal plants accounted for 32% of the total installed capacity, most of which are fueled by natural gas.[3] The rest of the capacity of the SIN belonged to producers using eolic technology (0.14%) and *cogeneration* (0.18%), a technology that combines production of therm and electric energy.

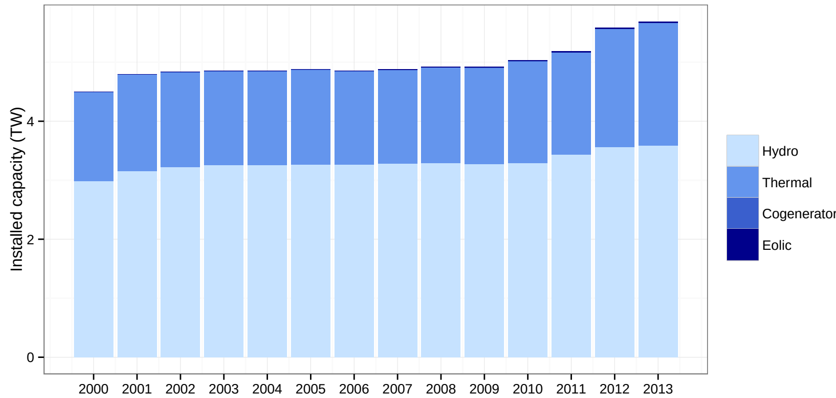
In terms of aggregate production, the share of hydro generation is even higher. Between 2000 and 2013, the yearly generation was between 41,278 and 62,197 GWh, with an average growth rate close to 4% (see Figure 1a). Under normal hydrological conditions hydro plants can reach up to 91% of this generation. This productive structure, however, makes the Colombian electricity industry very vulnerable to water scarcity periods, as pointed out by Stacchetti (1999). We illustrate this in Figure 2a. In periods of droughts as those caused by *El Niño* in 1992-1993 and 2009-2010, hydro generation share was close to 51% and 46%, respectively. Consequently, the spot price can also be severely affected by these extreme weather conditions. Figure 2b shows the evolution of the monthly average spot price. During the most severe events of *El Niño* in Colombia, the monthly average spot price increased 3.5 times from June, 1997 to February, 1998 and 1.2 times from April, 2009 to April, 2010.

Producers in the MEM are registered as *generators*. A generator definition depends on whether it uses hydro or thermal technology. In general, a generating firm may own more than one plant.

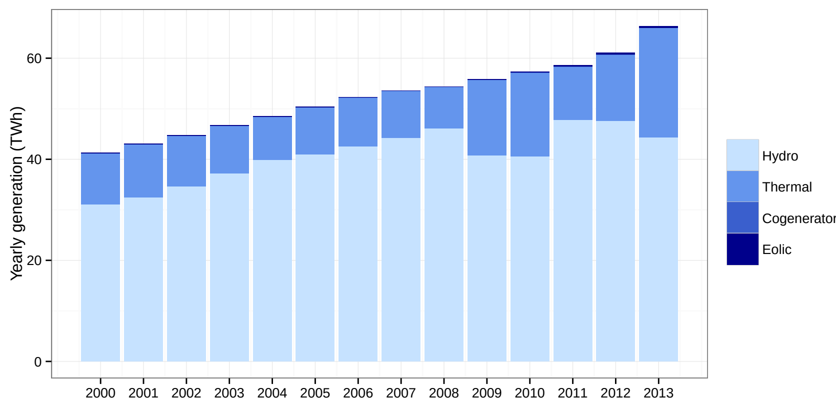
[3] We include combined cycle gas turbine power plants in the set of thermal technology.

Figure 1: Evolution of the Productive Structure

(a) Installed Capacity



(b) Aggregate Generation

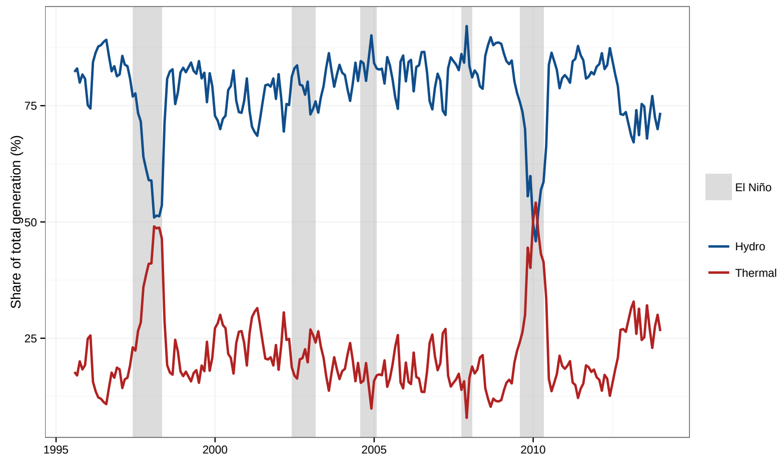


Within a given plant there may be more than one generation unit. Several hydro plants operating with the same dam or river form a *hydro chain*. Thus a hydro generator is defined as a plant or hydro chain (if that is the case) while a thermal generator is a generation unit of a thermal plant.

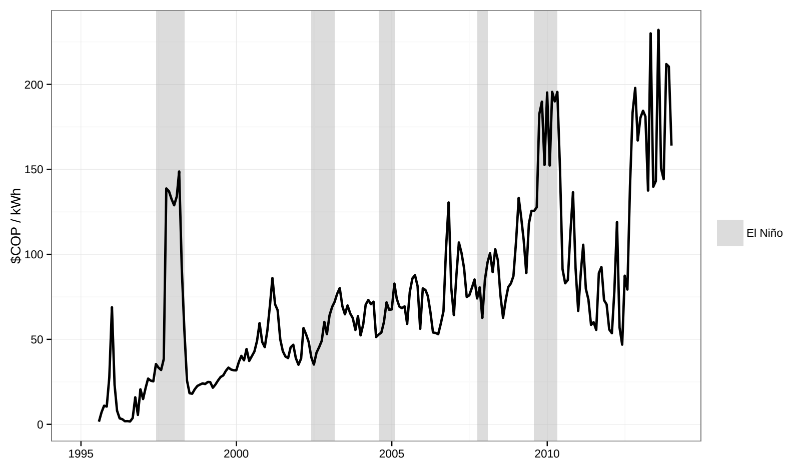
Generators in the MEM are also classified by size. This classification determines whether a generator is subject to central dispatch, that is, if the generator must participate in the electricity auction. Large generation units with a net effective capacity (NEC) above 20 MW are classified as *major* generators. Major generators are always centrally dispatched. Generators with a NEC below 20 MW are called *minor*. Generally, minor generators are not subject to central dispatch; however, when having a NEC between 10 an 20 MW, a minor generator may decide whether to be centrally dispatched or not. During our period of study most generators in the SIN were minor, accounting

Figure 2: Evolution of Hydro and Thermal Generation Shares and The Spot Price

(a) Generation



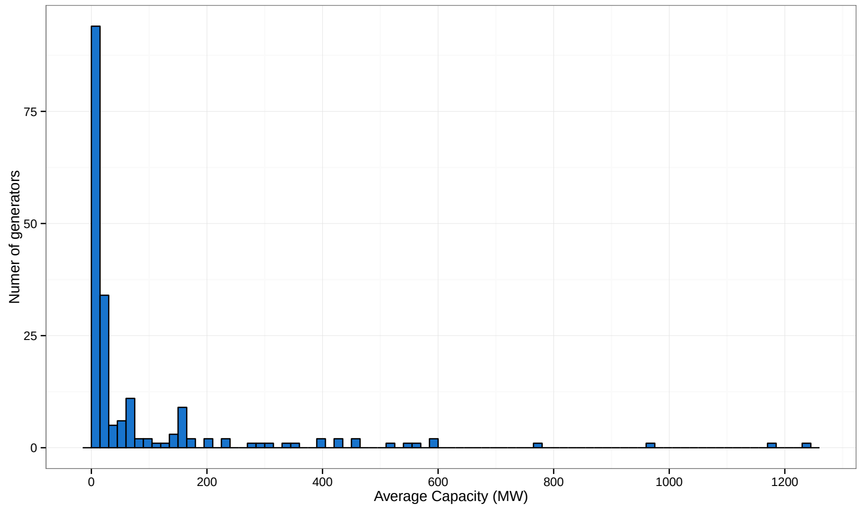
(b) Spot Price



for 61% of the all generators and 4% of the installed capacity of the SIN, while major generators accounted for about 34% of all the generators and almost 96% of total capacity (see Figure 3). The third group consists of all generators that use cogeneration and those, not connected to the SIN, that produce electricity for self-consumption called *autogenerators*. Neither autogenerators nor cogenerators are centrally dispatched.

Table 1 presents the distribution of plants and installed capacity across the different types of generation technologies at the end of 2008. The data shows that the majority of production capacity is owned by less than 19% of the firms. This productive structure was dominated by three large

Figure 3: Distribution of Installed Capacity



companies: *Emgesa*, *Empresas Públicas de Medellín* (EPM) and *Isagen*. These firms owned more than 56% of the SIN's installed net capacity and almost 70% of the total water storage capacity. The rest of production capacity was operated by 3 medium-size and 32 small firms. This structure has not changed much since then.

Table 1: Distribution of the Installed Capacity, December 2008

Type of generation		Number Firms[a]	Number Generators	Installed Capacity (MW)	Share (%)
Hydro	Dam	7	18	8,495	63.03
	Run-of-river	22	84	502	3.72
Thermo	Gas	14	17	3,551	26.34
	Coal	3	3	700	5.19
	Fuel[b]	1	1	187	1.39
Eolic		1	1	18	0.14
Cogeneration		5	7	25	0.18
Total		37	131	13,478	100

Source: Authors' calculations based on data from XM.
[a] The number of firms is defined as the number of agents that operate the plants in each category (row) as registered in the MEM. [b] Includes plants that use diesel, fuel-oil or a mix of gas and fuel.

4.2 The Rules of the Spot Market

From 2001 to 2009, procurement in the spot market was made through a uniform-price, multi-unit auction. All centrally dispatched generators were required always participate by submitting day-ahead bids consisting of a unique price and an hourly schedule of the maximum available capacity they expect to have for next day. Noncentrally dispatched generators, on the order hand, were not supposed to participate in the auction. Instead, they decided to submit an hourly power schedule they are willing to sell as price takers. The auction were conducted by the CND who defined a daily generation schedule that satisfies demand at minimum generation costs.

The process is described as follows. Every day before 8:00 AM, firms submitted a day-ahead bid schedule for each generator they owned.[4] Using these bids, the CND made a generation schedule that ensured energy supply at minimum production costs. This schedule, called *economic dispatch*, consisted of the amount of electricity every generator was required to produce in order to satisfy the expected demand for each hour of the next day. During the operation day, the CND was responsible for adjusting the economic dispatch for available capacity changes, network restrictions and deviations of real demand from the forecast. The schedule that accounted for these adjustments is called *real dispatch*. The day after, the CND conducted a multi-unit uniform-price auction to compute the hourly spot price. The resulting schedule, called *ideal dispatch*, accounted for observed information on demand and available capacity, assuming ideal network conditions. The last generation unit dispatched was called the marginal generator and was only dispatched for the residual demand not covered by the other dispatched generators. The spot price was set equal to the price submitted by the marginal bidder. Finally, all ideally dispatched units were paid with the spot price for to every kWh produced in the respective hour.

By Resolution CREG-55 of 1994 generators are required to bid according to their "variable costs", for thermal plants and their "water opportunity costs", for hydro plants. In this paper, we investigate if there are other determinants of the producers' bidding behavior. In particular, we

[4]Generators that did not submit their bids before 8:00 AM entered in the auction with the bid schedules they submitted in the last auction.

analyze if generation firms in this market behave as suggested by our dynamic profit maximization benchmark by testing the predictions of our model using data of the Colombian electricity market. The data are described below.

4.3 Description of the Database

For our empirical analysis, we use information of centrally dispatched generators on bid prices, demand levels, available capacity, water stocks and inflows, among other market variables from 2001 to 2008. The data is provided by XM and is public. The data also includes information on coal prices from the *Unidad de Planeación Minero Energética* (UPME).[5] We observe 2,922 days, 27 firms and 56 bidders (17 hydro and 39 thermal). During the sample period we also observe the entry of 6 bidders, 7 cases of bidder withdrawal and 13 changes of owner. The final database is an unbalanced panel of 146,542 observations.

Table 2 presents the definitions and units of measure of the variables included in our empirical analysis. The difference between $Avcap_{ikt}$ and $Avcapc_{ikt}$ is that the former corresponds to the expected available capacity that a centrally dispatched generator submits for the economic dispatch while the latter is the realized available capacity for the ideal dispatch. The usable stock for a given dam is defined as the amount of water stored above the respective minimum technical volume (MTV). As for the CERE variable, also known as *Costo Equivalente Real de Energía*, is a reference for the value of energy and is published every month by the CND to signal bidders expectations. Some summary statistics are presented in Table 3.

[5]UPME is a special administrative unit attached to *Ministerio de Minas y Energía* (the Ministry of Mines and Energy) responsible for planning energy mining development. See more at: http://www1.upme.gov.co

Table 2: Definition of sample variables

Variable	Unit of Measure	Definition
Bid_{ikt}	COP / KWh	Price bid by generator i of firm k on day t
$Stock_{ikt}$	GWh	Aggregate usable stock in dams of generator i owned by firm k on day t
$Flow_{ikt}$	GWh	Aggregate river flows that feed the dams of generator i owned by firm k on day t
$Size_{ikt}$	MW	Installed net effective capacity of generator i owned by firm k on day t
${Avcap_{ikt}}^{*}$	MW	Average available capacity bid by generator i owned by firm k for production on day t
${Avcapc_{ikt}}^{*}$	MW	Average realized available capacity of generator i owned by firm k for production on day t at hour h
${Prod_{ikt}}^{*}$	GWh	Total electricity produced by generator i owned by firm k on day t
${Csales_{kt}}^{*}$	GWh	Total electricity net contract sales of firm k on day t
${Demd_t}^{*}$	GWh	Total electricity consumed in Colombia on day t
${Price_t}^{*}$	COP / KWh	Average spot price on day t
${PC_t}^{\dagger}$	USD / MBTU	Average contract price observed on day t
${CERE_t}^{\dagger}$	COP / KWh	CERE observed observed on day t
${Coal_t}^{\dagger}$	USD / TON	Average price of coal for Colombian exports observed on day t

* Also available in hourly basis.
† Original data are in monthly series.

Table 3: Descriptive Statistics of Sample Data

Variable	Mean	Std. Dev.	Min	Max	Obs
Bid	281.42	330.58	23.85	3,947.87	146,542
Size	249.62	282.62	10.00	1,240.00	146,542
Avcapc	222.35	263.63	0.00	1,240.37	146,542
Prod	2.53	4.71	0.00	29.90	146,542
Csales	6.02	8.35	-2.41	35.75	54,966
Demd	131.28	13.82	89.61	160.05	2,922
price	68.99	20.83	29.52	182.80	2,922

Table 4: Mean of Main variables by Type of Generation

Year	Bid (COP/kWh)	Net Effective Capacity (MW)	Available Capacity (MW)	Generation (GWh)	Net Contract Position (GWh)
			Hydro Generators		
2001	85.39	483.82	435.29	5.31	12.99
2002	92.55	486.98	451.72	5.55	14.12
2003	99.52	488.12	433.67	5.67	14.47
2004	106.89	489.12	437.02	6.01	15.43
2005	117.77	489.12	444.09	6.16	15.81
2006	142.01	489.18	438.78	6.38	16.22
2007	202.30	491.77	443.06	6.65	18.08
2008	214.41	491.76	447.38	6.91	20.28
			Thermal Generators		
2001	241.05	119.01	102.29	0.77	7.06
2002	255.97	118.75	106.33	0.73	7.37
2003	277.22	124.26	97.12	0.74	7.27
2004	330.83	133.69	117.92	0.71	7.84
2005	356.00	135.87	122.59	0.79	7.12
2006	355.34	137.43	123.45	0.83	9.14
2007	360.50	137.68	118.37	0.80	10.24
2008	710.97	137.01	118.23	0.67	10.68

In Table 4, we compare the yearly sample means of the main variables between hydro and thermal generators. For every year of the sample, hydro producers submit lower average bid prices than do thermal generators. Although hydro plants that use dam are larger on average, thermal capacity has grown faster than hydro. Average real production and net contract sales are also higher for hydro producers.

Hydraulic variables include usable stock and river flows. Both variables are measured in equivalent energy units (GWh).[6] Table 5 presents the mean and standard deviation of both stock and inflows by generator and its operating firm. Although BETANIA and PRADO were initially operated by other firms, these periods are relatively small in our sample period. The largest dams (in terms of equivalent energy units) are operated by GUATAPE (EPM), PAGUA[7] (EMGESA), and GUAVIO (EMGESA). These generators also receive the highest average inflows. In Figure we present the evolution of the monthly average series of water stock and river flows for the three largest generators in terms of storage capacity.

In the following section we present the methodology and estimation results of our empirical analysis.

5 Empirical Analysis

We now test empirically if producers' behavior in the Colombian electricity market is consistent with our dynamic auction model, in which firms account for the strategic effects of their bids and the intertemporal opportunity cost of water. In particular, we test the predictions of the model using the data described above.

We regress different specifications of a reduced-form equation of equilibrium bids. The analysis is divided in two major parts. In the first part, we estimate our reduced-form equation at the generator level using the full sample. Hence, we define linear equations of observed bids by individual generators as function of its own and rivals' current stock, and other controls. We incorporate the

[6] For generators that use more than one dam, all hydraulic variables correspond to aggregate measures.

[7] PAGUA is an hydroelectric chain composed by the plants of Paraiso and Guaca. This chain uses water from three different dams.

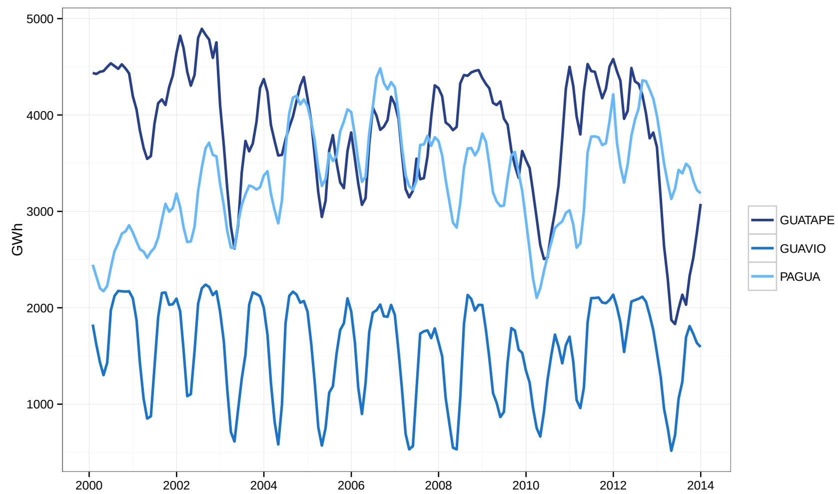
Table 5: Stocks and Inflows by Generator

		Usable Stock (GWh)		Inflows (GWh)	
Firm	Generator	Mean	Std. Dev.	Mean	Std. Dev.
CHIVOR	CHIVOR	725.56	334.39	13.21	13.72
EMGESA	PAGUA	3,343.14	576.02	15.47	13.95
	GUAVIO	1,518.24	533.75	16.89	14.74
	BETANIA*	108.51	34.21	6.04	3.51
EPM	GUATAPE	3,604.17	487.47	16.95	10.09
	LA TASAJERA	273.51	92.21	7.54	4.08
	GUATRON	222.74	55.73	9.33	4.50
	PLAYAS	78.63	19.28	5.62	3.39
	PORCE II	28.91	15.02	4.90	2.39
EPSA	CALIMA	136.80	59.67	0.55	0.39
	SALVAJINA	88.71	46.61	2.80	1.71
	PRADO*	34.06	16.38	0.57	0.74
	ALBAN	9.46	7.41	5.33	2.71
ISAGEN	JAGUAS	262.24	112.17	8.32	6.63
	MIEL I	83.10	50.31	3.94	2.24
	SAN CARLOS	37.65	20.59	3.06	3.03
URRA	URRA	100.47	36.95	3.68	2.27

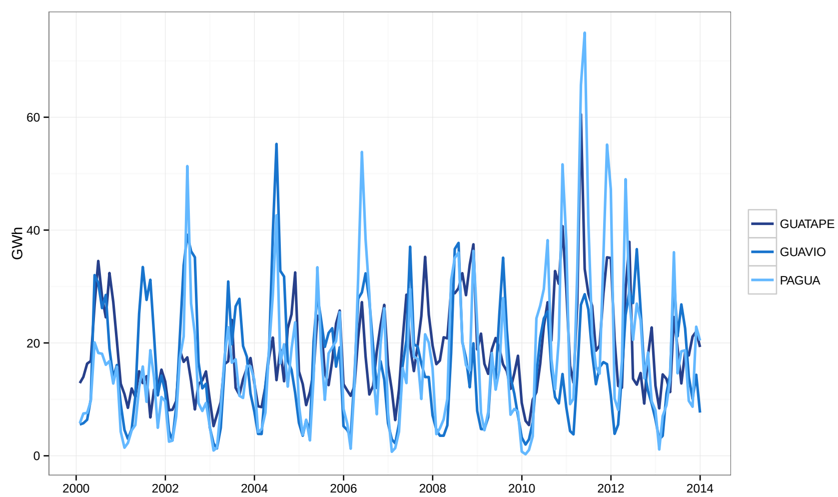
* Operated by other firms during the sample period.

Figure 4: Evolution of Hydraulic Variables for the Three Largest Generators

(a) Water Stocks



(b) Water Inflows



dynamic component of the model by including future realizations of each generator's aggregate river flow in the equilibrium bids equation as proxies of the bidders' expectations of future inflows.

In the second part, we consider the hypothesis that not all generators bid optimally, since most generation companies operate several generators. In particular, we consider two types of "optimal" bidders. On one hand, we assume that large producers behave closer to our optimal benchmark than smaller generators, and define a set of "large" bidders. On the other hand, we assume that each multi-plant firm bidding behavior is closer the optimal benchmark for its "marginal" generator than for its other units, and define a set of "marginal" bidders for each generation company.

We stress that we do not estimate causal parameters but rather correlates that allows us to verify if the data supports for the predictions of our model about the relationships between equilibrium bids and the state variables. Accordingly, when looking at the estimation results we will focus only on the sign and statistical significance of the estimated coefficients associated with the state variables rather than on their magnitude. We focus only on hydro generators that use dams but our results are robust to the inclusion of thermal generators[8]. We also exclude all observations with bid prices above 600 COP/KWh.[9]

5.1 Full Sample Approach

We begin by defining the following reduced-form equation of equilibrium bids

$$Bid_{ikt} = \eta_1 Ostock_{ikt} + \eta_2 Rstock_{ikt} + \mu_i + \tau_t + \varepsilon_{ikt}, \tag{17}$$

where

$$Ostock_{ikt} = 100 \times \frac{Stock_{ikt}}{Maxstock_{ikt}} \quad \text{and} \quad Rstock_{ikt} = 100 \times \frac{\sum_{j \neq i} Ostock_{jkt}}{\sum_{j \neq i} Maxstock_{jkt}}.$$

In other words, $Ostock_{ikt}$ is generator i's water stock defined as a fraction of its dam's maximum technical volume and $Rstock_{ikt}$ as the weighted average of this fraction across i's rivals.[10] The terms μ_{ik} and τ_t are plant and year fixed effects, respectively. Finally ε_{ikt} is the stochastic error term that we assume to be uncorrelated with the regressors.

We expect η_1 and η_2 to be negative as suggested by predictions 1 and 3. Table 6 presents the OLS estimates of equation (17) for hydro generators only. In Column 1 we run a simple regression of generator i's equilibrium bid on its current water stock. As suggested by the predictions of our model, those generators facing a lower current stock bid, on average, higher prices. In the next three

[8]See Appendix B.

[9]These outliers account for less than 5% of total observations of the final database.

[10]For generators that use more than one dam, the maximum technical volume is defined as each generator's aggregate maximum technical volume.

columns, this result remains unaffected even after we add plant and year fixed effects. In columns 5-8 we include the aggregate stock of generator i's rivals. Although the estimated coefficient is not of the expected sign, it's statistically different from zero. This supports the hypothesis that, conditional on its own stock, generator i's equilibrium bid is correlated with its rivals' stock. In particular, the results suggest that, given its own stock, generator i's will, on average, bid less aggressively if its rivals' aggregate stock increases. These results are robust to the inclusion of thermal plants as shown in Table 11 of Appendix B.

Table 6: Regression Coefficients of Equilibrium Bids on Current Stock

	Dependent variable: Equilibrium Bids							
Ostock	-0.805***	-0.626***	-0.787***	-0.635***	-0.917***	-0.794***	-0.882***	-0.785***
	(0.017)	(0.017)	(0.016)	(0.018)	(0.019)	(0.020)	(0.018)	(0.020)
Rstock					0.661***	0.652***	0.663***	0.654***
					(0.039)	(0.036)	(0.042)	(0.038)
Plant FE	NO	YES	NO	YES	NO	YES	NO	YES
Year FE	NO	NO	YES	YES	NO	NO	YES	YES
Number of obs.	45,945	45,945	45,945	45,945	45,945	45,945	45,945	45,945
R^2	0.05	0.35	0.08	0.36	0.06	0.35	0.08	0.36

Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Overall, this evidence supports our prediction about a negative relationship between each generator's equilibrium bid and its current stock. Furthermore, these findings provide strong evidence in favor of strategic behavior. In a competitive environment, after controlling for its own state variables, generator i's equilibrium bid should not be correlated with its rivals state variables. Nevertheless, we find that conditional on its own stock, generator i's equilibrium bid is correlated with its rivals' current stock.

Future Inflow Expectations

In this subsection we account for the dynamic part of our model by including each generator's future river flows in the equilibrium bid equation as a proxy for future inflow expectations. In particular, we use the realization of the bidder's aggregate river flow one day ahead of current period. Notice that, by using this measure, we are implicitly assuming perfect foresight of generator i about its own and rivals' future inflows. Hence, the reduced-form equation of equilibrium bids is redefined as

$$\begin{aligned} Bid_{ikt} = \eta_1 Ostock_{ikt} + \eta_2 Rstock_{ikt} + \eta_3 Oflow_{ikt+1} + \eta_4 Rflow_{ikt+1} \\ + \mathbf{x}'_{ikt}\boldsymbol{\gamma} + \mu_i + \tau_t + \vartheta_t + \varepsilon_{ikt}, \end{aligned} \tag{18}$$

where

$$Oflow_{ikt} = 100 \times \frac{Flow_{ikt}}{Maxstock_{ikt}} \quad \text{and} \quad Rflow_{ikt} = 100 \times \frac{\sum_{j \neq i} Oflow_{jkt}}{\sum_{j \neq i} Maxstock_{jkt}}.$$

Analogously to the definition of the stock variables, $Oflow_{ikt+1}$ is the one day ahead realization of generator i's river flow defined as a fraction of its dam's maximum technical volume and $Rflow_{ikt+1}$ as the weighted average of this fraction across i's rivals. The term $\mathbf{x}'_{ikt}$ is a vector of controls for generator- and market-specific characteristics.

We expect η_1, η_2, η_3 and η_4 to be negative as suggested by predictions 1–4. The regression coefficients are presented in Table 7. All specifications include plant and year fixed effects. As controls we include: the generator's relative size ($Size$), defined as its installed capacity over the aggregate market capacity; the firm's contract net sales position ($Csales$); aggregate daily demand ($Demd$); the total number of bidders that participate in the auctions; and the observed CERE and coal price series.[11] In Column 1 we regress each generator's equilibrium bid on its own current stock and future inflow. Both coefficients are of the expected sign. Hence, even when controlling for the bidder inflows, bidder i's equilibrium bid price is on average, higher when its own stock decreases. Likewise, conditional on its own current stock, generator i bids less aggressively when expecting a decrease in its future inflows.

In Column 2 of Table 7 we add the rivals' stock variable and find that, as in previous results, even after controlling for its own stock and future inflows (and other characteristics of the plant and year), generator i's equilibrium bid is statistically associated with its rivals' aggregate stock. In columns 3 and 4 we include the rivals' inflow variable. Hence, even when conditioning on its current stock and expected inflows, and its rivals' stock, we find evidence supporting the hypothesis

[11] See Table 2 for the definitions of these variables.

that the generator i's bid price is negatively correlated with its rivals' future inflows.

Table 7: Regression Results for Equilibrium Bids on Stocks and Inflows

	Dependent variable: Equilibrium Bids							
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Ostock	-0.599***	-0.751***	-0.786***	-0.753***	-0.599***	-0.728***	-0.764***	-0.729***
	(0.018)	(0.021)	(0.020)	(0.021)	(0.018)	(0.020)	(0.020)	(0.020)
Oflow	-1.483***	-1.386***		-1.289***	-1.548***	-1.454***		-1.388***
	(0.105)	(0.106)		(0.111)	(0.106)	(0.106)		(0.111)
Rstock		0.644***	0.675***	0.653***		0.617***	0.648***	0.622***
		(0.038)	(0.038)	(0.038)		(0.040)	(0.040)	(0.040)
Rflow			-4.901***	-2.279**			-4.530***	-1.623*
			(0.877)	(0.923)			(0.937)	(0.981)
Controls	NO	NO	NO	NO	YES	YES	YES	YES
Plant FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Number of obs.	38,250	38,250	38,250	38,250	38,250	38,250	38,250	38,250
R^2	0.41	0.41	0.41	0.41	0.42	0.42	0.42	0.42

Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

The results are robust to the inclusion several controls for generator- and market-specific characteristics. (See columns 5–8 of Table 7) Furthermore, when including of thermal plants in the estimation sample we also obtained quite similar results. However, we find a rather positive relationship between generator i's equilibrium bid and its rivals' expected future inflow. (See Table 12 in Appendix B)

We also performed an exercise analogous to the one shown in Table 7 using different definitions of inflows measures. In particular, we used: *i*) the realization of the bidder's aggregate river flow in the current period, *ii*) the realization of the bidder's aggregate river flow for more than one day ahead, and *iii*) the bidder's accumulated river flows between previous and future periods. The regression coefficients for these specifications are quite similar to those described in Table 7 supporting the predictions of our model. However, we find that as we moved further to future periods, the estimated correlation becomes weaker.

The bottom line for this part of our empirical analysis is that in all cases considered we find strong support for our predictions In particular, we find that each generator's bid price is negatively associated with its current stock and future inflows, which is consistent with predictions 1 and 2. We also find evidence supporting for strategic interactions; that is, we find that, conditioning on its own stock and inflows, and other characteristics, each generator's equilibrium bid is correlated with its rivals' state variables.

Nevertheless, for the rivals' stock variable, the sign of the estimated coefficient is always positive, contrary to prediction 3. This suggests that at least not all hydro generators bid as predicted by our dynamic model. Several empirical works on electricity markets agree that only a subset of bidders behave optimally as predicted by the theoretical models. (See Wolfram (1998), Hortacsu and Puller (2008), and Ciarreta and Espinosa (2010)) Therefore, in the next subsection we focus in some subsets of bidders that we believe behave more accordingly with our optimal dynamic benchmark.

5.2 Optimal Bidder Approach

The Large-Bidder Approach

For our first definition of "optimal" bidder, we consider the hypothesis that the bidder's size is associated with its ability to set the market price, that is, its market power. Several studies in the literature on electricity markets are consistent with this hypothesis. The works by von der Fehr and Harbord (1993), Stacchetti (1999), Ciarreta and Espinosa (2010) and Hortacsu and Puller (2008), for instance, consider size as a characteristic that enhances the firm's ability to exercise market power. In particular, Hortacsu and Puller (2008) find that, large firms performed close to the static profit maximization behavior, while smaller firms significantly deviate from their theoretical benchmark. Similarly, Ciarreta and Espinosa (2010) argues that larger generators are very often price setters creating an incentive for this agents to shade their bids more than smaller generators.

In the same spirit of these studies, we assume that large bidders are more likely to influence the market clearing price, and thus are more likely to exercise market power. In first-order conditions (6) and (12), this is equivalent to assume that H_S is higher for large bidders. Consequently, large bidders will have more margin for strategic behavior and, therefore, will perform closer to our dynamic benchmark.

We begin by defining $\mathfrak{L}$ as the set of large generators and $D_{S,i}$ as equal to 1 if $i \notin \mathfrak{L}$ and 0 otherwise. Thus, a modified version of equilibrium bid equation (18), that allows us to efficiently estimate different coefficients for large bidders, can be written as follows

$$\begin{aligned} Bid_{ikt} &= \eta_1 Ostock_{ikt} + \eta_2 Rstock_{ikt} + \eta_3 Oflow_{ikt+1} + \eta_4 Rflow_{ikt+1} + \mathbf{x}'_{ikt}\boldsymbol{\gamma} \\ &\quad + D_{S,i} \times \left(\eta_1^{D_S} Ostock_{ikt} + \eta_2^{D_S} Rstock_{ikt} + \eta_3^{D_S} Oflow_{ikt+1} + \eta_4^{D_S} Rflow_{ikt+1} + \mathbf{x}'_{ikt}\boldsymbol{\gamma}^{D_S}\right) \\ &\quad + \varepsilon_{ikt}. \end{aligned} \tag{19}$$

Note that each coefficient η_1, η_2, η_3 and η_4 can be interpreted as the average change in the equilibrium bid of a large bidder associated with a variation in the realized stocks and expected inflows. On the other hand, each one of $\eta_1^{D_L}$, $\eta_2^{D_L}$, $\eta_3^{D_L}$ and $\eta_4^{D_L}$ is the average slope difference for the respective state variable in the equilibrium bid equation between small and large generators. For example, the average slope difference for the own stock variable between a small and a large generator is given by

$$\left.\frac{\partial Bid_{ikt}}{\partial Ostock_{ikt}}\right|_{i\notin\mathfrak{L}} - \left.\frac{\partial Bid_{ikt}}{\partial Ostock_{ikt}}\right|_{i\in\mathfrak{L}} = \eta_1^{D_S}.$$

Hence, we can verify if the bidding behavior is statistically different for the two groups of bidders by performing a test of joint significance. In particular, we test the following linear hypotheses

$$H_0 : \eta_1^{D_S} = ... = \eta_4^{D_S} = \gamma_1^{D_S} = ... = \gamma_q^{D_S} = 0 \tag{20}$$

$$H_0 : \eta_1^{D_S} = ... = \eta_4^{D_S} = 0 \tag{21}$$

where q is the number of controls included in $\mathbf{x}_{ikt}$.

For this large-bidder approach, we expect η_1, η_2, η_3 and η_4 each to be negative in support for the predictions of our dynamic model; and at least one of $\eta_1^{D_L}$, $\eta_2^{D_L}$, $\eta_3^{D_L}$ and $\eta_4^{D_L}$ to be statistically different from zero in support for different bidding behavior between large and small generators.

We estimate equilibrium bid equation (19) using production and storage capacity as two sepa-

Table 8: Large Capacity Hydro Generators

	Production Capacity		Storage Capacity	
Ranking	Generator	(MW)	Generator	(GWh)
1	SAN CARLOS	1,240	PAGUA	5,750
2	GUAVIO	1,200	GUATAPE	4,905
3	CHIVOR	1,000	GUAVIO	2,484
4	PAGUA	600	CHIVOR	1,341
5	GUATAPE	560	LA TASAJERA	531
6	BETANIA	540	JAGUAS	511
7	GUATRON	512	GUATRON	423
8	ALBAN	439	BETANIA	322
9	PORCE II	405	CALIMA	304
10	MIEL I	396	MIEL I	240

Notes: production and storage capacity values correspond to the respective sample period maximum.

rated size criteria for the definition of the large-bidder set. Table 8 shows the 10 largest generators according to each of these two criteria. We construct four different large-bidder sets consisting of: 1) the top-10 largest generators in terms of production capacity; 2) the top-5 largest generators in terms of production capacity; 3) the top-10 largest generators in terms of storage capacity; and 4) the top-5 largest generators in terms of storage capacity.

The coefficient estimates are presented in Table 9. Columns 1-4 and 5-8 show the regression results without and with controls. Additionally, we include quarter fixed effects to control for potential seasonal shocks. We focus on the coefficients for large bidders.

Column 1 shows the results when the large-bidder set consists of the top-10 largest production capacity hydro generators. All the large-bidder coefficient estimates associated with the state variables are negative and significant at 1%. We find that the equilibrium bid submitted by (large) generator *i* is, on average, higher when its aggregate stock is relatively low. Likewise, that generator will, on average, increase its bid price when expecting low inflows in the future. These results also suggest that, conditional on its own stock and expected inflows, generator *i*'s bid is expected to be higher when its rivals' aggregate stock is low or when its rivals' future inflows are expected to be low. These results are robust to the inclusion of the control variables, as shown in Column 5.

Table 9: Regression Coefficients for Equilibrium Bids on Stocks and Inflows, Large-Bidder Approach

	Dependent variable: Equilibrium Bids							
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Ostock	-0.748***	-0.271***	-0.812***	-0.242***	-0.728***	-0.266***	-0.806***	-0.242***
	(0.023)	(0.018)	(0.033)	(0.020)	(0.023)	(0.018)	(0.033)	(0.021)
Rstock	-0.220***	-0.365***	0.039	-0.186***	-0.144**	-0.298***	-0.109	-0.173***
	(0.062)	(0.073)	(0.083)	(0.062)	(0.063)	(0.076)	(0.084)	(0.064)
Oflow	-0.999***	-0.320***	-3.923***	-4.219***	-0.997***	-0.360***	-3.552***	-4.125***
	(0.121)	(0.115)	(0.390)	(0.323)	(0.119)	(0.108)	(0.382)	(0.320)
Rflow	-9.651***	-7.968***	-1.370	-0.736	-6.554***	-5.548***	1.187	0.303
	(0.973)	(1.033)	(1.355)	(0.822)	(1.019)	(1.085)	(1.395)	(0.864)
$D_S \times$ Ostock	0.203***	-0.568***	0.140***	-0.589***	0.074*	-0.567***	0.129***	-0.581***
	(0.045)	(0.034)	(0.046)	(0.035)	(0.044)	(0.033)	(0.046)	(0.034)
$D_S \times$ Rstock	0.873***	0.754***	0.339**	0.578***	0.680***	0.590***	0.580***	0.514***
	(0.189)	(0.126)	(0.169)	(0.131)	(0.193)	(0.129)	(0.172)	(0.134)
$D_S \times$ Oflow	-0.601*	-0.863***	3.049***	3.189***	-0.749**	-0.919***	2.467***	2.918***
	(0.343)	(0.184)	(0.413)	(0.348)	(0.351)	(0.180)	(0.405)	(0.345)
$D_S \times$ Rflow	12.303***	4.276**	-4.767*	-4.461**	14.740***	6.027***	-2.787	-0.040
	(2.915)	(1.871)	(2.604)	(1.988)	(3.008)	(1.943)	(2.678)	(2.059)
Controls	NO	NO	NO	NO	YES	YES	YES	YES
Plant FE	YES	YES	YES	YES	YES	YES	YES	YES
Quarter FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Linear restrictions tests								
F-Test 1	19.98***	89.36***	20.24***	84.89***	32.39***	64.42***	21.05***	68.19***
F-Test 2	19.98***	89.36***	20.24***	84.89***	11.46***	90.40***	17.21***	81.10***
Number of obs.	38,250	38,250	38,250	38,250	38,250	38,250	38,250	38,250
R^2	0.42	0.42	0.42	0.42	0.44	0.43	0.43	0.43

F-Test 1 evaluates the restriction that there are no differences in slopes between small and large bidders. F-Test 2 evaluates the restriction that there are no differences in slopes for the state variables between small and large bidders. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

In columns 2 and 6 we restrict the large-bidder set to only the top-5 of largest production capacity hydro generators. Both sets of coefficient estimates, without and with controls, are of the expected sign. In general, when using this set, we obtain the same general conclusion about a significant negative relationship between large generators' equilibrium bids and the state variables, as in the econometric exercise performed in columns 1 and 5 of Table 9.

A potential concern is that a bidder's dynamic behavior might be more related with its storage capacity, rather than its production capacity. For this reason, in the estimations shown in columns 3 and 4 we consider the top-10 and top-5 of the largest storage capacity hydro generators, respectively. As with previous large-bidder sets, the coefficient estimates associated with generator i's current stock and future inflows are negative at 1% of significance. Hence, a large storage capacity generator will, on average, bid more aggressively when facing a relatively high own stock or when, conditional on its own stock, its future inflows are expected to increase. However, we cannot always reject the null hypothesis that a large-storage generator's bid is affected by its rivals' aggregate stock or future inflows. In fact, we only find a statistically negative relationship between i's equilibrium bids and its rivals' aggregate stock for the top-5 large-storage bidders. These conclusions remain practically unchanged with the inclusion of our set of control variables as shown in columns 7 and 8.

We also find evidence in support for different bidding behavior between large and small bidders. The results of the joint significance tests for each of the linear restrictions (20) and (21) are presented in Table 9 as F-Test 1 and F-Test 2, respectively. For all specifications, both null hypotheses are rejected at 1% of significance.

In the analogous exercise with thermal generators we also find evidence in favor to our predictions. The respective coefficient estimates are presented in Table 13 of Appendix B. These results also support for both dynamic and strategic behavior. In particular, for a sample consisting on the top-10 largest hydro generators plus the top-5 largest thermal generators suggest a significant negative relationship between a large-bidder's equilibrium bid en the state variables.

Summarizing, these findings for our large-bidder sets provide strong evidence in support of our predictions. In particular, we find that large generators in terms of production capacity perform closer to our dynamic optimization benchmark than the set of largest storage capacity generators.

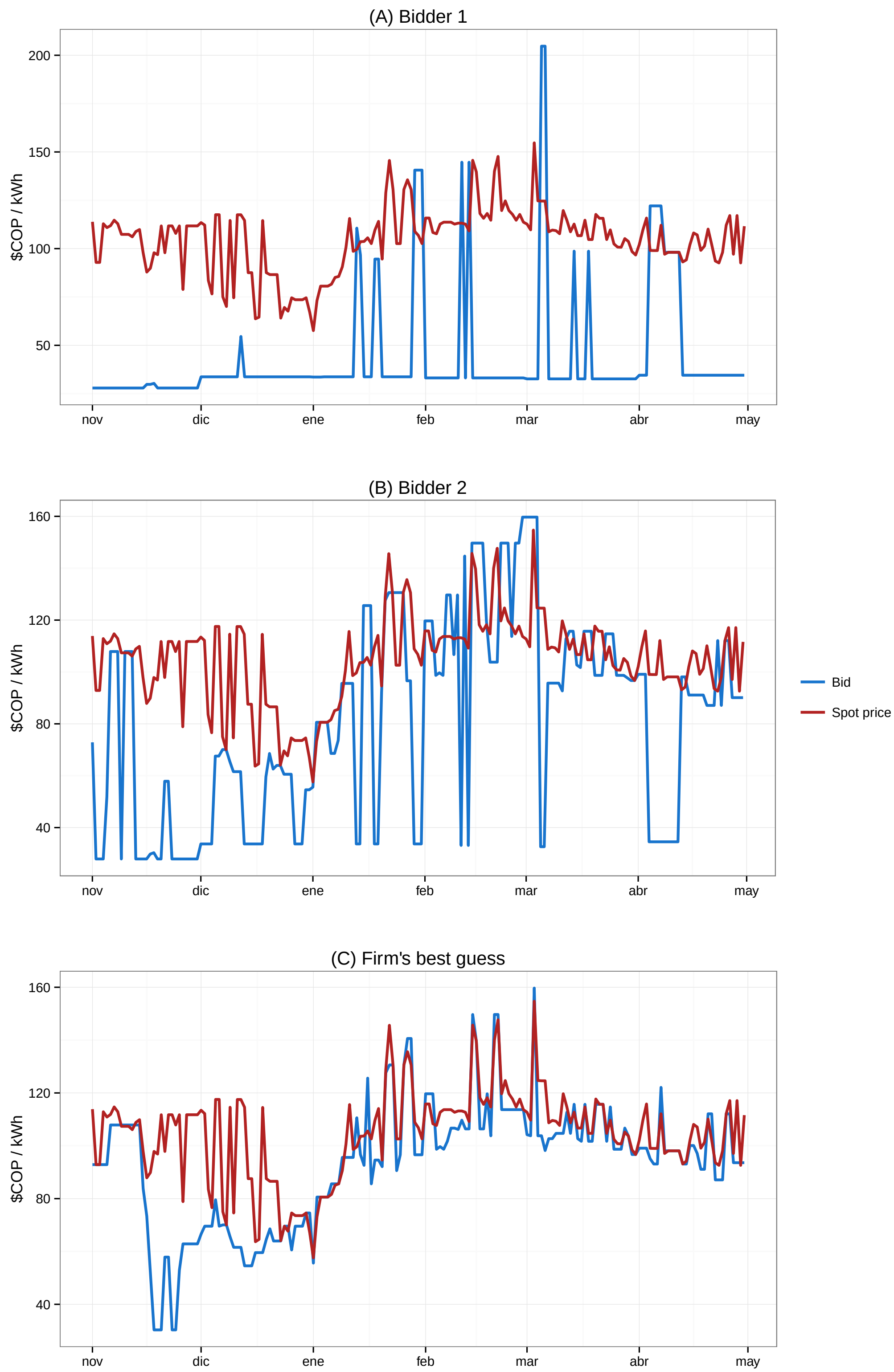
The Marginal-Bidder Approach

For our second definition of "optimal" bidder we need to drop our initial assumption that firms submit independent bids for each generator they control. Instead, we hypothesize that firms coordinate their generators' bids to jointly maximize profits. This hypothesis is also supported by several studies, such as von der Fehr and Harbord (1993), Wolfram (1998), Wolak (2003 and 2007), and Ciarreta and Espinosa (2010). For instance, Ciarreta and Espinosa (2010) argue that a multi-plant firm will account for the effect that its production decisions on one plant have on the profits it may earn from the other sets it owns. Thus, any firm owning several units will calculate an optimal supply schedule to maximize joint profits. Likewise, the model proposed by Wolfram (1998) suggests that a firm with multiple units will maximize joint payoffs by increasing the bid price of the unit that is more likely to set the market clearing price.

In this part of our empirical analysis we follow this notion and consider the hypothesis that each firm is able to coordinate its generators' bid schedules. In particular, we assume that each firm only bids optimally, according to our dynamic profit maximization benchmark, for the generator that is more likely to be the "price setter" (marginal bidder). Our assumption is based on the theoretical prediction of demand-reduction (see Ausubel and Cramton (2002)). Due to the uniform-price setting, each bidder knows that the price it bids will affect the price paid to all the dispatched generators. Hence, a multi-plant firm that maximizes joint profits will charge a greater markup its highest-price inframarginal generator. Therefore, we expect that each firm performs closer to our dynamic behavior benchmark for its marginal bidder, since the for this unit there is more room for strategic behavior.

Although the rules of the MEM require firms to submit independent supply schedules for each generator they own, Figure 5 shows a real example that is consistent with this assumption. In this figure we present the daily equilibrium bids of a given firm that we named A during a six

Figure 5: Bidding Pattern of Firm A



months period. The spot price series correspond to the 7:00 PM demand period. When observed by separated, A's ability to "set" the market clearing price seems very low. Each bidder's submitted price can be less than a half of the spot price on one day and just above it on the other. However when we take all its generators into account, the distance between the A's bid price and the realized spot price is less that 1% in almost 64% of the cases. We observe this same pattern for other 4 multi-plant firms with similar characteristics and for different demand hours and time periods.

We begin by defining $\Im_k$ as the set of generators controlled by firm k. Hence, we define the marginal bidder of firm k as the generator $i^* \in \Im_k$ such that the probability for k to set the market clearing price with the price offer Bid_{i^*kt} is maximized. Given this generic definition, we define $D_{N,i}$ as equal to 1 if $i \neq i^*$ and 0 otherwise. Thus, we rewrite our equilibrium bid equation (18) at the firm level as follows

$$\begin{aligned} Bid_{ikt} &= \eta_1 Ostock_{kt} + \eta_2 Rstock_{kt} + \eta_3 Oflow_{kt+1} + \eta_4 Rflow_{kt+1} + \mathbf{x}'_{kt}\boldsymbol{\gamma} \\ &\quad + D_{N,i} \times \left(\eta_1^{D_N} Ostock_{kt} + \eta_2^{D_N} Rstock_{kt} + \eta_3^{D_N} Oflow_{kt+1} + \eta_4^{D_N} Rflow_{kt+1} + \mathbf{x}'_{kt}\boldsymbol{\gamma}^{D_N} \right) \\ &\quad + \varepsilon_{ikt}. \end{aligned} \tag{22}$$

where

$$Ostock_{kt} = 100 \times \frac{\sum_{i \in \Im_k} Stock_{ikt}}{\sum_{i \in \Im_k} Maxstock_{ikt}} \quad \text{and} \quad Rstock_{kt} = 100 \times \frac{\sum_{i \notin \Im_k} Stock_{jkt}}{\sum_{i \notin \Im_k} Maxstock_{jkt}}.$$

In other words, $Ostock_{kt}$ is firm k's aggregate stock defined as a fraction of its dams' aggregate maximum technical volume and $Rstock_{kt}$ as the weighted average of this fraction across k's rivals. Analogously, the river flow variables are redefined at the firm level as follows

$$Oflow_{kt} = 100 \times \frac{\sum_{i \in \Im_k} Flow_{ikt}}{\sum_{i \in \Im_k} Maxstock_{ikt}} \quad \text{and} \quad Rflow_{kt} = 100 \times \frac{\sum_{i \notin \Im_k} Flow_{jkt}}{\sum_{i \notin \Im_k} Maxstock_{jkt}}.$$

The variables in $\mathbf{x}'_{kt}$, originally available at the generator level, are also redefined in aggregates by firm. Consequently, $Rsize_{kt}$ variable corresponds to the aggregate capacity of firm k as a fraction of the system total capacity and $Avcap_{kt}$ is the total available capacity of firm k on day t. Additionally, the variable N_t is modified as the number marginal bidders on day t. Similarly, we include firm fixed effects, μ_k, rather than plant fixed effects.

As in previous section, we adopt this specification to test for difference in slopes between "marginal" bidders and the rest of hydro generators participating in the auction. Thus, each coefficient η_1, η_2, η_3 and η_4 corresponds to the average change in the equilibrium bid of firm k's marginal bidder associated with a variation in the realized stocks and expected inflows. Meanwhile, each one of $\eta_1^{D_N}$, $\eta_2^{D_N}$, $\eta_3^{D_N}$ and $\eta_4^{D_N}$ is the average slope differences for the respective state variable in the equilibrium bid equation between nonmarginal and marginal bidders. Therefore, the average slope difference for the own stock variable between a nonmarginal and a marginal generator is given by

$$\left.\frac{\partial Bid_{ikt}}{\partial Ostock_{ikt}}\right|_{i\neq i^*} - \left.\frac{\partial Bid_{ikt}}{\partial Ostock_{ikt}}\right|_{i=i^*} = \eta_1^{D_N}.$$

Also, we can verify significant differences of bidding behavior for the two groups of bidders by testing the following linear hypotheses

$$H_0 : \eta_1^{D_N} = ... = \eta_4^{D_N} = \gamma_1^{D_N} = ... = \gamma_q^{D_N} = 0, \tag{23}$$

$$H_0 : \eta_1^{D_N} = ... = \eta_4^{D_N} = 0. \tag{24}$$

For this marginal-bidder approach, we expect each of η_1, η_2, η_3 and η_4 to be negative in support for the predictions of our dynamic model; and at least one of $\eta_1^{D_N}$, $\eta_2^{D_N}$, $\eta_3^{D_N}$ and $\eta_4^{D_N}$ to be statistically different from zero in support for different bidding behavior between nonmarginal and marginal bidders.

We estimate the equilibrium bid equation (22) for six different definitions of the marginal-bidders set. For each criteria we consider the following measure of distance

$$d_{ikt} \equiv 1 - \frac{Bid_{ikt}}{Price_t} \tag{25}$$

where Bid_{ikt} is the price bid by generator i of firm k on day t and $Price_t$ is the average spot price on day t. Also, let I_{ikt} be an indicator variable which equals 1 when $|d_{ikt}| \leq 1\%$ and 0 otherwise and denote T as the number of days in the full estimation sample. Hence, we define the marginal bidder of firm k as the generator $i^* \in \Im_k$ such that:

M1: $\sum_{t=1}^{T} I_{i^*kt} = \max\limits_{i \in \Im_k} \left\{ \sum_{t=1}^{T} I_{ikt} \right\}$.

M2: $\sum_{t \in \tau} I_{i^*kt} = \max\limits_{i \in \Im_k} \{ \sum_{t \in \tau} I_{ikt} \}$, for a given year τ.

M3: $d_{i^*kt} = \min\limits_{i \in \Im_k} \{ |d_{ikt}| \}$, for a given day t.

M4: $d_{i^*kt} = \min\limits_{i \in \Im_k} \{ d_{ikt} \mid d_{ikt} \geq 0 \}$, for a given day t.

M5: $d_{i^*kt} = \min\limits_{i \in \Im_k} \{ |d_{ikt}| \mid -0.2 \leq d_{ikt} \leq 0.2 \}$, for a given day t.

M6: $d_{i^*kt} = \min\limits_{i \in \Im_k} \{ d_{ikt} \mid 0 \leq d_{ikt} \leq 0.2 \}$, for a given day t.

The coefficient estimates are presented in Table 10. Each column shows the eregression results for a different set of marginal bidders satisfying each of the six conditions defined above. For this approach, we also include quarter fixed effects. Below we discuss these results focusing only the coefficients for the marginal bidders.

Column 1 shows the coefficient estimates of equation (22) using a set of marginal bidders satisfying condition M1. This set takes each firm's most frequent marginal bidder during our sample period. All the coefficient estimates associated with the state variables are negative and significant at 1%. We find that firm k submits a higher bid price for its most frequent marginal bidder when its aggregate stock decreases. Likewise, that firm will, on average, increase its bid price for its most frequent marginal bidder when expecting low future inflows. These results also support for strategic interactions. Conditional on its current stock and future inflows, firm k's marginal bid is expected to be higher when its rivals' aggregate stock is low or when its rivals' future inflows are expected to be low.

A potential concern about using condition M1 is that whether the firm systematically submits its closest bid to the *ex post* spot price with the same generator or if it eventually switches to other generators. We address this concern by making some refinements to our marginal-bidder set. In

Table 10: Regression Coefficients for Equilibrium Bids on Stocks and Inflows, Marginal-Bidder Approach

	Dependent variable: Equilibrium Bids					
Variables	(1)	(2)	(3)	(4)	(5)	(6)
Ostock	-0.518***	-0.620***	-0.652***	-0.119***	-0.178***	-0.146***
	(0.033)	(0.035)	(0.036)	(0.010)	(0.011)	(0.013)
Rstock	-0.930***	-0.583***	-0.815***	-0.487***	-0.956***	-0.875***
	(0.099)	(0.091)	(0.098)	(0.035)	(0.038)	(0.042)
Oflow	-7.433***	-7.781***	-7.167***	-0.402***	-0.901***	-0.756***
	(0.586)	(0.601)	(0.583)	(0.127)	(0.143)	(0.157)
Rflow	-10.423***	-7.931***	-9.671***	-6.076***	-6.326***	-7.509***
	(1.435)	(1.558)	(1.452)	(0.481)	(0.477)	(0.516)
$D_N\times$ Ostock	-1.130***	-0.817***	-0.898***	-1.235***	-1.136***	-0.974***
	(0.070)	(0.057)	(0.074)	(0.052)	(0.048)	(0.042)
$D_N\times$ Rstock	1.316***	0.720***	1.115***	0.574***	1.194***	1.015***
	(0.136)	(0.101)	(0.136)	(0.098)	(0.103)	(0.094)
$D_N\times$ Oflow	8.430***	8.820***	6.752***	-0.922	-5.519***	-3.904***
	(1.071)	(1.003)	(1.089)	(0.783)	(0.751)	(0.650)
$D_N\times$ Rflow	13.304***	9.251***	11.758***	10.246***	7.024***	6.704***
	(2.059)	(2.047)	(2.087)	(1.627)	(1.569)	(1.453)
Controls	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES
Quarter FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Linear restrictions tests						
F-Test 1	54.23***	57.00***	36.74***	178.97***	141.80***	157.24***
F-Test 2	102.38***	93.93***	65.43***	166.52***	221.36***	196.40***
Number of obs.	38,501	38,501	38,501	38,501	38,501	38,501
R^2	0.41	0.41	0.40	0.49	0.41	0.35

F-Test 1 evaluates the restriction that there are no differences in slopes between nonmarginal and marginal bidders. F-Test 2 evaluates the restriction that there are no differences in slopes for the state variables between nonmarginal and marginal bidders. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Column 2 we use condition M2, where we consider the possibility that the identity of firm *k*'s most frequent marginal bidder changes from one year to another. All coefficients remain of the expected sign, suggesting a statistically negative relationship between firm *k*'s marginal bid and each of the state variables. This general result also remains practically unchanged when we consider possibility of a more sort run "switching" behavior. In Column 3 we estimate equation (22) with a marginal-bidder set satisfying condition M3, where the identity of firm *k*'s marginal bidder can change from one day to another. As in previous exercise, the results the sign and significance of the coefficients remain practically unchanged.

A more restrictive approach is shown in Column 4, where by condition M4 we only consider as marginal bidders those included in M3 that bid below the *ex post* spot price. This definition of marginal bidder excludes uni-plant firms are less likely to be dispatched. As pointed out by Wolfram (1998), since the probability that these bidders affect the market clearing price is very low, it is not likely that the behave optimally. The results for this regression still suggest a significant negative relationship between firm *k*'s marginal bid and each of the state variables.

Using conditions M5 and M6 we restrict further the marginal-bidder definition by excluding those bidders whose submitted prices are substantially far from the *ex post* realized spot price. Because of condition M5, the data used for the results in Column 5 excludes firms whose marginal bid price is farther than 20% from the *ex post* spot price.[12] Condition M6 is even more restrictive since is it only considers the firms whose marginal bid price is not above the *ex post* spot price. Using these conditions we increase the probability of having a sample where the firms that systematically deviate from our dynamic optimization benchmark have a low weight in the estimation.

In columns 5 and 6 of Table 10 we obtain similar results concerning the coefficients associated with the state variables, for both conditions M5 and M6, respectively. Again, we find that all these coefficients are statistically negative at 1% of significance. Thus, other things equal, firm *k* submits a higher bid price for its marginal bidder when its aggregate stock decreases. At the same time, conditional on its current aggregate stock, if that firm expects low future inflows, the equilibrium

[12] Other distance values such as 5%, 15% and 30% result in exactly the same marginal-bidders set implying no differences in the estimation outcomes.

bid price for its marginal bidder is expected to be higher. This correlation is particularly more severe for the M5 definition than for the M6 one. These results also support for strategic behavior. In particular, the results suggest that, conditional on its current stock and future inflows, firm k's marginal bid is expected to be higher when its rivals face a low aggregate stock or low expected inflows in the future.

The results also support for the marginal-bidder approach as there is statistical evidence suggesting that marginal bidders behave differently from the rest of generators. The results of the joint significance tests for each of the linear restrictions (23) and (24) are presented in Table 10 as F-Test 1 and F-Test 2, respectively. For all specifications, both null hypotheses are rejected at 1% of significance.

There is also empirical evidence in support for dynamic and strategic behavior when including thermal generators. The respective results are presented in Table 14 of Appendix B. For all samples we find a negative relationship between a marginal generator's bid and the firm's state variables. Moreover, for the samples satisfying conditions M4, M5 and M6 the results perform better according to our predictions. All the coefficient estimates associated with the state variables are negative and significant at 1%.

Overall, we consider these findings as strong evidence in support of our predictions. At the firm level, the empirical results are supporting our predictions. In particular, we find that, according to our specific definitions, each firm performs closer to our dynamic optimization benchmark at its marginal generator.

6 Conclusions

In this paper we investigate if the market prices of a deregulated electricity market respond to other determinants different from production costs. In particular, we analyze if the bidding behavior of generation firms of an hydropower dominated electricity market is consistent with a dynamic profit maximization benchmark. To assess this, we propose a dynamic multi-unit auction model characterized by a perfect Markovian Equilibrium based on the studies of Hortacsu and Puller (2008) and Balat (2014). Our model suggests that when the intertemporal opportunity cost of water is sufficiently high, hydro producers will submit bids above its marginal production costs whether to save water for future production or to set a market price that maximizes its payoffs. There is thus a significant negative relationship between each firm's equilibrium bid prices and the state variables; specifically, its own stock, own expected inflows, its rival's stock and its rivals expected inflows.

We test the predictions of our model using data of the Colombian electricity market where hydro producers hold more 63% of total installed capacity. Overall, the regression results provide evidence in support of both dynamic and strategic behavior. A given firm's bid price is negatively correlated with its own current aggregate stock. Results also suggest that, given its own stock, that firm will, on average, bid less aggressively if its rivals' aggregate stock is relatively low. At the same time, higher bid prices are associated with low expected inflows. A given bidder will submit higher bid prices when expecting low inflows for its rivals' dams. We also find evidence supporting the hypothesis that bidding behavior of different sets of "optimal bidders" is closer to our notion of dynamic profit maximization. Our findings are robust to different specifications, different definitions of future inflows and different sets of bidders.

References

Ausubel, L., & Cramton, P. (2002). *Demand reduction and inefficiency in multi-unit auctions.* (Working paper, University of Maryland)

Balat, J. (2014). *Highway procurement and the stimulus package: Identifcation and estimation of dynamic auctions with unobserved heterogeneity.* (Working paper)

Borenstein, S., & Bushnell, J. (1999). An empirical analysis of the potential for market power in california's electricity industry. *The Journal of Industrial Economics*, *47*(3), 285-323.

Carranza, J. E., Riascos, A. J., & Morán, J. J. (2014). *Mecanismos de mercado e instituciones del* *sector eléctrico colombiano.* (Documento de trabajo, Banco de La República Colombia)

Ciarreta, A., & Espinosa, M. (2010). Market power in the spanish electricity auction. *Journal of Regulatory Economics*, *37*, 42–69.

Crawford, G. S., Crespo, J., & Tauchen, H. (2007). Bidding asymmetries in multi-unit auctions: Implications if bid function equilibria in the British spot market for electricity. *International Journal of Industrial Organization*, *25*(2007), 1233–1268.

de Castro, L., Oren, S., Riascos, A., & Bernal, M. (2014). *Transition to centralized unit commitment: An econometric analysis of Colombia's experience.* (Working paper)

de Castro, L., & Riascos, A. (2009). Characterization of bidding behavior in multi-unit auctions. *Journal of Mathematical Economics*, *45*(2009), 559–575.

Espinosa, M. A., & Riascos, A. J. (2010). *Strategic behaviour, resource valuation and competition in electricity markets* (Documentos CEDE No. 2010-10). Universidad de los Andes-CEDE.

Garcia, A., & Arbeláez, L. E. (2002). Market power analysis for the colombian electricity market. *Journal of Energy Economics*, *24*, 217-229.

Garcia, A., Campos, E., & Reitzes, J. (2005). Dynamic pricing and learning in electricity markets. *Operations Research*, *55*(2), 231-241.

Garcia, A., Reitzes, J. D., & Stacchetti, E. (2001). Strategic pricing when electricity is storable. *Journal of Regulatory Economics*, *20*(3), 223-247.

Green, R. J. (1996). Increasing competition in the British electricity spot market. *The Journal of Industrial Economics*, *44*(2), 205-216.

Green, R. J., & Newbery, D. M. (1992). Competition in the British electricity spot market. *The Journal of Political Economy*, *100*(5), 929-953.

Hortacsu, A., & Puller, S. L. (2008). Understanding strategic bidding in multi-unit auctions: A case study of the Texas electricity spot market. *RAND Journal of Economics*, *39*(1), 86–114.

Jofre-Bonet, M., & Pesendorfer, M. (2003). Estimation of a dynamic auction game. *Econometrica*, *71*(5), 1443–1489.

Klemperer, P. D., & Meyer, M. A. (1989). Supply function equilibria in oligopoly under uncertainty. *Econometrica*, *57*(6), 1243-1277.

Reguant, M. (2014). *Complementary bidding mechanisms and startup costs in electricity markets.* (Working paper. Stanford GSB and NBER)

Stacchetti, E. (1999). *Auction design for the Colombian electricity market.* (Working paper, University of Michigan)

Vegard Hansen, P. (2009). Inflow uncertainty in hydropower markets. *Scandinavian Journal of Economics*, *111*(1), 189–207.

von der Fehr, N.-H. M., & Harbord, D. (1993). Spot market competition in the UK electricity industry. *The Economic Journal*, *103*(418), 531-546.

Wilson, R. B. (1979). Auctions of shares. *Quarterly Journal of Economics*, *93*(4), 675–689.

Wolak, F. A. (2000). An empirical analysis of the impact of hedge contracts on bidding behavior in a competitive electricity market. *International Economic Journal*, *14*(2), 1–39.

Wolak, F. A. (2003). Identification and estimation of cost functions using observed bid data: An application to electricity markets. In M. Dewatripont, L. P. Hansen, & S. J. Turnovsky (Eds.), *Advances in economics and econometrics* (pp. 133–169). Cambridge University Press.

Wolak, F. A. (2007). Quantifying the supply-side benefits from forward contracting in wholesale electricity markets. *Journal of Applied Econometrics*, *22*(7), 1179–1209.

Wolfram, C. D. (1998). Bidding in a multiunit auction: An empirical analysis of bids to supply electricity in England and Wales. *The RAND Journal of Economics*, *29*(4), 703-725.

Wolfram, C. D. (1999). Measuring duopoly power in the British electricity spot market. *American Economic Review*, *89*(4), 805-826.

Appendix A Derivation of the First-Order Condition of Optimality for the Dynamic Model

We begin by solving the integral inside the maximum operator in equation (11). Integration by parts yields a constant term plus the flowing:

$$L\left(p, \hat{S}_i(p), \hat{S}_i'(p)\right) = -\left[\hat{S}_i(p) + \left(p\hat{S}_i(p) - C_i'\left(\hat{S}_i(p)\right)\right)\hat{S}_i'(p) + \beta\left(\sum_{j\in -i}\frac{\partial V_i}{\partial \omega_j} - \frac{\partial V_i}{\partial \omega_i}\right)\hat{S}_i'(p)\right]H\left(p, \hat{S}_i(p)\right).$$

The Euler-Lagrange necessary condition for $L\left(p, \hat{S}_i(p), \hat{S}_i'(p)\right)$ to be maximized at $S^*(p)$ is given by:

$$\frac{d}{dp}L_{S'} = L_S.$$

The respective derivatives are defined as follows

$$-L_S = H_S S_i + H_S S_i'\left[p - C_i' + \beta\left(\sum_{j\in -i}\Psi_j - \Psi_i\right)\right] + H\left[1 + \beta\left(\sum_{j\in -i}\frac{\partial \Psi_j}{\partial S_i} - \frac{\partial \Psi_i}{\partial S_i}\right)S_i'\right]$$

$$-L_{S'} = H\left[p - C_i' + \beta\left(\sum_{j\in -i}\Psi_j - \Psi_i\right)\right]$$

Now, by taking the total derivative of $L_{S'}$ with respect to p, we obtain

$$-\frac{d}{dp}L_{S'} = \left(H_p + H_S S_i'\right)\left[p - C_i' + \beta\left(\sum_{j\in -i}\Psi_j - \Psi_i\right)\right] + H\left[1 + \beta\left(\sum_{j\in -i}\frac{\partial \Psi_j}{\partial S_i} - \frac{\partial \Psi_i}{\partial S_i}\right)S_i'\right]$$

Hence, after canceling some terms, we obtain

$$H_p\left[p - C_i' + \beta\left(\sum_{j\in -i}\Psi_j - \Psi_i\right)\right] = H_S S_i,$$

which is implies that

$$p = C_i' + S_i\frac{H_S}{H_p} + \beta\left(\Psi_i - \sum_{j\in -i}\Psi_j\right).$$

Appendix B Empirical Results When Including Thermal Plants

In this appendix we show the results of the empirical exercises performed in Section 5 when including thermal generators in the respective samples. Accordingly, we adjust the definitions of $Ostock_{it}$ and $Oflow_{it}$ as

$$\tilde{Ostock}_{it} = \begin{cases} Ostock_{it}, & \text{if } i \text{ uses dam} \\ 0, & \text{otherwise} \end{cases} \quad \text{and} \quad \tilde{Oflow}_{it} = \begin{cases} Oflow_{it}, & \text{if } i \text{ uses dam} \\ 0, & \text{otherwise} \end{cases}$$

By the same logic, we adjust the definitions of $Ostock_{kt}$ and $Oflow_{kt}$ for the estimations at the firm level as

$$\tilde{Ostock}_{kt} = \begin{cases} Ostock_{kt}, & \text{if } k \text{ controls a dam} \\ 0, & \text{otherwise} \end{cases} \quad \text{and} \quad \tilde{Oflow}_{it} = \begin{cases} Oflow_{kt}, & \text{if } k \text{ controls a dam} \\ 0, & \text{otherwise} \end{cases}$$

Note that for corresponding versions of the equilibrium bid equation, the coefficients η_1 and η_3 are interpreted as the interaction between having a dam and the respective value of aggregate stock and river flow, respectively. As an additional control for the difference between the two generation technologies, we include a thermal dummy variable Dt for the intercept of the equilibrium bid equation.

Table 11 presents the results for the analogous to the one exercise performed in 6. The results are quite similar to those presented in Table 6, even for all different combinations of plant and year fixed effects. Also, we find that, as expected, thermal generators submit higher bid prices. In particular, this difference is around 130 COP/KWh on average.

The inclusion of thermal plants, however does change some of the results describes in Table 7. We present this in Table 12. For this sample, we find that the sign of the coefficient associated with the rivals' inflow variable becomes positive for all combinations of fixed effects an controls. The rest of the coefficients remain practically unchanged, except for that associated with rivals' stock which seems to increase in size.

Table 11: Regression Coefficients of Equilibrium Bids on Current Stock (Hydro and Thermal Bidders)

	Dependent variable: Equilibrium Bids							
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Ostock	-0.805***	-0.626***	-0.640***	-0.539***	-0.934***	-0.874***	-0.762***	-0.761***
	(0.017)	(0.017)	(0.018)	(0.018)	(0.018)	(0.019)	(0.018)	(0.020)
Rstock					0.756***	0.963***	0.890***	1.023***
					(0.033)	(0.029)	(0.034)	(0.029)
Plant FE	NO	YES	NO	YES	NO	YES	NO	YES
Year FE	NO	NO	YES	YES	NO	NO	YES	YES
Number of obs.	127,135	127,135	127,135	127,135	127,135	127,135	127,135	127,135
R^2	0.29	0.51	0.35	0.55	0.29	0.51	0.35	0.55

Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 12: Regression Results for Equilibrium Bids on Stocks and Inflows (Hydro and Thermal Generators)

	Dependent variable: Equilibrium Bids							
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Ostock	-0.503***	-0.730***	-0.775***	-0.720***	-0.500***	-0.695***	-0.732***	-0.682***
	(0.019)	(0.020)	(0.020)	(0.020)	(0.019)	(0.020)	(0.020)	(0.020)
Oflow	-1.651***	-1.502***		-2.208***	-1.496***	-1.343***		-2.014***
	(0.121)	(0.122)		(0.133)	(0.122)	(0.123)		(0.133)
Rstock		1.021***	0.975***	0.962***		1.018***	0.977***	0.965***
		(0.029)	(0.029)	(0.029)		(0.031)	(0.031)	(0.031)
Rflow			15.079***	16.801***			15.229***	16.821***
			(0.796)	(0.816)			(0.828)	(0.848)
Controls	NO	NO	NO	NO	YES	YES	YES	YES
Plant FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Number of obs.	126,877	126,877	126,877	126,877	126,877	126,877	126,877	126,877
R^2	0.54	0.55	0.55	0.55	0.55	0.55	0.55	0.56

Robust standard errors in parentheses
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 13 presents the large-bidder results with thermal generators. For obvious reasons, here we only consider the production capacity criteria for the definition of large bidder. In columns 1 and 3 we show the regression results for a sample consisting on the top-10 largest hydro generators plus the top-5 largest thermal generators TEBSAB, TERMOSIERRAB, FLORES 1, FLORES 2 and FLORES 3. The coefficient estimates associated with the state variables are of the expected sign and significant at 1%, without and with controls. In Column 3, however, the coefficient of the rivals' inflow variable is not statistically significant. In columns 2 and 4 we show the regression results for a sample consisting on the top-5 largest hydro generators plus TEBSAB and TERMOSIERRAB. The coefficient estimates associated with own stock and own inflows remain negative and significant at 1%. However, the coefficients of the rivals' stock and inflow are statistically positive and not different form zero, respectively.

Table 14 presents the marginal-bidder results with thermal generators. In columns 1-3 we show the respective results for conditions M1, M2 and M3. On one hand, the coefficient estimates associated with own stock and own inflows are negative and significant at 1%. On the other, those coefficients associated with rivals' stock and rivals' inflows are statistically positive in most cases. Although not of the expected sign, these results still provides strong evidence in support for strategic behavior in the sense that, conditional on its own states, a firm's equilibrium bid also depends on its rivals' states. In columns 4-6 for conditions M4, M5 and M6, respectively, the results perform better according to our predictions. All the coefficient estimates associated with the state variables are negative and significant at 1%.

Table 13: Coefficients Estimates for Equilibrium Bids on Stocks and Inflows, Large-Bidder Approach (Hydro and Thermal)

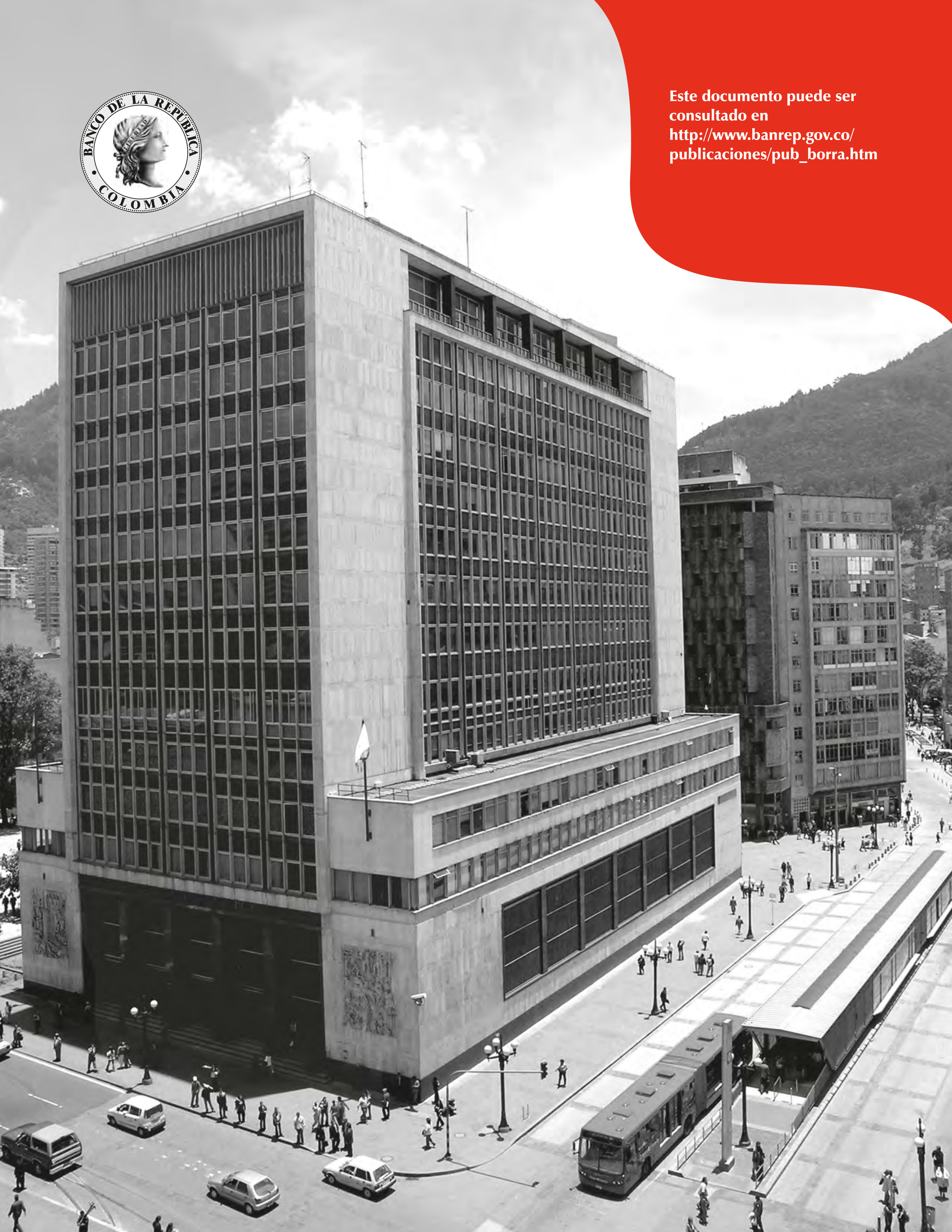
	Dependent variable: Equilibrium Bids			
Variables	(1)	(2)	(3)	(4)
Ostock	-0.668***	-0.382***	-0.568***	-0.381***
	(0.025)	(0.020)	(0.024)	(0.020)
Rstock	-0.304***	0.385***	-0.172**	0.390***
	(0.085)	(0.084)	(0.084)	(0.090)
Oflow	-1.293***	-1.062***	-0.949***	-0.915***
	(0.129)	(0.137)	(0.131)	(0.135)
Rflow	-3.028**	0.143	-1.954	-0.605
	(1.299)	(1.332)	(1.300)	(1.350)
Dt	142.585***	210.328***	247.973***	205.171***
	(3.419)	(6.676)	(4.158)	(55.746)
$D_L \times$ Ostock	0.210***	-0.322***	0.084*	-0.305***
	(0.044)	(0.035)	(0.044)	(0.035)
$D_L \times$ Rstock	2.124***	0.827***	2.045***	0.949***
	(0.125)	(0.115)	(0.129)	(0.122)
$D_L \times$ Oflow	-0.028	-0.098	-0.469	-0.122
	(0.362)	(0.211)	(0.365)	(0.211)
$D_L \times$ Rflow	12.469***	5.517***	10.124***	5.606***
	(1.873)	(1.763)	(1.903)	(1.799)
$D_L \times$ Dt	-156.100***	-81.338***	351.502***	-202.770***
	(6.705)	(6.115)	(57.486)	(52.729)
Controls	NO	NO	YES	YES
Plant FE	YES	YES	YES	YES
Quarter FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Restricted model linear test				
F-Test 1	103.93***	34.90***	150.08***	75.21***
F-Test 2	103.93***	34.90***	76.53***	35.42***
Number of obs.	106,068	106,068	106,068	106,068
R^2	0.58	0.57	0.59	0.58

F-Test 1 evaluates the restricted model where all slopes are not different between the full sample and the Large bidders sample. F-Test 2 evaluates the restricted model where the slopes of the state variables are not different between the full sample and the Large bidders sample. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 14: Coefficients Estimates for Equilibrium Bids on Stocks and Inflows, Marginal-Bidder Approach (Hydro and Thermal)

	Dependent variable: Equilibrium Bids					
Variables	(1)	(2)	(3)	(4)	(5)	(6)
Ostock	-0.728***	-0.323***	-0.661***	-0.095***	-0.169***	-0.124***
	(0.033)	(0.031)	(0.032)	(0.010)	(0.010)	(0.011)
Rstock	0.412***	0.023	0.229***	-0.528***	-0.782***	-0.753***
	(0.085)	(0.074)	(0.082)	(0.034)	(0.037)	(0.039)
Oflow	-9.331***	-7.839***	-8.780***	-0.640***	-0.933***	-0.772***
	(0.620)	(0.599)	(0.589)	(0.135)	(0.148)	(0.163)
Rflow	0.044	-2.925**	2.085*	-7.685***	-4.795***	-6.510***
	(1.258)	(1.224)	(1.201)	(0.461)	(0.422)	(0.454)
Dt	-58.630***	-56.739***	-66.081***	-23.408***	-31.825***	-24.361***
	(7.476)	(7.095)	(7.177)	(1.588)	(1.760)	(1.929)
$D_N\times$ Ostock	0.488***	-0.377***	0.301***	-0.413***	-0.280***	-0.333***
	(0.061)	(0.039)	(0.060)	(0.041)	(0.040)	(0.037)
$D_N\times$ Rstock	0.246*	1.072***	0.529***	1.183***	1.376***	1.314***
	(0.131)	(0.096)	(0.127)	(0.079)	(0.081)	(0.077)
$D_N\times$ Oflow	8.661***	4.356***	8.533***	-2.410***	-6.466***	-5.587***
	(1.105)	(1.022)	(1.112)	(0.767)	(0.742)	(0.658)
$D_N\times$ Rflow	4.334**	10.223***	1.169	11.474***	9.429***	10.307***
	(1.930)	(1.866)	(1.868)	(1.254)	(1.243)	(1.208)
$D_N\times$ Dt	366.355***	234.667***	285.964***	21.374**	-122.265***	-99.359***
	(52.792)	(36.010)	(49.302)	(8.820)	(8.727)	(7.593)
Controls	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES
Quarter FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Restricted model linear test						
F-Test 1	209.15***	300.24***	510.86***	1023.28***	830.92***	1024.65***
F-Test 2	45.38***	67.43***	32.44***	104.63***	120.59***	133.12***
Number of obs.	106,324	106,324	106,324	106,324	106,324	106,324
R^2	0.53	0.53	0.56	0.57	0.54	0.53

F-Test 1 evaluates the restricted model where all slopes are not different between the full sample and the Marginal bidders sample. F-Test 2 evaluates the restricted model where the slopes of the state variables are not different between the full sample and the Marginal bidders sample. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$



BANCO DE LA REPÚBLICA
COLOMBIA

Este documento puede ser consultado en http://www.banrep.gov.co/publicaciones/pub_borra.htm