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The effects of changes in the regulation of the Colombian wholesale electricity market in a structural model of complex auctions

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El efecto de cambios en la regulación del mercado mayorista de electricidad en Colombia en un modelo estructural de subastas complejas

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Resumen

En este documento investigamos los efectos de un cambio en la regulación del mercado *spot* de electricidad en Colombia, que tuvo lugar en 2009. Específicamente, la regulación cambió de un esquema de subastas simples a uno de subastas complejas para permitir a los generadores hacer ofertas separadas de los componentes fijos y variables de sus costos. El aumento en la flexibilidad tuvo como objeto la reducción de las ineficiencias que resultan de las no-convexidades en las estructuras de costos de los generadores térmicos. Estimamos y computamos un modelos estructural que cuantifica los efectos de este cambio en la eficiencia del despacho de energía y en los precios mayoristas. De forma consistente con resultados descriptivos previos, encontramos que bajo el nuevo mecanismo de despacho se incrementó la eficiencia, pero los precios se incrementaron.

Palabras clave: Subastas, estimación estructural, mercados de electricidad

Clasificación JEL: C57, Q4, L94

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Abstract

We investigate the effects of a change in the regulation of the spot market for electricity in Colombia that took place in 2009. Specifically, the regulation switched from an auction mechanism with simple bids to one with complex bids to allow generators to separately bid on variable and quasi-fixed components. This greater flexibility was introduced to reduce production inefficiencies that arise from non-convexities in the cost structures of thermal generators. In this paper, we estimate and compute a structural model to quantify the effects of this change on allocation efficiency along with the effects on the wholesale price of electricity in Colombia. Consistently with previous reduced form evidence, we show that the production efficiency increased under the new dispatch mechanism, but prices increased.

Keywords: Auctions, structural estimation, electricity markets

JEL codes: C57, Q4, L94

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1 Introduction

Markets for electricity are complex due to the interactions between the economic incentives and technical constraints the different parties face at both the production and distribution levels. As a result, regulation can have unintended effects on market outcomes. In this paper, we investigate a major change in the regulation of the Colombian electricity market, introduced in 2009, that switched from simple to complex bids in the spot market electricity auctions.

Colombia became the first Latin American country, in 1994, to structure its electricity market following the English model of production allocation and price determination through auctions. The wholesale electricity market in Colombia, known as Mercado de Energía Mayorista (MEM, henceforth), was established in 1994 when generation and trade were deregulated. The MEM is a centralized market encompassing a national network of interconnected electricity generators. As is common in other countries, the MEM consists of two separate markets: forward and spot markets.[1] While most of the electricity is traded in the forward market through bilateral contracts between generators and distributors, all production decisions are centralized and determined in the spot market. Since its inception, two key regulatory interventions have affected the Colombian spot market. In the period from 1994 to 2001, generators were required to submit 24 bids corresponding to the hourly prices at which they would be willing to produce electricity in the following day and to report their production capacity. The production allocation to satisfy the (expected) demand and the wholesale electricity price were determined on an hour-by-hour basis through uniform-price auctions. In 2001, the Colombian energy regulatory agency, or Comisión de Regulación de Energía y Gas (CREG, henceforth), changed the way firms bid in the spot market: generators were only allowed to submit a single bid for the entire upcoming 24-hour period.[2]

Subsequently, the CREG recognized that the market design may have generated productive inefficiencies due to the heterogeneity in production technologies across the different generators and the lack of flexibility in their bidding to account for them.[3] In particular, such inefficiencies may arise from non-convexities in the cost structures of thermal generating units due to start-up and shut-down costs. These costs were not explicitly accounted for in the dispatch optimization algorithm.[4] Thus, from the suppliers' perspective, thermal units faced an unnecessary risk when restricted to submit a single bid, since if a unit was dispatched, the market clearing price would have needed to be sufficiently high to compensate for the start-up costs.

Following recommended international best practices and the academic literature, the CREG undertook an overhaul of the spot market in 2009. From then on, generators were allowed to separately bid on a variable and a quasi-fixed component through (day-ahead) complex bids. Along with their bids, generators were still required to report their production capacity. With this information at hand, the system operator determines the cost-minimizing production allocation needed to satisfy (expected) demand on an hour-to-hour basis, setting the market clearing price equal to the variable component of the bid from the marginal plant. In addition to their energy sales revenues, firms receive compensation for their start-up and shut-down costs.

[1] In Colombia, the spot market is, in fact, a day-ahead market since, as we describe in following sections, the spot price is determined using bids placed the day before. Nevertheless, we follow de Castro, Oren, Riascos, and Bernal (2014) and refer to this market and its price as "spot market" and "spot price", respectively.

[2] See Resolution CREG-026 (2001).

[3] See Document CREG–011 (2009), Resolution 051 (2009) and subsequent modifications.

[4] The economic and engineering literature has extensively discussed the fact that, in the presence of non-convexities, uniform-price auctions (with simple bids) can lead to productive inefficiencies. See, for example, Sioshansi, Oren, and O'Neill (2008); Sioshansi et al. (2008); Sioshansi, Oren, and O'Neill (2010).

Under the new system, the operator could, in principle, determine the efficient production allocation if firms bid their true fixed and marginal costs. However, in reality, due to the strategic interaction between the firms in the spot market auctions, firms have incentives to bid above their true costs. Therefore, in a setting in which bidders are asymmetric, which is the case in the Colombian market, it is not clear whether the new system could achieve a more efficient allocation. In fact, the theoretical results regarding the performance ranking of one design relative the other are ambiguous. Similarly, the effect of the change in the regulation on the electricity spot prices are ambiguous and depend on how each firm's markup is affected. Therefore, the question of how the switch to complex bids that took place in 2009 affected both the allocative efficiency and market prices remains an empirical one and in this paper we attempt to answer it.

The contributions of this paper are twofold. First, to carry out our analysis, we set up and estimate a structural model of bidding behavior in the spot market. The model has three key features. First, we allow for complex bids and control for the dynamic incentives of thermal generators following Reguant (2014). The dynamic problem of thermal units arises due to the existence of ramp-up and start-up costs. These costs introduce an inflexibility in a thermal unit to rapidly change its production level. Second, following Balat, Carranza, and Martin (2015), the model also takes into account the dynamic incentives of hydro generators which arise due to their ability to store energy through the use of water reservoirs. This feature is relevant in a country like Colombia since hydro generators represent most of the installed capacity in the electricity market. Third, the model allows for the complexity of the Colombian electricity market dispatching algorithm following Camelo, de Castro, Papavasiliou, Riascos, and Oren (2016). To the best of our knowledge, we are the first study to incorporate into a single model these three important features of the market.

The model allows us to estimate marginal production costs for thermal units using the first order conditions implied by profit-maximizing behavior. In a first stage, we use simple bids (i.e., pre 2009) to estimate marginal costs, using the identification strategy suggested by Wolak (2007). This strategy relies on the fact that variations in the observed contract sales position in the forward market affect firms' markups but not their costs. To approximate the firms' expectations about the market outcomes we rely on the bootstrapping method suggested by Hortacsu and McAdams (2010).

Having estimated the structural parameters of the model, we then evaluate the effects of the 2009 market design overhaul. Specifically, we estimate counterfactual market outcomes for the period August 2011 to December 2012 that result from restricting firms to simple bids (i.e., the pre 2009 market design) and compare them to the observed market outcomes under the new design. The computation of the counterfactual equulibrium, however, presents us with two challenges that we need to address. First, as is usual with dynamic games like the one in our setting, there might exist multiple equilibria. But, even if we focus on a particular type of equilibria, a second challenge still remains: we need to compute the distribution of firms' expectations over a combination of market structure and state space that is not observed in the data. To address these issues, we assume that, in each of the two market designs (i.e., simple and complex bids), the firms play the same equilibrium as we observe in the data for each design. In other words, we assume that the conditional distribution of firm expectations we observe in the data can be extrapolated as a market-design- specific function of the observed state variables. This is similar to the approach in Carranza, Houde, and Clark (2011) and, to the best of our knowledge, we are the first to implement it in the context of electricity auctions.

Our second contribution is empirical. We present two results. First, the more flexible market design that allows for complex bids results in a more efficient production allocation. In particular, it achieves a 6% reduction in the total cost of the electricity produced compared to the previous market design. This result is despite the fact that the generators' bids include a markup above their true costs. The second main result is that the 2009 market design change resulted in higher prices in the spot market for electricity. According to our results, Colombian consumers could have saved about 786 billion COP in our analysis period had there not been a change in the market design in 2009. These two results suggest that, although the current mechanism reduces the total cost of the daily energy dispatch, the underlying incentives of the firms to increase their markups are such that the current design benefits firms at the expense of consumers.

Our paper is related to recent studies that estimate marginal costs and markups in electricity markets, for example, Hortacsu and Puller (2008), Wolak (2000, 2003). Gans and Wolak (2008), Ciarreta and Espinosa (2010). These studies, however, consider only the static bidding problem ignoring the dynamic incentives that arise due to the presence of non-convexities in the costs of thermal units or to the ability of water storage for large hydro units. On the other hand, most of the research that completely characterize the dynamic incentives of hydro generators are theoretical and often restrict their empirical analysis to testing the predictions of the underlying models (see, for example, Stacchetti (1999), Garcia, Reitzes, and Stacchetti (2001), Garcia, Campos, and Reitzes (2005), Vegard Hansen (2009)). At the same time, Riascos, Bernal, de Castro, and Oren (2016) and Camelo et al. (2016) are successful in analyzing the dynamic incentives of the thermal units in a setting with complementary bidding mechanisms. However, they restrict their analysis to reduced-form estimates of the costs and bidding functions to address their empirical questions. To our knowledge, only the work by Reguant (2014) estimates the costs of thermal units allowing for the dynamic incentives that arise due to the presence of start-up costs and Balat et al. (2015) and Martin (2015) are the only studies to fully characterize the dynamic incentives of hydro generators and provide an empirical strategy to identify and estimate the implied opportunity cost of the water based on observed bid data. Nevertheless, these papers do not simultaneously account for the interactions between the dynamic incentives associated with the two production technologies.

The remainder of the paper is structured as follows. In Section 2 we describe Colombian electricity market. Section 3 presents the structural dynamic model of bidding behavior. In Section 4 we outline our estimation methodology. Section 5 presents the estimation results, introduces our counterfactual simulation exercise, and shows the main results of the paper. Finally, Section 6 concludes.

2 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, Morán, and Bermeo (in press) 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 Energia y Gas* (CREG), the regulatory agency.

The MEM consists of two separated markets: the forward market and the spot market.[5] 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 cleared in the spot market.

Procurement in the spot market settle using a mechanism similar to a multi-unit uniform-price auction where generators 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 2010–2015 period when the auction design incorporates complex bids.

2.1 Productive structure

The Colombian electricity generation technology is primarily hydroelectric (hydro) and themo-electric (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.[6] The rest of the capacity of the SIN belonged to producers using eolic technology (0.14%) and *cogeneration* (0.18%), a technology that produces electricity from the thermal energy generated from other productive activities.[7]

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

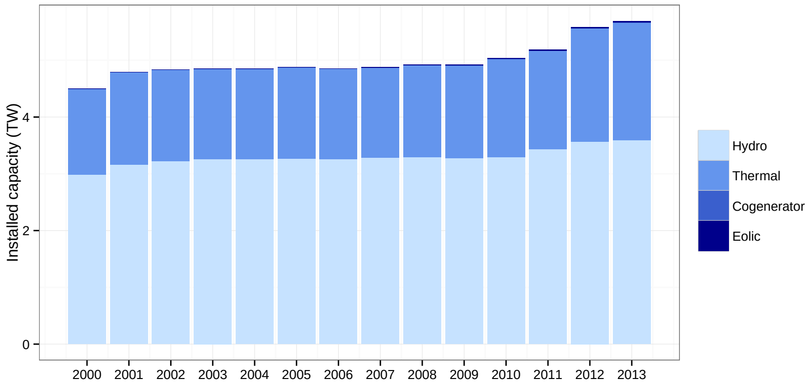
[5]As mentioned before, this is rather a day-ahead market but we will follow the usual practice in Colombia and refer to this market and its price as “spot market” and “spot price”, respectively.

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

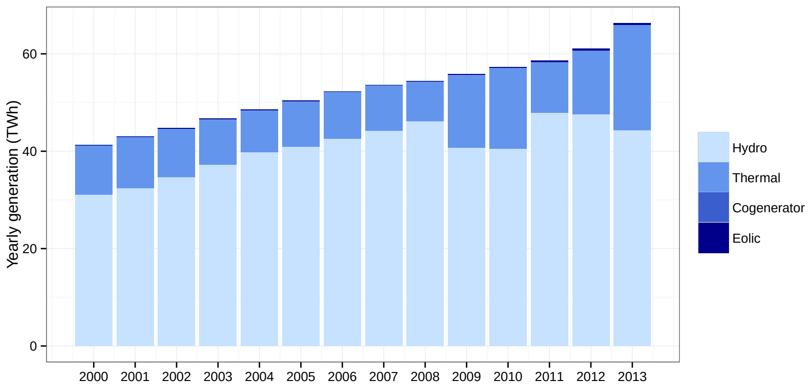
[7]In Colombia the main source of cogeneration is the sugar industry.

Figure 1: Evolution of the Productive Structure

(a) Installed Capacity



(b) Aggregate Generation



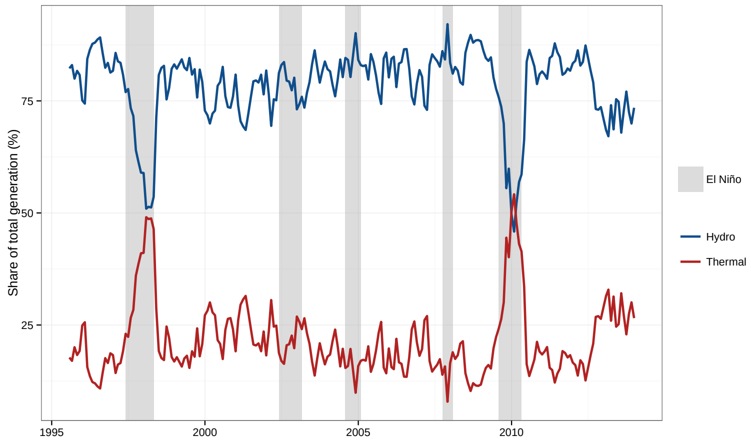
one plant. Within a given plant there may be more than one generation unit. Several hydro plants operating with the same dam or river form a *hydro chain*. Thus a hydro generator is defined as a plant or hydro chain (if that is the case) while a thermal generator is a generation unit of a thermal plant.

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 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.

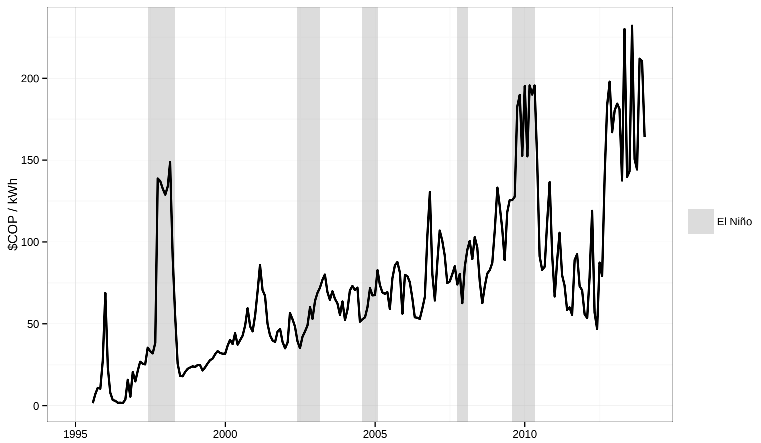
Table 1 presents the distribution of plants and installed capacity across the different types of generation technologies at the end of 2015. The data shows that the majority of production capacity is owned by less than 20% of the firms. Three large companies: *Emgesa*, *Empresas PÃºblicas de MedellÃn* (EPM) and *Isagen* dominate the productive structure. These firms

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

(a) Generation



(b) Spot Price



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.

Figure 3: Distribution of Installed Capacity

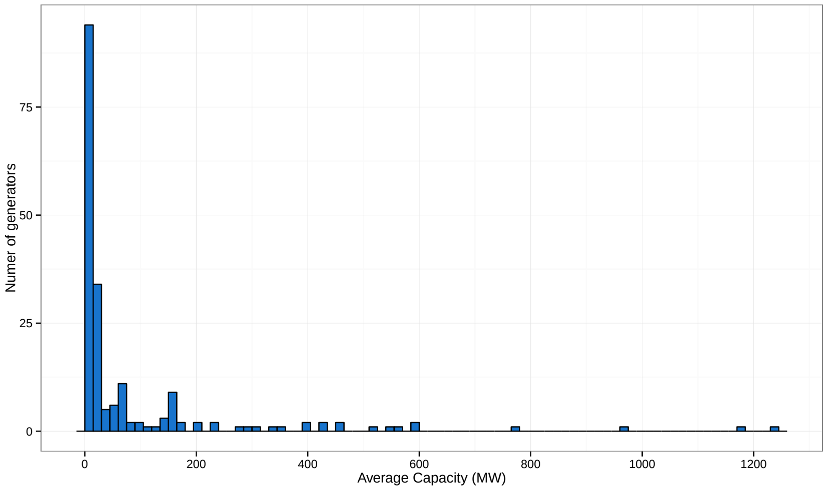


Table 1: Distribution of the Installed Capacity, December 2015

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.

2.2 The Spot Market

From 2009 to the present, procurement in the spot market has been made through a daily optimization process that resembles a uniform-price multi-unit auction. All centrally dispatched generators (units) are required to participate by submitting day-ahead bids consisting of a unique price and an estimate of the maximum available capacity they expect to have for each hour of the next day. Additionally, at the beginning of every quarter of the year, firms are also required to submit a monetary start-up cost bid for each thermal unit the operate.[8] The auction is conducted by the CND who defines a daily generation schedule that satisfies demand at minimum generation costs.

The process is described as follows. Every day before 8:00 AM, firms submit a day-ahead bid

[8]Noncentrally dispatched generators, on the order hand, are not supposed to participate in the auction. Instead, they are asked to submit an hourly power schedule they are willing to sell as price takers.

schedule for each unit they owned.[9] Using these bids, the CND calculates a generation schedule that ensured energy supply at minimum production costs. This schedule, called *economic dispatch*, consists of the amount of electricity every generator is required to produce in order to satisfy the expected demand for each hour of the next day. The purpose of the economic dispatch is to define a day-ahead operation plan that aims to satisfy the forecasted demand based on the expected production availability and network performance. This dispatch does not involve the definition of any monetary variable.

During the operation day, the CND is 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 objective of the real dispatch is to coordinate supply and demand according to the technical constraints that have to be met in a real time basis. The main difference in respect to the economic dispatch is the realization of demand and unexpected technical flaws of generating units and network congestion.

The day after, the CND computes the hourly spot price by solving the dispatch optimization problem taking into account the realized demand and actual supply but assuming ideal network conditions. The resulting schedule is called *ideal dispatch*. The last generation unit dispatched is called the marginal generator and is only dispatched for the residual demand not covered by the other dispatched units. The objective of the ideal dispatch is to define the monetary variables of the market. In particular, the hourly spot price is set equal to the highest price among the flexible dispatched units. Finally, similar to a uniform-price auction, all ideally dispatched units are paid with the spot price for every kWh produced in the respective hour.

2.3 Description of the Database

For our empirical analysis, we use information of centrally dispatched generators on bid prices, aggregate demand, available capacity, water storage and inflow levels, among other market variables from 2010 to 2016. The data is provided by XM and is of public domain. The data also includes information on fossil fuel prices from the *Unidad de Planeación Minero Energetica* (UPME).[10] We observe 1826 days, 27 firms and 63 generation units (20 hydro and 43 thermal). The final database is an unbalanced panel of 146,542 observations.

3 A multi-unit auction model with complex bids

We now describe a model of multi-unit auctions that incorporates the features of the Colombian wholesale electricity market, and that we can estimate with the available data. In the model, there are $i = \{1, \ldots, N\}$ firms that operate $j = \{1, \ldots, J_i\}$ generation units, and compete in a daily multi-unit auction for the right to produce electricity. There are two main generation technologies, hydro and thermal. For every firm i, each thermal unit j's hourly production is represented by $q_{ijh} \in [\underline{q}_{ij}, \overline{q}_{ij}]$.

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

[10] 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

3.1 The auction rules

The auction design follows the rules of the Colombian electricity spot market. Throughout the paper we refer to simple bids as the collection of price and quantity bids, and to complex bids as the quasi-fixed cost component, i.e. the start-up cost bid.

Every quarter of the year, τ, firms submit a set of complex bids consisting of a monetary start-up and shut-down costs for each thermal unit the own. The complex bid for unit j owned by firm i is denoted by A_{ij} and the collection of all complex bids is represented by $\mathbf{c}$. Then, every day within a given quarter, firms submit for each unit a set of simple bids which consist of a unique daily price and 24 available (declared) capacity values, one for each hour of the day. The simple bid submitted by firm i for unit j is represented as $\{b_{ij}, g_{ijh}\}$ and the collection of all simple bids is denoted by the array $\mathbf{b}$.

The market clearing algorithm searches all technically feasible combinations of units and production schedules that satisfy demand at the minimum cost. Both simple and complex bids are used by the market operator to define the daily dispatch (also known as *ideal dispatch*), which is defined as the combination of generating units and production schedules that minimize the daily cost of energy supply. Below we formally define this algorithm. To ease notation we temporarily omit the day and quarter subscripts.

Define demand for electricity D_h at hour h, as the sum of a deterministic price-inelastic component, D_h, and a stochastic component, ε_h, that is $\tilde{D}_h \equiv D_h + \varepsilon_h$. While D_h is known by all agents, firms are *ex ante* uncertain about the realization of ε_h. However, the process that generates ε_h is common knowledge and is represented by $F_\varepsilon(\varepsilon_h)$.

Let $\mathbf{k}^1_{ijh}$ and $\mathbf{k}^2_{ijh}$ be a set of multiple nonlinear vector functions specific to firm i's unit j at hour h, and let $\mathbf{r}_{ij}$ be the collection of all technical parameters for unit j. The equilibrium dispatch is defined as the feasible combination of generating units s and daily production schedule $\{q_{ijh}\}$ that solves the following optimization problem

$$\min_{\{q_{ijh}\}} \quad \sum_{h=0}^{23} \sum_{i=1}^{N} \sum_{j=1}^{J_i} b_{ij} q_{ijh} + A_{ij} \mathbf{1}^{\text{start}}_{ijh} \tag{1a}$$

subject to

$$\left\{ \sum_{i=1}^{N} \sum_{j=1}^{J_i} q_{ijh} - \tilde{D}_h \right\} \geq \mathbf{0} \tag{1b}$$

$$\left\{ \mathbf{k}^1_{ijh}(q_{ijh}, s_{ijh}, \mathbf{r}_{ijh}) \right\} = \mathbf{0} \tag{1c}$$

$$\left\{ \mathbf{k}^2_{ijh}(q_{ijh}, s_{ijh}, \mathbf{r}_{ijh}) \right\} \geq \mathbf{0} \tag{1d}$$

Equation (1b) represents the market clearing condition, which is a usual restriction in most energy auctions. On the other hand, equations (1c) and (1d) are the most particular characteristic of represent the set of technical restrictions that need to be satisfied in order for the dispatch to be technically feasible.

In other words, the market operator solves the optimization problem (1) to find the lowest cost feasible dispatch. The market clearing price p_h is the price vector that corresponds to the solution of the problem. Notice that this optimization problem is complicated, but we observe the optimal dispatch given the bids, and the observed state variables. Therefore, we can approximate the solution to the dispatch problem (1) from the observed data.

3.2 Firms' Profits

As discussed above, all dispatched units are paid p_h for each kWh produced at the respective hour of the day. Additionally, given the production schedule and submitted bids, the market operator defines for each unit a daily minimum revenue requirement characterized by the submitted bid price and start-up cost. According to the rules of the Colombian electricity market, every thermal unit whose gross revenue, characterized by the hourly market clearing price, is below its minimum revenue requirement is also paid with an uplift for each kWh produced during the day.

Formally, let

$$R_{ij} = \sum_{h=1}^{23} p_h q_{ijh} \quad \text{and} \quad \underline{R}_{ij} = \sum_{h=1}^{23} b_{ij} q_{ijh} + A_{ij}\mathbf{1}_{ijh}^{\{\text{start}\}}, \tag{2}$$

be the daily gross and minimum revenue of unit j, respectively. Notice that the minimum revenue incorporates the complex bids submitted by generators every quarter.

Then every thermal unit j for which $R_{ij} < \underline{R}_{ij}$, is also paid with an uplift to the hourly price, denoted by ΔI, which depends on the market outcomes and is defined as follows:

$$\Delta I(\mathbf{b}, \mathbf{c}) = \frac{\sum_{i=1}^{N} \sum_{j=1}^{J_i} \Big(\max\{0, \underline{R}_{ij} - R_{ij}\} + \sum_{h=0}^{23} d_{ijh} q_{ijh} [\max\{p_h, RP_{ij}\} - p_h] \Big)}{\sum_{h=0}^{23} \tilde{D}_h} \tag{3}$$

where RP_{ij} is the exogenous positive reconciliation price. [11]

At the time of bidding, firms are still uncertain about other firms' strategies as well as the realization of ε_h. Therefore, firm i will choose a bidding strategy in order to maximize its expected profits, conditional on a given distribution of other firms' bids as well as on a set of common public information and independent private shocks.

We assume that the set of public information common to all firms includes demand forecasts, dams' water storage levels and inflows, fossil fuel prices as well as the technical parameters of all generating units. We denote the set of public information known to all firms at the time of bidding by ω. On the other hand, a given firm's private values may consist on information such as maintenance strategy or unit unavailabilities and bilateral contracts. Given the available information set, firm i's expectations about the market outcomes of are taken over a taken over its own beliefs about other firms' strategies.

Denoting S as the set of all feasible combinations of units being dispatched,[12] the expected profits of firm i conditional on the state variables for a given day can be expressed as

$$E_{-i}[\Pi_i(\mathbf{b}, \mathbf{c}) \mid \omega] = \sum_{s \in S} \Pr(s \mid \mathbf{b}_i, \mathbf{c}_i)\, E_{-i}[\Pi_i(\mathbf{b}_s, \mathbf{c}_s) \mid \omega, s]\,, \tag{4}$$

where $\Pr(s \mid \mathbf{b}_i, \mathbf{c}_i)$ defines the probability that a combination of units s is dispatched, conditional on firm i's own bids. Notice that, conditional on a given state $\{\omega, s\}$, the market outcomes are only determined by the set of bids that are dispatched, denoted by $\{\mathbf{b}_s, \mathbf{c}_s\}$. To simplify notation for the rest of the document we state that expectations are always taken conditional on ω.

[11] The reconciliation price is an exogenous price set by the regulator in order to make sure that all units generating in the actual dispatch on $t + 1$ are paid according to their bids. For the objectives of this study, an explicit definition of this price is not relevant.

[12] That is, those satisfying the market clearing conditions (1b), as well as technical restrictions (1c) and (1c).

For any realization of the states s and bid strategies $\{\mathbf{b}_s, \mathbf{c}_s\}$, the firm i's profit function is given by:

$$\begin{aligned}\Pi_i(\mathbf{b}_s, \mathbf{c}_s) = \Bigg[&\sum_{h=0}^{23} (Q_{ih}(\mathbf{b}_s, \mathbf{c}_s) - v_{ih})\, p_h(\mathbf{b}_s, \mathbf{c}_s) - \Delta I(\mathbf{b}_s, \mathbf{c}_s) v_{ih} \\ &+ \Delta I(\mathbf{b}_s, \mathbf{c}_s) \sum_{j=1}^{J_i} \mathcal{I}_{ij}(\mathbf{b}_s, \mathbf{c}_s) q_{ijh}(\mathbf{b}_s, \mathbf{c}_s) \Bigg] \\ &- \sum_{j=1}^{J_i} C_{ij}(\mathbf{q}_{ij}(\mathbf{b}_s, \mathbf{c}_s)),\end{aligned} \tag{5}$$

where $Q_{ih}(\cdot)$ is the total quantity produced by firm i at hour h, v_{ih} is the firm's aggregate net sales position in the market of bilateral contracts, $\mathcal{I}_{ij}$ is an indicator function defined as follows

$$\mathcal{I}_{ij} = \begin{cases} 1, & \text{if } j \text{ is thermal and } R_{ij} < \underline{R}_{ij} \\ 0, & \text{otherwise} \end{cases} \tag{6}$$

and $C_{ij}(\cdot)$ represents the total daily costs function of unit j, which depends on the vector of hourly equilibrium unit quantities. Note that firms' dynamic incentives are summarized by their cost structures.

The dynamic problem of the thermal units arises due to the existence of ramping and start-up costs. These costs represent the inflexibility of a thermal unit to rapidly change its production levels throughout the day. For thermal units we use the costs specification proposed by (Reguant, 2014):

$$C_{ij}(\mathbf{q}_{ij}) = \sum_{h=0}^{23} \gamma_{ij1} q_{ijh} + \frac{\gamma_{ij1}}{2} \tilde{q}_{ijh}^2 + \frac{\gamma_{ij3}}{4} (q_{ijh} - q_{ijh-1})^2 + \alpha_{ij} \mathbf{1}_{ijh}^{\{\text{start}\}}, \tag{7}$$

where γ_{ij1} and γ_{ij2} represent j's marginal costs of production, γ_{ij3} represents the ramping costs, $\tilde{q}_{ijh} = \max\{q_{ijh} - \underline{q}_{ij}, 0\}$ is the unit's production over its minimum level, and α_{ij} is the total cost incurred whenever j gets switched on.

On the other hand, the dynamic problem of hydro units arises because their capacity to store energy in the form of water. This implies an intertemporal opportunity cost defined as the value of future payoffs that the firm gives up in order to produce energy (by releasing the water) in the current period. Under standard Markovian assumption of observed states, this dyanamic problem of hydro units can be written as a function of all the current states that firms use to condition their actions. Specifically, we follow the characterization proposed by Balat et al. (2015) and define the cost function for hydro units using a reduced form as follows:

$$C_{ij}(\mathbf{q}_{ij}) = \Psi_{ij}(\mathbf{q}_{ij}, \boldsymbol{\omega}), \tag{8}$$

where$\Psi_{ij}(\cdot)$ absorbs each firm i's marginal generation cost plus the sum of its future expected profits associated with unit j, which depend on the production output $\mathbf{q}_{ij}$ as well as on the current state of water storage and inflows levels, $\boldsymbol{\omega}$. It is important to note that this value of the dynamic problem of hydro units incorporates the strategic behavior of all the generators and is therefore specific to the observed equilibrium.

Notice also that at the time of making their simple bids, the firms take the quarterly complex bids and their contract positions as given. As we show below, our estimation strategy will focus on this stage of the problem. We also take these variables as given in our counterfactual analysis, which at this point is a limitation of our work.

3.3 Equilibrium and optimality conditions

We characterize the equilibrium of this model as the solution to a generic two-stage game with incomplete information. In the initial stage firms make irrevocable decisions about their complex bids. Once firms have submitted their complex bid schedules, a competition stage begins. In the second stage, all firms play in a sequence of 90 repeated sub-games. Each sub-game is characterized as multi-unit auction in which profits are determined according to the rules of the Colombian Spot Market. For any given day during the competition stage, we also assume that firm i's information set also includes information about the market outcomes of the previously disputed competition sub-games.

Given the sequential nature of the game we use backward induction to characterize the optimal strategies for both simple and complex bids. That is, for each firm i we start by deriving the optimality conditions for simple bids conditional on a fixed complex bid strategy. Then, the resulting simple bid strategy is incorporated in the firm's decision problem during the first stage to compute the respective optimality conditions for complex bids. As stated above, our analysis is based on the simple bidding or competition stage of the problem, taking the complex bids as given.

3.3.1 Optimality conditions for simple bids

The Markovian structure of the cost functions for both hydro and thermal units allows us to solve each sub-game of the competition stage as a conditionally independent simultaneous auction. This implies that, in each day within a given quarter of the year, firms will choose simple bid strategies as to maximize their expected daily profits:[13]

$$\max_{\mathbf{b}_i} \sum_{s \in S} \Pr\left(s \mid \mathbf{b}, \mathbf{c}\right) E_{-i}[\Pi_i((\mathbf{b}_i, \mathbf{b}_{-i}), \mathbf{c}) \mid s, \mathbf{c}_i] \,. \tag{9}$$

As usual in the literature for energy auctions we focus on the first-order conditions with respect to the price offers (Hortacsu & Puller, 2008; Kastl, 2011; Reguant, 2014; Wolak, 2003).[14] Then, the optimal strategy for simple bidding must satisfy the following first-order condition:

$$\sum_{s \in S} \Pr\left(s \mid \mathbf{b}, \mathbf{c}\right) \frac{\partial E_{-i}[\Pi(\mathbf{b}, \mathbf{c}) \mid s, \mathbf{c}_i]}{\partial b_{ij}} + \sum_{s \in S} \frac{\partial \Pr\left(s \mid \mathbf{b}, \mathbf{c}\right)}{\partial b_{ij}} E_{-i}[\Pi(\mathbf{b}, \mathbf{c}) \mid s, \mathbf{c}_i] = 0. \tag{10}$$

This expression allows us to analyze separately the process that determines the combination units that are going to be dispatched form the one that defines prices and quantities.

The first term can be interpreted in a similar fashion as in a usual multi-unit auction setup. However, there is a important difference. In a standard uniform-price multi-unit auction, small changes b_{ij} can only affect firm i's expected profits, if b_{ij} is likely to be marginal and, therefore, to determine the market clearing price. In the Colombian auction design, even after conditioning on s, small changes b_{ij} can still affect i's profits through the uplift component ΔI, even if b_{ij} does not set the market price. For example, an optimal strategy for firm i could be to slightly decrease b_{ij} in order to increase ΔI, which will be paid to all the units that are unlikely to meet their minimum revenue requirement.

[13]Notice that we also need to assume that the dynamic problem of thermal units has an horizon of one day. This is also the procedure followed by Reguant (2014).

[14]According to the Colombian regulation, firms are requested to submit an estimate of the hourly maximum available capacity, which is supposed to change only due to technical failures or maintenance. Hence, firms would not be able use it directly as a strategic variable without drawing attention form the market regulator.

On the other hand, the second term in equation (10) arises due to the existence of complex bids and the particularities of the Colombian dispatch optimization algorithm. This term is similar to the one derived by Reguant (2014) for the Spanish market. It represents the effect of b_{ij} on i's expected profits through the probability that a particular set of units is dispatched. That is, the extent to which small changes in b_{ij} affect the probability that any unit belonging to firm i will sell a positive quantity of electricity during the day. Notice that, given a set of technical parameters, this derivative is only non-zero when b_{ij} or A_{ij} are high enough so that j is the most costly unit in s, and there is unit $l \notin s$, such that the alternative combination of units $\hat{s} = \{s_{-j}, l\}$ is technically feasible and that the cost of the resulting dispatch is sufficiently low. Since the probability that these events occur simultaneously is likely to be small, we follow Reguant (2014) by assuming that

$$\sum_{s\in S} \frac{\partial \Pr(s \mid \mathbf{b}, \mathbf{c})}{\partial b_{ij}} E_{-i}[\Pi(\mathbf{b}, \mathbf{c}) \mid s, \mathbf{c}_i] \approx 0. \tag{11}$$

This assumption allows us to express the optimality conditions for simple bids focusing only on the first term of equation (10).

Thus, based on assumption (11) and the fact that small changes in b_{ij} only affect the expected market price if b_{ij} is likely to be the marginal bid, we rearrange terms from first-order condition (10) and express firm i's optimal simple bid for unit j, conditional on $\mathbf{c}_i$ and s as follows:

$$\begin{aligned} b_{ij} = \bar{\zeta}_{ij} - \frac{\sum_{h=0}^{23} E_{-i}\left[Q_{ih} - (1 + \frac{\partial \Delta I}{\partial b_{ij}}) v_{ih} \,\middle|\, s, p_h = b_{ij}\right]}{\sum_{h=0}^{23} E_{-i}\left[\frac{\partial Q_{ih}}{\partial b_{ij}} \,\middle|\, s, p_h = b_{ij}\right]} + \\ \frac{\sum_{l=1}^{J_i} \sum_{h=0}^{23} E_{-i}\left[\frac{\partial \Delta I}{\partial b_{ij}} q_{ilh} + \frac{\partial q_{ilh}}{\partial b_{ij}} \Delta I \,\middle|\, s, \mathcal{I}_{il} = 1\right] \phi_{il}}{\sum_{h=0}^{23} E_{-i}\left[\frac{\partial Q_{ih}}{\partial b_{ij}} \,\middle|\, s, p_h = b_{ij}\right]} + \\ \frac{\sum_{l=1}^{J_i} \sum_{h=0}^{23} E_{-i}[\Delta I \times q_{ilh} \mid s, \mathcal{I}_{il} = 1] \frac{\partial \phi_{il}}{\partial b_{ij}}}{\sum_{h=0}^{23} E_{-i}\left[\frac{\partial Q_{ih}}{\partial b_{ij}} \,\middle|\, s, p_h = b_{ij}\right]}, \end{aligned} \tag{12}$$

where $\bar{\zeta}_{ij}$ represents a weighted average of the daily marginal cost of unit j owned by firm i at hour h:

$$\bar{\zeta}_{ij} = \frac{\sum_{h=0}^{23} E_{-i}\left[\frac{\partial C_{ij}}{\partial q_{ijh}} \left(\frac{\partial q_{ilh}}{\partial b_{ij}}\right) \,\middle|\, s, p_h = b_{ij}\right]}{\sum_{h=0}^{23} E_{-i}\left[\frac{\partial Q_{ih}}{\partial b_{ij}} \,\middle|\, s, p_h = b_{ij}\right]}, \tag{13}$$

and $\phi_{ij}(\mathbf{b}_i) \equiv \Pr(\mathcal{I}_{ij} = 1 \mid \mathbf{b}_i)$ defines the probability for unit j of being paid the extra price-uplift ΔI, conditional on the firm's simple bid strategy and the state variables of the public information set.

According to equation (12), i's optimal simple bid for unit j is equal to the average marginal cost plus a shading factor or markup. This markup consists of three separate terms. The first term is standard in static models of uniform-price auctions (Gans & Wolak, 2008; Hortacsu & Puller, 2008; Wolak, 2000, 2003). It is composed by the expected inframarginal quantity produced by the firm when the unit is accepted, divided by its effect on equilibrium quantities, which is equivalent to its effect on the residual demand. The other two terms arise due to the presence of the minimum revenue requirement and the incremental price component ΔI, which are particular to the Colombian electricity market.

3.3.2 Optimality conditions for complex bids

For completion, we now proceed to derive the optimality conditions for complex bids, corresponding to the first stage of the sequential game. In this stage of the game, firms are aware that their complex bids decisions will be committed for each of the 90 sub-games of the second stage. Firm i will choose a complex bid strategy, $\mathbf{c}_i$, so as to maximize the total sum of its expected profits during the following 90 days.

It is worth mentioning that, because of the imposed backward induction characterization of the equilibrium, $\mathbf{c}_i$ will affect i's profits not only directly, but through its own simple bid strategy as well. We allow firm i to account for this feature at the time of submitting its complex bids strategy. Formally, let B and C denote the space of simple and complex bids, respectively. Also, let Ω be the state space. Define firm i's optimal strategy for simple bids at auction t as the vector function $\boldsymbol{\beta} : C \times \Omega \rightarrow B$ such that, for any given $\mathbf{c}_i \in C$ and $\omega_t \in \Omega$, $\mathbf{b}_{it} = \boldsymbol{\beta}_i(\mathbf{c}_i, \omega_t)$ satisfies the conditions implied by equation (12).

Then, adding the day subscript, we can write firm i's optimization problem at the first stage of the game as follows:

$$\max_{\mathbf{c}_i} \; E_{-i}\left[\sum_{t=1}^{90} \Pi_i(\mathbf{b}_t, \mathbf{c})\right], \quad \text{s.t. } \mathbf{b}_{it} = \boldsymbol{\beta}_{it}(\mathbf{c}_i) \equiv \boldsymbol{\beta}_i(\mathbf{c}_i, \omega_t). \tag{14}$$

Consequently, the first-order necessary conditions for this optimization problem are given by,

$$\begin{aligned} \sum_{t=1}^{90}\sum_{s\in S} \Pr\left(s \mid \boldsymbol{\beta}_{it}(\mathbf{c}_i), \mathbf{c}\right) \frac{\partial E_{-i}[\Pi_i(\boldsymbol{\beta}_{it}(\mathbf{c}_i), \mathbf{c}) \mid s]}{\partial A_{ij}} + \\ \sum_{t=1}^{90}\sum_{s\in S} \frac{\partial \Pr\left(s \mid \boldsymbol{\beta}_{it}(\mathbf{c}_i), \mathbf{c}\right)}{\partial A_{ij}} E_{-i}[\Pi_i(\boldsymbol{\beta}_{it}(\mathbf{c}_i), \mathbf{c}) \mid s] = 0. \end{aligned} \tag{15}$$

Notice that, complex bids affect firm i's daily profits through both probability of having any of its unit dispatched and through the definition of prices and quantities. Nevertheless, conditional on the given complex bids, the subsequent competition game in which simple bids are chosen is independent, as assumed.

4 Estimation Procedure

In this section we propose an estimation methodology to recover the structural parameters of the costs functions for each centrally dispatched generator based on the observed bidding data of the Colombian electricity market. In particular, we estimate the structural parameters of the cost function defined in equation (7) for every firm i:

$$\boldsymbol{\theta}_i = \{\alpha_i, \gamma_i, \lambda_i\}. \tag{16}$$

As is usual in the empirical literature for energy auctions, we use the empirical moments implied by the optimality conditions of the bidding game defined by equations (10) and (47). Below we discuss the methodology employed for the construction of these empirical moments as well as the intuition behind identification.

4.1 Estimation of firms' expectations

To estimate the unit-specific costs parameters, we use the generalized method of moments procedure based on the first order conditions implied by equation (10). Specifically, we adapt the procedure used in previous studies in the multi-unit auction literature to the particular auction design of the Colombian electricity spot market. Intuitively, our estimation is based on finding the parameters of the model that make the first order conditions of the bidding game as close to zero as posible.

To construct the empirical analog of first order conditions for the simple bids, we first need to estimate each firm's expectations terms. We follow the bootstrapping procedure used by Hortacsu and McAdams (2010) and Kastl (2011), which consists of simulating firm i's beliefs about other firms' strategies based on the available data. For a particular day, firm i's strategies are held fixed. For other firms different form i, strategies are randomly drawn form the sample data, approximating the uncertainty that the firm faces at the time of bidding. For a particular draw, and given the dispatch algorithm defined in (1a), we compute simulated equilibrium outcomes which determine the firm i's profits. Repeating this procedure for a sufficiently large number of times, it is possible to obtain consistent estimates of the firm's expected profits.

The consistency of the estimators of the firm's beliefs with this procedure depends on how the sampling step is done. For example, when firm i's beliefs are not generated by the same distribution between auctions, estimators of the expectation terms might be biased if the sampling of other firms' strategies does not condition on similar auctions. Therefore, we control for all variables included in the information set available for the firm at the time of bidding as observed in the data. In particular, we condition the sampling set of similar days on water inflows, fuel prices, demand forecasts, average prices of bilateral contract sales, as well as on the day of the week.[15]

Another feature of the data that can affect the precision of the estimators is the existence of affiliated private values. Given the time series nature of the data, auctions are likely to be serially correlated. Conditioning on observed state variables of the information set is also useful when dealing with a potential bias driven by this feature. In fact, we assume that after controlling for the observed variables that are potentially serially correlated, the distribution of firm i's beliefs at the time of bidding is stochastically independent between auctions.

The bootstrapping algorithm we employ for this study can be summarized as follows:

1. Fix bidder i's strategies in auction t
2. Randomly draw strategies of other firms $k \neq i$ from a sample of N similar days, conditioning on a set of observed state variables
3. Compute the market equilibrium using the computational algorithm proposed by Camelo et al. (2016)
4. Repeat steps 2-3 M times to obtain a distribution of market outcomes

There are two aspects that make our bootstrap simulation procedure similar to the one used by Reguant (2014) and different from other applications. First, the market clearing is defined as the solution to a complex optimization problem and cannot be necessarily replicated through a standard uniform-price multi-unit auction. Second, as in the model introduced by Reguant

[15]This approach is based on the works by Gans and Wolak (2008) and Reguant (2014), who also pool similar days to construct the sample analogues of moment conditions.

(2014), firms also face uncertainty over their own equilibrium supply curve as the set of units that will be dispatched is also random due to the presence of complex bids.

However, our model differs form the one of Reguant (2014) mainly in the fact that complex bids are submitted on a quarterly basis. This would requires us to compute an estimate of the firms' expected sequence of their profits for the following 90 days. Because the available data for complex bids is short, we cannot directly estimate the underlying joint distribution of this sequence. Hence, in the current version of the study we do not estimate the implicit start-up costs of thermal units. Moreover, although we are still able to estimate the expectation terms for the first order condition of simple bids and the parameters of the marginal cost function (23), we have to assume that firms submit truthful bids about their start-up costs in order to compute a counterfacutal experiment.

For the second point of the bootstrap algorithm described above, we define a sample of similar days to t, as follows. The similarity criteria between days is defined according to state variables we assume firms use to condition their expectations; namely, the price of Fuel No. 6, as well as to the aggregate water stock and river flow. Hence, we define a vector consisting of the three variables previously mentioned for day t, denoted as $\mathbf{x}_t$. Then we define from the sample the set of all days with the same day of the week as t as WD_t and build the sequence of vectors $\{\mathbf{x}_\tau\}_{\tau\in\mathrm{WD}_t}$. Given the sequence of approximately 74 days,[16] we measure the euclidean distance between $\mathbf{x}_t$ and $\mathbf{x}_\tau$ for every $\tau \in \mathrm{WD}_t$ and select the vectors associated with the N smallest computed distance. We set $N = 30$ which gives us samples for bootstrapping i's competitors strategies of size between 1200 and 1470. Notice that since we match similar days without conditioning of firm-specific features, we can use the same sample of bidding strategies for every firm i.

4.2 Approximation of derivatives

Once market outcomes are simulated, the challenge that remains is the computation of the derivative terms involved in the optimality conditions for both simple and complex bids. To address this problem, we follow an smoothing approach that has become frequent in the context of electricity auctions (Gans & Wolak, 2008; Wolak, 2007).

The approximate versions of the derivative terms used to construct the empirical moments are the following:

$$\widehat{\frac{\partial D_{iht}^{R,bs}}{\partial b_{ijt}}} = \frac{1}{\nu}\sum_{k\neq i}\sum_{(k,j)\in s^{bs}} g_{kjht}\mathcal{K}\left(\frac{b_{ljt}-p_{ht}^{bs}}{\nu}\right) \tag{17}$$

$$\widehat{\frac{\partial Q_{iht}^{bs}}{\partial b_{ijt}}} = \frac{1}{\nu}\sum_{(i,j)\in s^{bs}} g_{ijht}\mathcal{K}\left(\frac{b_{ijt}-p_{ht}^{bs}}{\nu}\right) \tag{18}$$

where $\mathcal{K}$ is a Kernel density weight and ν is a bandwith parameter. In particular, we set $\mathcal{K}$ as the normal density function and ν following the rule of thumb for every different firm.

[16] That is, 53 weeks in 1.4 years.

4.3 Identification and econometric specification

Following equation (7), the econometric specification of the daily weighted average marginal costs for a thermal unit j is the following:

$$\bar{\zeta}_{jt}^{\text{therm}}(\gamma_{jt}) = \gamma_{jt1} + \gamma_{jt2} \sum_{h} \tilde{q}_{ijh} + \gamma_{ijt3} \sum_{h} (2q_{ijh} - q_{ijh-1} - q_{ijh+1}) + \epsilon_{jt}^{\text{therm}}, \tag{19}$$

where $\epsilon_{jt}^{\text{therm}}$ represents the econometric specification error. As suggested by Reguant (2014), this error term can also be interpreted as a shock on marginal costs known to the firm or as an optimization error. Notice that the cost parameters are both unit and day-specific. We allow the cost derivatives to vary over time in order to capture the effect of fuel prices on both variable and ramping costs. In particular we specify each parameter as follows:

$$\gamma_{jt1} = \gamma_{j1}^{\text{cons}} + \gamma_{j1}^{\text{Pfuel}} \ln \text{Pfuel}_{jt} + \gamma_{j1}^{\text{Foil6}} \ln \text{Foil6}_{t} + \gamma_{j1}^{\text{TRM}} \ln \text{TRM}_{t} + \gamma_{j1}^{\text{CERE}} \ln \text{CERE}_{t} + \gamma_{j1}^{\text{FAZN}} \ln \text{FAZN}_{t}, \tag{20}$$

$$\gamma_{jt2} = \gamma_{j2}^{\text{cons}} + \gamma_{j2}^{\text{Pfuel}} \ln \text{Pfuel}_{jt} + \gamma_{j2}^{\text{Foil6}} \ln \text{Foil6}_{t} + \gamma_{j2}^{\text{TRM}} \ln \text{TRM}_{t}, \tag{21}$$

$$\gamma_{jt3} = \gamma_{j3}^{\text{cons}} + \gamma_{j3}^{\text{Pfuel}} \ln \text{Pfuel}_{jt} + \gamma_{j3}^{\text{Foil6}} \ln \text{Foil6}_{t} + \gamma_{j3}^{\text{TRM}} \ln \text{TRM}_{t}, \tag{22}$$

where Pfuel_{jt} is the current price in day t for the fuel used by unit j; Foil6 is the price of the Fuel Oil No. 6, used by most thermal units as a substitute of their main fuel; TRM is the COP/USD daily average exchange rate; CERE and FAZN denote the taxes firms must pay for each KWh generated.

In this study we focus on estimating the marginal cost function for thermal units only. However, in the estimation process we do control for river flows and water stock in order to account for the dynamic incentives of hydroelectric units.

Marginal cost parameters, γ_{jt}, can be identified given the observed position of contract sales. The intuition is that variations in the contract sales positions affect markups but not costs. Therefore, since the quantity sold by the firm in bilateral contracts is not defined at the same time as the price bids, marginal production costs can be identified with enough variation in the contract sales position. This identification strategy has become standard in energy markets (see Hortacsu and Puller (2008) and Wolak (2007)).

4.4 Estimation method

In the current version of the study we restrict to estimate only the parameters of the marginal cost function (19). Consequently, we define the set of parameters to estimate for firm i as $\theta_i = \{\gamma_{it}\}_{t=1}^{T}$.

The empirical moment conditions implied by equation (12) are given by

$$\begin{aligned} m_{ijt}(\theta_i, \nu, M) = \frac{1}{M} \sum_{bs=1}^{M} \sum_{h=0}^{23} \mathbf{1}\{j \text{ in}\} \Bigg[\widehat{\frac{\partial p_{ht}^{bs}}{\partial b_{ijt}}} \Bigg(\big(b_{ijt} - \bar{\zeta}_{ijt}(\theta_i)\big) \widehat{\frac{\partial D_{iht}^{R,bs}}{\partial b_{ijt}}} + Q_{ih}^{bs} - \Bigg(1 + \widehat{\frac{\partial \Delta I_t^{bs}}{\partial b_{ijt}}}\Bigg) v_{ih} \Bigg) + \\ \sum_{l=1}^{J_i} \mathbf{1}\Big\{\mathcal{I}_{ilt}^{bs} = 1\Big\} \Bigg(\Bigg(\widehat{\frac{\partial \Delta I_t^{bf}}{\partial b_{ijt}}} q_{ilht}^{bs} + \widehat{\frac{\partial q_{ilht}^{bs}}{\partial b_{ijt}}} \Delta I_t^{bs} \Bigg) \hat{\phi}_{ilt}^{bs} + \Big(\Delta I_t^{bs} \times q_{ilht}^{bs}\Big) \widehat{\frac{\partial \phi_{ilt}^{bs}}{\partial b_{ijt}}} \Bigg) \Bigg]. \end{aligned} \tag{23}$$

Then, the Generalized Method of Moments (GMM) estimator for the parameters is defined as follows:

$$\theta_i^* = \arg\min_{\theta_i} \big[Z_t' m_{ijt}(\theta_i, \nu, M)\big]' \, \Phi \big[Z_t' m_{ijt}(\theta_i, \nu, M)\big] \tag{24}$$

where Z is a matrix of instruments assumed to be orthogonal to ϵ, and Φ is a weighting matrix. Among the instruments we include fixed effects for days of the week, months of the year, observed load demand, aggregate river flows, fuel prices, firms' net contract position in the forward market, the monthly average of contract prices as well as forecast probabilities for *El Niño* events. The weighting matrix is computed according to the two-stage estimator where the initial guess is the identity matrix.

It is worth mentioning that, even though we do not estimate the cost parameters for hydro units, we do account for hydro units incentives when computing the moment conditions defined above, since we control for water stocks and river flows when building the bootstrap sample in the procedure of estimating firm i's expectation terms. Therefore, if the assumptions we have made so far hold, the solution to equation (24) should be a consistent estimator of a restricted version of the full parametric model.

5 Estimation results

In this section we show the estimated parameters of the marginal costs function for thermal units defined in (23) as well as the estimated series and the implied bid-cost mark-ups.[17] The results presented below are generated using the bootstrap algorithm described in subsection 4.1 and the GMM estimator defined by equation (24) on auction data at the generator level from August 13th, 2011 to December 31st, 2012.

Table 2 presents weighted averages of the estimated values for γ_{jt1}, γ_{jt2} and γ_{jt3} across time and units, by fuel type.[18] The average constant marginal cost, $\bar{\gamma_1}$, is positive and higher for those units using the most expensive fuels (i.e. diesel and fuel oil). For example, average constant marginal cost for coal-fueled units is about 172 COP/KWh, while for those using diesel the cost is about 258 COP/KWh. The variable part of the marginal cost, $\bar{\gamma_2}$, suggest a reduction on the total marginal cost for every KWh generated over the unit's minimum production level. In other words, on average, thermal units face a higher cost when generating during their soak or desynchronization phases. Moreover, this effect is higher in magnitude for coal units and substantially lower for gas units. In particular, results suggest that coal units face, on average, a marginal cost 18.54 COP/KWh lower for every KWh produced over their minimum level, whereas for gas units the respective reduction is 3.02 COP/KWh. Finally, the average ramping cost, denoted by $\bar{\gamma_3}$, are in most cases positive. This suggests that, except for fuel oil units, the average marginal cost of a thermal unit increases whenever the unit has to change its output in less than one hour. In particular, the extra cost of changing output is on average 0.14, 0.10 and 0.04 COP/KWh for coal, gas and diesel units, respectively.

[17]Although the other units were taken into account in the bootstrap algorithm the parameter estimates for their marginal costs were not directly estimated.

[18]See tables 7-10 of Appendix C.1 where we show the coefficient estimates of the cost function for each thermal generating unit.

Table 2: Average estimate of the marginal costs coefficient by fuel type

Fuel	$\bar{\gamma}_1$	$\bar{\gamma}_2$	$\bar{\gamma}_3$
Diesel	258.11	-10.05	0.04
Coal	171.86	-18.64	0.14
Fuel oil	250.37	-13.15	-0.12
Gas	177.09	-3.02	0.10

Source: Authors' own calculations based on the parameter estimates, and information from XM.

Given the parameter estimates we are able to project an estimate of the average marginal cost for each unit across the sample period and compute the implied bid-cost markup. First, we compare our estimates of the average marginal costs with those computed by de Castro et al. (2014) using the following engineering expression:

$$mc_{jt}^{\text{en}} = \frac{\text{HR}_j}{\text{CP}_j} \times \text{Pfuel}_{jt} + \text{VOM}_t + \text{CERE}_t + \text{FAZN}_t, \tag{25}$$

where HR and CP denote the unit's heat rate and calorific power value, respectively, and VOM represents the variable operating and maintenance costs.

Below, Table **??** compares the weighted means and standard deviations of our marginal costs estimates with those implied by equation (25) for the same period, by fuel type. Notice that on average the engineering approximation underestimates the firm's valuation for each KWh to be sold since it does not account for the non-convexities associated with each unit's technological restrictions, as well as unobserved opportunity costs associated with fuel prices and exchange rates.[19]

Table 3: Sample averages of the marginal costs series implied by the model estimates and the engineering formula (COP / KWh)

Fuel type	Model estimate	Engineering formula
Diesel	161.83	113.29
Coal	128.53	93.82
Fuel oil	386.12	165.68
Gas	127.20	116.13

Source: Authors' own calculations based on the model estimates, the engineering formula (25), and information from XM.

Then, we analyze the implied bid-cost markups implied by the difference between the observed bids and the estimated daily average of the marginal costs. In Table 3, we show the weighted mean, weighted standard deviation, minimum and maximum of the implied bid-cost markups by fuel type. The results suggest that the highest markups are charged in average by fuel oil units, while coal units charge the lowest. At the same time, we observe more dispersion on other fuel type technologies than on those using fuel oil, as suggested by the standard deviation. That is, coal units not only charge the highest markup on average, but they also exercise such market power consistently along the sample period.[20]

[19] See figures 14-18 of Appendix C.2 for further detail on this comparison.

[20] For further detail, we also present the daily series of the estimated marginal costs and observed bids by generator in figures 14-18 of Appendix C.2

In Table 3 we compute the weighted mean, weighted standard deviation, minimum and maximum of the implied bid-cost markups by fuel type. The results suggest that the highest markups are charged in average by fuel oil units, while coal units charge the lowest. At the same time, we observe more dispertion on other fuel type technologies than on those using fuel oil, as suggested by the standard deviation. That is, coal units not only charge the highest markup on average, but they also exercise such market power consistently along the sample period.

Table 4: Summary statistics of estimated mark ups by fuel tipe

Fuel	Mean	Std.Dev	Min	Max
Diesel	21.79	571.04	-11535.39	1248.20
Coal	2.97	33.04	-213.96	159.20
Fuel oil	386.64	154.73	-96.74	785.19
Gas	15.78	66.93	-89.78	1049.76

Source: Authors' own calculations based on the parameter estimates, and information from XM.

6 Counterfactual experiment

The purpose of this study is to answer the question about whether the current dispatch mechanism for generation in the Colombian electricity market led to a reduction in the energy cost for the consumers. In particular, we propose a counterfactual experiment that allows us to compare the realized cost of the energy sold between August, 2011 and December, 2012 with the cost that the system would have faced if the dispatch mechanism was the previous self unit commitment mechanism used in Colombia before Resolution 051 was introduced, for the same period. The results of such experiment allow us to conclude that the aggregate cost of energy sold would was lower during the perior August, 2011 and December, 2012 with the current centralized unit commitment mechanism in cpmparasson to the conuterfactual, self unit commitment mechanism.

To perform such experiment we need to simulate an equilibrium, in which firms play their optimal strategies according with an environment where state variables are the ones observed during our period of study but the game corresponds to the previous auction format used in the Colombian market. There are many reasons why the computation of such equilibrium is complicated. First, we have to recognize the multiplicity of equilibria in the game described by previous auction format, which makes it hard to pin down one particular counterfactual equilibrium or even to put bounds on the set of plausible equilibria. Second, even if we focus on a particular type of equilibria, we need to compute the counterfactual distribution of firms' expectations over a combination of market structure and states that may not be observed in the data.

These complexities are usually the reason why previous studies in electricity markets have not been able to perform counterfactual experiments in which firms play a game other than a Vickrey-equivalent mechanism. Among the few empirical works on energy markets that are able to estimate parameters of the marginal costs, most limit their analyses to description of costs statistics, measuring market power through price-cost markups and to verify theoretical predictions. For example, Hortacsu and Puller (2008) use their estimations on contract positions to verify how well the optimal bidding predicted by their model fits the observed bids. Martin (2015) focus on the analysis of the water opportunity costs to identify if peaks in prices during shortage periods where associated with strategic behavior or as a result of an increase in the dynamic incentives to store water. Even in the work by Reguant (2014), the estimates of marginal and start-up costs parameters are only used to measure market power and identify difference in productive efficiency across fuel types. To our knowledge, there are no studies that are able to perform counterfactual experiments that are able to compare the equilibria between different market structures.

In our analysis below we overcome these difficulties making two major assumptions. Specifically, we assume that firms always play the same symmetric equilibrium for the respective game that we observe in the data for each of the two dispatch mechanisms (i.e. the previous auction format and the current dispatch with complex bids used in Colombia). In other words, we assume that, outside of the estimation sample, the conditional distribution of expectations can be extrapolated as a game-specific function of the observed state variables.

Formally, let T_a and T_b be the set of auctions observed between January, 2007 and December, 2008 when the dispatch mechanism was similar to a uniform-price auction and between August, 2011 and December, 2012, when the dispatch mechanism was the one described by the model presented in section 3, respectively. We define $S_i^a : S_{-i}^a \times \Omega \to \mathbb{R}_+$ be firm i's optimal strategy profile that describes the simple bids submitted by firm i for the set of equilibria observed in T_a, and $S_i^b : S_{-i}^b \times \Omega \to \mathbb{R}_+$ as firm i's optimal strategy profile describing the simple bids submitted by firm i observed in T_b.

Thes strategy profiles generate dispatch distributions $\Pr_a(s \mid \mathbf{b}, \mathbf{c}, \omega_a)$ and $\Pr_b(s \mid \mathbf{b}, \mathbf{c}, \omega_b)$ for each time window T_a and T_b, respectively. These distributions assign a probability to any possible dispatch allocation s, given the observed states ω and complex bids $\mathbf{c}$. These probabilities incorporate both the technical restrictions of the system and the equilibrium behavior of all generators. Moreover, these probabilities can be inferred directly from the data as follows:

$$\begin{aligned} \hat{\Pr}_a(s \mid \mathbf{c}, \omega_a) &= \Omega_a(s, \omega_a, \mathbf{c}) \\ \hat{\Pr}_b(s \mid \mathbf{b}, \mathbf{c}, \omega_b) &= \Omega_b(s, \omega_b, \mathbf{b}, \mathbf{c}) \end{aligned} \tag{26}$$

where $\Omega(.)$ describes the dispatch probability in the give equilibrium as a function of observed states. Notice that Ω_a does not contain the complex bids, since there were none during the time T_a.

We are interested in computing the counterfactual performance of the market during the time T_b, under the market rules in effect during T_a. Under our assumptions, one possible counterfactual equilibrium is given by the strategy profile $\tilde{s}_i = S_i^a(\tilde{s}_{-i}, \boldsymbol{\omega}_{T_b})$. This strategy profile would generate the following counterfactual dispatch probabilities:

$$\tilde{\Pr}(s \mid \mathbf{b}, \omega_b) = \Omega_a(s, \omega_b, \mathbf{c}). \tag{27}$$

We can therefore use these probabilities (26) to compute the counterfactual behavior of firms during the time frame T_b, but under the rules and equilibrium behavior that were in effect during time T_a. In our application we sample the bids directly from the data, as we describe below[21].

In our experiment we simulate an equilibrium in which firms play their optimal strategies according with an environment where the game corresponds to the previous auction format with simple bids between August, 2011 and December, 2012. Below we describe the procedure using the available data. First we define firm i's optimal strategy for simple bids, $S_i^a(\cdot)$, by the well known first-order conditions of the uniform-price auction game:

$$\sum_{h=1}^{24} b_{ijt} - MC_{ijth} + \frac{E[Q_{ith} - v_{ith} \mid p_{ith} = b_{ijt}]}{\partial E[Q_{ith} - v_{ith} \mid p_{ith} = b_{ijt}] / \partial b_{ijt}} = 0. \tag{28}$$

[21]This approach is described by Carranza et al. (2011) and, to the best of our knowledge, has never been used to compute counterfactual experiments in the field of energy markets.

Then, to compute equation (28) for the period of study we need to simulate two unobserved terms: marginal costs and the expectation terms.

For thermal units, we use our parameter estimates from section 5 to simulate the marginal costs that firms would face under different generation schedules. As for the expectation terms, we rely on our assumption that any firm's expected payoffs at the time of bidding can be expressed as a function of the state variables, the active units and the dispatch mechanism. In particular, we apply the bootstrapping algorithm on observed data between January, 2007 and December, 2008, to estimate a function of expectations for each firm which is associated to the previous auction format with simple bids and which can be conditioned on the state variables observed during our period of study. Formally, the estimation of the expectation terms implied in (28) is as follows:

1. For any day t in the original sample period (i.e. from August, 2011 to December, 2012), define the vector of state variables, $\mathbf{x}_t$, including: price of fuel oil No. 6, aggregate water stock and river flows.
2. In the outside sample (i.e. from January, 2007 to December, 2008) select a subsample of the same days of the week as t and with same active units.
3. For each day τ in the subsample built in step 2, define the vector of state variables as specified in step 1, $\mathbf{x}_\tau$.
4. Compute the Euclidean distance between $\mathbf{x}_t$ and $\mathbf{x}_\tau$ for every τ.
5. Select the days of the subsample built in step 2 associated with the lowest 30 distances computed between the state variable vectors.
6. Use the bids of those 30 days to perform a bootstrapping algorithm to estimate firm i's expectations in the previous dispatch mechanism setting[22].

A second challenge that remains, however, is the projection of hydro units' optimal bids. This occurs because we do not directly estimate the parameters of the cost function for hydro units we need. Hence, for hydro units, we do not compute the optimal bidding strategy following the the structural first-order condition defined in (28). Instead, we use the estimated reduced form of their dynamic problem, which varies across observed states, but ignore the fact that it may change across equilibria.

Given the optimal bidding functions, the expectations and marginal cost estimates, we are able to compute the equilibrium for an hypothetical scenario in which generating firms in Colombia play the previous auction setting with simple bids between August 1st, 2011 and December 31st, 2012. Hence, the underlying consumer cost difference between the observed equilibrium for the current dispatch and the simulated one for the previous auction format will serve to answer which mechanism was more efficient when accounting for strategic behavior during a period of normal hydrologic conditions.

Below, we present the results of our counterfactual experiment. These results allows us to conclude that the aggregate cost of energy sold between August, 2011 and December, 2012 would have been lower if the dispatch mechanism was under the previous auction setting, instead of the current dispatch with complex bids.

[22]Notice that under the proposed algorithm, bids are sampled directly from the data within bands of observed states to compute expectation in (28). We can do this thanks to the richness of our dat. Alternatively, we could have estimated the probabilities using more restrictive estimators.

Figure 4 shows the comparison between the daily average of the observed and the simulated spot price. Moreover, we present the percentage difference between the two series in Figure 4. The results show that the current dispatch mechanism is associated with higher prices in average. In other words, before taking into account start-up costs, we find that the aggregate cost of energy sold is systematically higher under the current dispatch mechanism. Such conclusion is expected *a priori* as the dispatch defined by (1a) does not only accounts for the variable cost of energy but also the start up costs of thermal units but for the start-up costs as well. In mathematical terms, this is equivalent to compare the minima between a constrained (current dispatch) and an unconstrained (previous dispatch) optimization problem.

Figure 4: Evolution the daily average of observed and simulated spot price between August 1st, 2011 and December 31st, 2012.

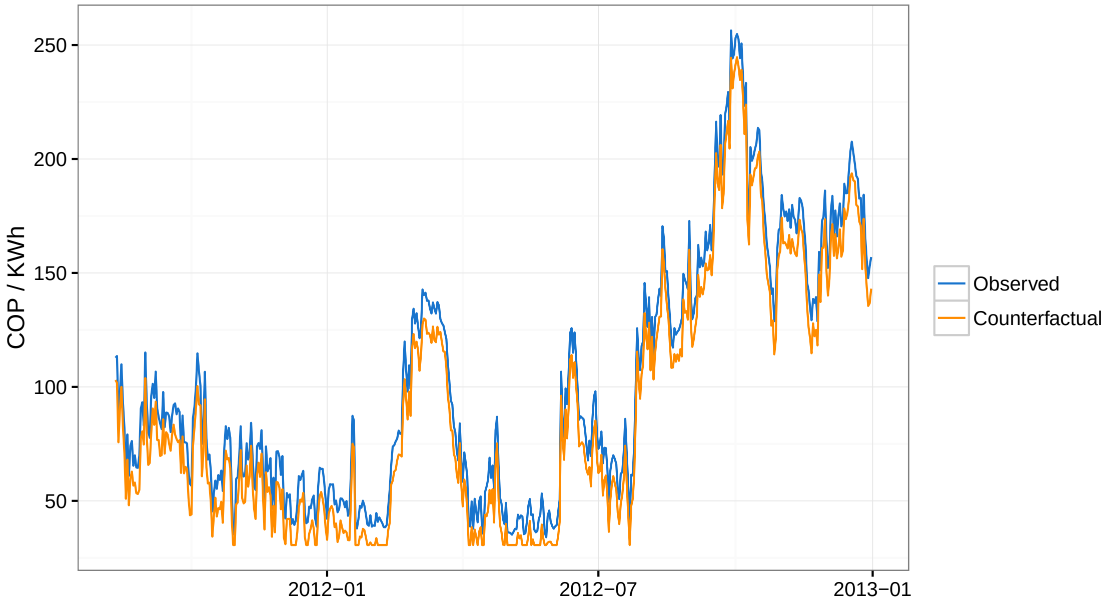
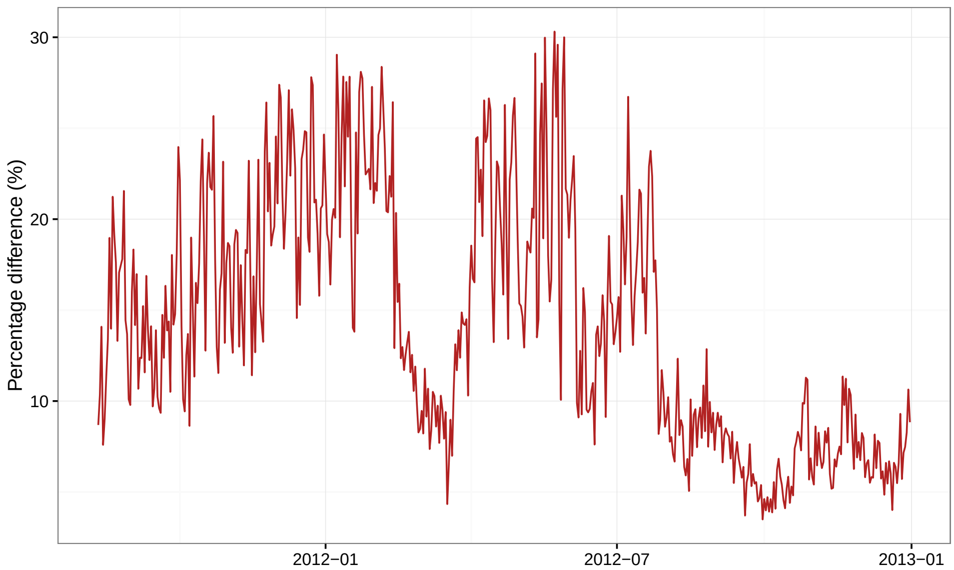


Figure 5: Evolution the percentage difference between the daily average of the observed and simulated spot price, between August 1st, 2011 and December 31st, 2012.



However, we also find that spot prices increase not only because the marginal bidder submits a higher price. As we present in Table 4, submitted bids under the observed equilibrium are systematically higher as well. In other words, the actual submitted bid prices are much higher in average than those which firms would have bid in the previous auction environment. This result is consistent with the economic intuition. Specifically, since firms' expect higher spot prices in the equilibrium of the current dispatch mechanism, they find optimal to increase their bid prices.

Table 5: Summary statistics of actual vs. simulated bids between August 1st, 2011 and December 31st, 2012 (COP/KWh)

Mechanism	Mean	Std.Dev.	Min	Max
Current dispatch	270.01	295.48	30.62	2113.91
Previous dispatch	258.62	300.47	30.62	2550.14

Nevertheless, it is important to compare also the total costs and revenue, which include start up costs. For both scenarios we compute, on every day:

$$Cost = \sum_{h=0}^{23}\sum_{i=1}^{N}\sum_{j=1}^{J_i} \hat{mc}_{ij} q_{ijh} + A_{ij}\mathbf{1}_{ijh}^{\text{start}}, \tag{29}$$

as the total cost of energy produced, and

$$Revenue = \sum_{h=0}^{23}\sum_{i=1}^{N}\sum_{j=1}^{J_i} b_{ij} q_{ijh} + A_{ij}\mathbf{1}_{ijh}^{\text{start}}, \tag{30}$$

as the total revenue of energy sold on the respective day.

The aggregate cost and revenue for both regimes between August 1st, 2011 and December 31st, 2012 are presented in Table 5. The results show that the old auction format is associated with the higher aggregate costs of generation but also with lower aggregate revenue of energy sold for the firms. This suggests that, although the current dispatch mechanism is designed to reduce the total cost of the daily energy dispatch, the underlying incentives of the firms to increase bid markups is such that the efficiency gains of the new dispatch benefits firms over consumers. In other words, if the assumptions of our model and counterfactual exercise hold, Colombian consumers would have saved about 786 billions of COP between 2011 and 2012 if the dispatch mechanism was the previous simple-bid auction as used to be before 2009.

Table 6: Aggregate cost measures of dispatch between August 1st, 2011 and December 31st, 2012 (billions of COP)

	Current mechanism	Previous dispatch
Cost of energy produced	8,671.95	9,214.84
Revenue of energy sold	13,760.84	12,974.52

7 Conclusions

In this study we estimate a structural model of bidding behavior that accounts for the presence of complex bids and the dynamic incentives of both hydro and thermal generators in the Colombian electricity market. The purpose of this study was to evaluate the impacto on efficiency and prices of the shift to the current dispatch mechanism for generation.

Using observed auction data and bilateral contract sales position, we are able to identify the unobserved distribution of expectations and marginal production costs of thermal generators, which are used in turn to perform a counterfactual experiment that allows us to compare the realized cost of the energy sold between August, 2011 and December, 2012 with the cost the system would have faced if the dispatch mechanism was the previous simple-bid auction format as before Resolution 051 (2009), for the same period.

The estimation algorithm relies on a bootstrapping strategy, standard in the literature for energy markets, by using a computational model introduced by Camelo et al. (2016) to compute the bootstrapped moments. Average estimates of the marginal costs parameters are in average consistent with the intuition about the differences in costs across fuel types and the non-convexities of thermal generation technology. In other words, marginal costs are higher for fuel oil units than for units that use natural gas. At the same time, coal units show a higher scale efficiency. That is, marginal costs decrease faster as output increases over the minimum output for coal units than for other fuel types.

We develop an approach to compute a counterfactual experiment, using observed auction data under different dispatch mechanisms to compute the counterfactual decisions of firms. In particular, we use the observed behavior of firms under the previous simple-bid auction systems, to simulate their counterfactual behavior during a time window when the new mechanism was already in place.

The results imply that the aggregate cost of energy sold during our period of study would have been higher if the dispatch mechanism was under the previous auction setting, instead of the current dispatch with complex bids. However, at the same time, we find that the aggregate revenue for all the energy sold during the evaluation period is higher under the current dispatch as firms have more incentives to increase their markups. In other words, after accounting for strategic behavior, the current dispatch mechanism used in the Colombian electricity market between August, 2011 and December, 2012 increased both efficiency and prices. This result is consistent with descriptive evidence shown in Riascos et al. (2016).

Our study relies on two assumptions that facilitated the estimation and computation of the model. First, we have assumed that contract positions are exogenous and fixed them across counterfactual equilibria. Second, we have approximated the behavior of hydro units using a reduced form that is not necessarily stable across counterfactual equilibria. Relaxing these assumption requires the addition of structure to the model, and will be the focus of future research.

References

Balat, J., Carranza, J. E., & Martin, J. D. (2015). *Dynamic and strategic behavior in hydropower-dominated electricity markets: Empirical evidence for colombia.* (Working paper. Borradores de Economía No. 886. Banco de La República.)

Camelo, S., de Castro, L., Papavasiliou, A., Riascos, A., & Oren, S. (2016). *A structural model to evaluate the transition from self-commitment to centralized unit commitment.* (Working paper. Borradores de Economía No. 992. Banco de La República.)

Carranza, J. E., Houde, J.-F., & Clark, R. (2011). *Dynamic entry and firm reconfiguration in the canadian gasoline markets.* (Working paper.)

Carranza, J. E., Riascos, A. J., Morán, J. J., & Bermeo, L. (in press). *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.

de Castro, L., Oren, S., Riascos, A., & Bernal, M. (2014). *Transition to centralized unit commitment: An econometric analysis of Colombia's experience.* (Working paper. Borradores de Economía No. 830. Banco de La República.)

Gans, J. S., & Wolak, F. A. (2008). *A comparison of ex ante versus ex post vertical market power: Evidence from the electricity supply industry.* (SSRN Working Paper)

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.

Hortacsu, A., & McAdams, D. (2010). Mechanism choice and strategic bidding in divisible good auctions: an empirical analysis of the Turkish treasury auction market. *Journal of Political Economy*, *118*(5), 833–865.

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.

Kastl, J. (2011). Discrete bids and empirical inference in divisible good auctions. *Review of Economic Studies*, *78*(3), 974–1014.

Martin, J. D. (2015). *Identification of water opportunity costs in hydropower dominated electricity markets.* (M.S. Thesis. Icesi University.)

Reguant, M. (2014). Complementary bidding mechanisms and startup costs in electricity markets. *Review of Economic Studies*, *81*(4), 1708-1742.

Riascos, A., Bernal, M., de Castro, L., & Oren, S. (2016). Transition to centralized unit commitment: An econometric analysis of colombia's experience. *The Energy Journal*, *37*(3).

Sioshansi, R., Oren, S., & O'Neill, R. (2008). Economic consequences of alternative solution methods for centralized unit commitment in day-ahead electricity markets. *IEEE Transactions on Power Systems*, *23*, 344-352.

Sioshansi, R., Oren, S., & O'Neill, R. (2010). Three-part auctions versus self-commitment in day-ahead electricity markets. *Utilities Policy*, *18*, 165-173.

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.

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.

Appendix

A The computational model for the dispatch

As mentioned in the previous sections, we use the dispatch model introduced by Camelo et al. (2016) in order to estimate each firm's expectations about its competitors' strategies. In this section we provide a detailed description of our model of ideal dispatch. The model is cast as a mixed integer linear program. We also highlight the main differences with the ISO ideal dispatch model.

A.1 Model setup

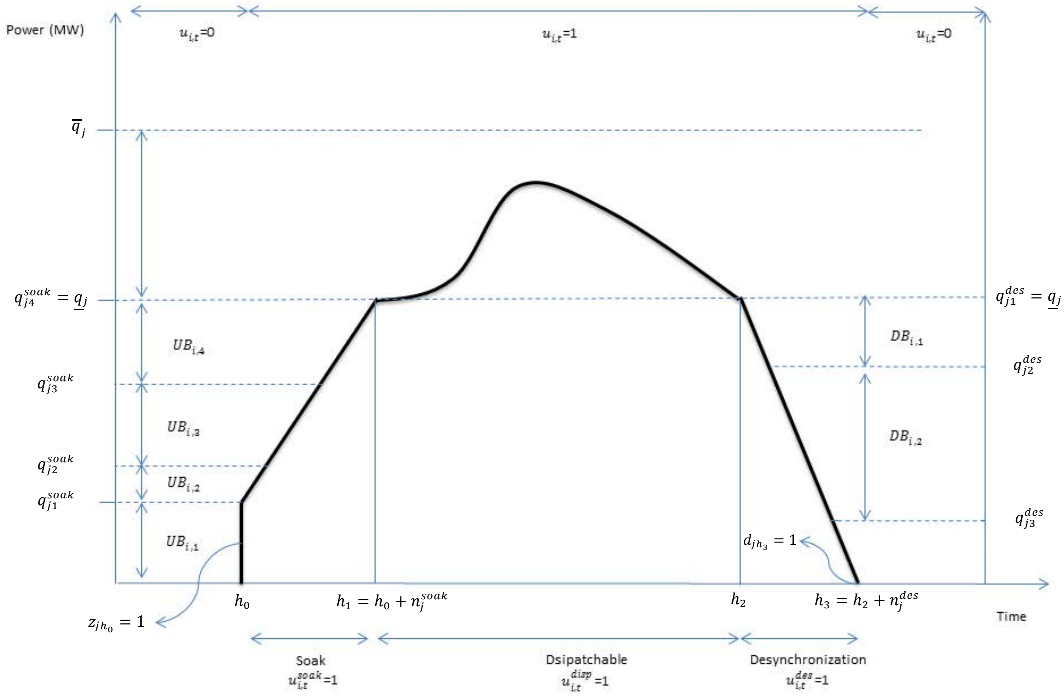
A.1.1 Additional Nomenclature

- q_{jh}^{soak} is the power provided by unit j during hour h and start-up phase.
- q_{jh}^{des} is the power provided by unit j during hour h and de-synchronization phase.
- UB_{jk} is the k-th ramp up blocks of unit j.
- DB_{jk} is the k-th ramp down blocks of unit j.
- u_{jh} is a binary variable indicating if unit j is up in period h.
- z_{jh} is a binary variable indicating if unit j is started in period h.
- d_{jh} is a binary variable indicating if unit j is stopped in period h.
- u_{jh}^{soal} is a binary variable indicating if unit j is in the start-up phase.
- u_{jh}^{dis} is a binary variable indicating if unit j is in the dispatch phase.
- u_{jh}^{des} is a binary variable indicating if unit j is in the shut-down phase.
- n_{jh}^{soak} represents the number of hours during the start-up phase (since start-up until output is at the technical minimum).
- n_{jh}^{des} represents the number of hours during shut-down phase (from a technical minimum to shut-down).
- n_{jh} is the minimum up-time of unit j.
- l_{jh} is the minimum down-time of unit j.

A.1.2 Ramp model

The ramp model is similar to Simoglou et al (2010). We assume that thermal units follow three consecutive phases of operation: (i) soak or start-up phase (from zero to technical minimum), (ii) dispatchable (when output is between the technical minimum and maximum feasible power output) and (iii) de-synchronization phase (when output is below the technical minimum and just before shut-down). In the soak phase, the power output follows a block model.

Figure 6: Ramp model of a thermal unit



Source: Camelo et al. (2016)

In the dispatchable phase we assume an affine model for power. In the de-synchronization phase we assume a block model. Figure 6 shows an example of the assumed ramp model for a thermal unit with a ramp of $K = 4$ blocks.

A.1.3 Optimization problem

The ideal dispatch is the solution to the following optimization problem. It is a mixed integer linear program.

Objective function

$$\min_{q_{jh}, q_{jh}^{\text{soak}}, q_{jh}^{\text{disp}}, q_{jh}^{\text{des}}, z_{jh}, d_{jh}, u_{jh}, u_{jh}^{\text{soak}}, u_{jh}^{\text{disp}}, u_{jh}^{\text{des}}} \quad \sum_{h=0}^{23} \sum_j b_j q_{jh} + A_j z_{jh} \tag{31}$$

Restrictions

Feasible output:

$$\tilde{D}_h \leq \sum_j q_{jh}, \quad \forall h \in \{0, \ldots, 23\} \tag{32}$$

Soak phase starts immediately following start-up:[23]

$$\sum_{\tau=h-n_j^{\text{soak}}+1}^{h} z_{i\tau} = u_{jh}^{\text{soak}} \tag{33}$$

Now let Q_{jr}^{soak} be the power provided by unit j during period r following start-up:

$$Q_{jr}^{\text{soak}} = \sum_{k=1}^{r} \text{UB}_{jk}.$$

Then, during soak phase, the power output of the unit is constrained by:

$$\sum_{\tau=h-n_j^{\text{soak}}+1}^{h} z_{i\tau} Q_{jh-\tau+1}^{\text{soak}} = q_{jh}^{\text{soak}} \tag{34}$$

Dispatch phase: We simplify the current model by assuming linear up and down ramp constraints.

$$q_{jh} \leq \frac{UR + b \times q_{jh-1}}{a} + N(u_{jh}^{\text{soak}} + u_{jh}^{\text{des}}) \tag{35}$$

$$q_{jh} \geq \frac{-DR + c \times q_{jh-1}}{d} - N(u_{jh}^{\text{soak}} + u_{jh}^{\text{des}} + d_{jh}), \tag{36}$$

where N is a sufficiently large parameter.[24]

The de-synchronization phase starts before shut-down:

$$\sum_{\tau=h+1}^{h+n_j^{\text{des}}} d_{j\tau} = u_{jh}^{\text{des}}. \tag{37}$$

Now let the power provided by plant j, for s periods after de-synchronization is started be defined as:

$$Q_{jH^{\text{des}}-r+1}^{\text{des}} = \sum_{k=1}^{r} \text{DB}_{jk}$$

Then, during the de-synchronization phase the power output of a unit is constrained by:[25]

$$\sum_{\tau=h+1}^{h+n_j^{\text{des}}} d_{j\tau} Q_{jh+1-\tau+n_j^{\text{des}}}^{\text{des}} = q_{jh}^{\text{des}} \tag{38}$$

Minimum up time. Units are constrained to be up for n_j^{up} periods after they are started up:

$$\sum_{\tau=h+n_j^{up}+1}^{h} z_{j\tau} \leq u_{jh} \tag{39}$$

[23]We make two simplifications with respect to the Colombian ISO ideal dispatch model. We only consider one type of start-up (as opposed to a cold, warm, or hot, start-up) and we only consider one type of configuration per plant (i.e., a fixed ramp per plant). Not sure what ramp has to do with configuration.

[24]We have approximated the ISO model for the dispatchable region. The ISO model is based on maximum and minimum power variations depending on the level of outputs (segments model called Model number 2 by ISO). Our model for the dispatchable region is a special case of ISO model number 3 used by some plants as an alternative to model 2. This discussion is esoteric and should probably be removed.

[25]This is a simplification of the current Colombian dispatch model on two dimensions. We do not consider an alternative shut down ramp whenever output is not at the technical minimum.

Minimum down time. Units are constrained to be down for n_j^{down} periods after they are shut down:

$$\sum_{\tau=h+n_j^{down}+1}^{h} d_{j\tau} \leq 1 - u_{jh} \tag{40}$$

Power Output Constraints:

$$q_{jh} \geq q_{jh}^{\text{soak}} + q_{jh}^{\text{des}} + q_{jh}^{\text{soak}} + \underline{q}_j u_{jh}^{\text{disp}} \tag{41}$$

$$q_{jh} \leq q_{jh}^{\text{soak}} + q_{jh}^{\text{des}} + q_{jh}^{\text{soak}} + \overline{q}_j u_{jh}^{\text{disp}} \tag{42}$$

$$q_{jh} \leq q_{jh}^{\text{soak}} + q_{jh}^{\text{des}} + q_{jh}^{\text{soak}} + \overline{q}_j u_{jh}^{\text{disp}} + (\underline{q}_j - \overline{q}_j) z_{jh+n_j^{\text{des}}} \tag{43}$$

Logical status of commitment. The following are restrictions required for the transition of the binary variables:

$$u_{jh} = u_{jh}^{\text{soak}} + u_{jh}^{\text{disp}} + u_{jh}^{\text{des}} \tag{44}$$

$$z_{jh} - d_{jh} = u_{jh} - u_{jh-1} \tag{45}$$

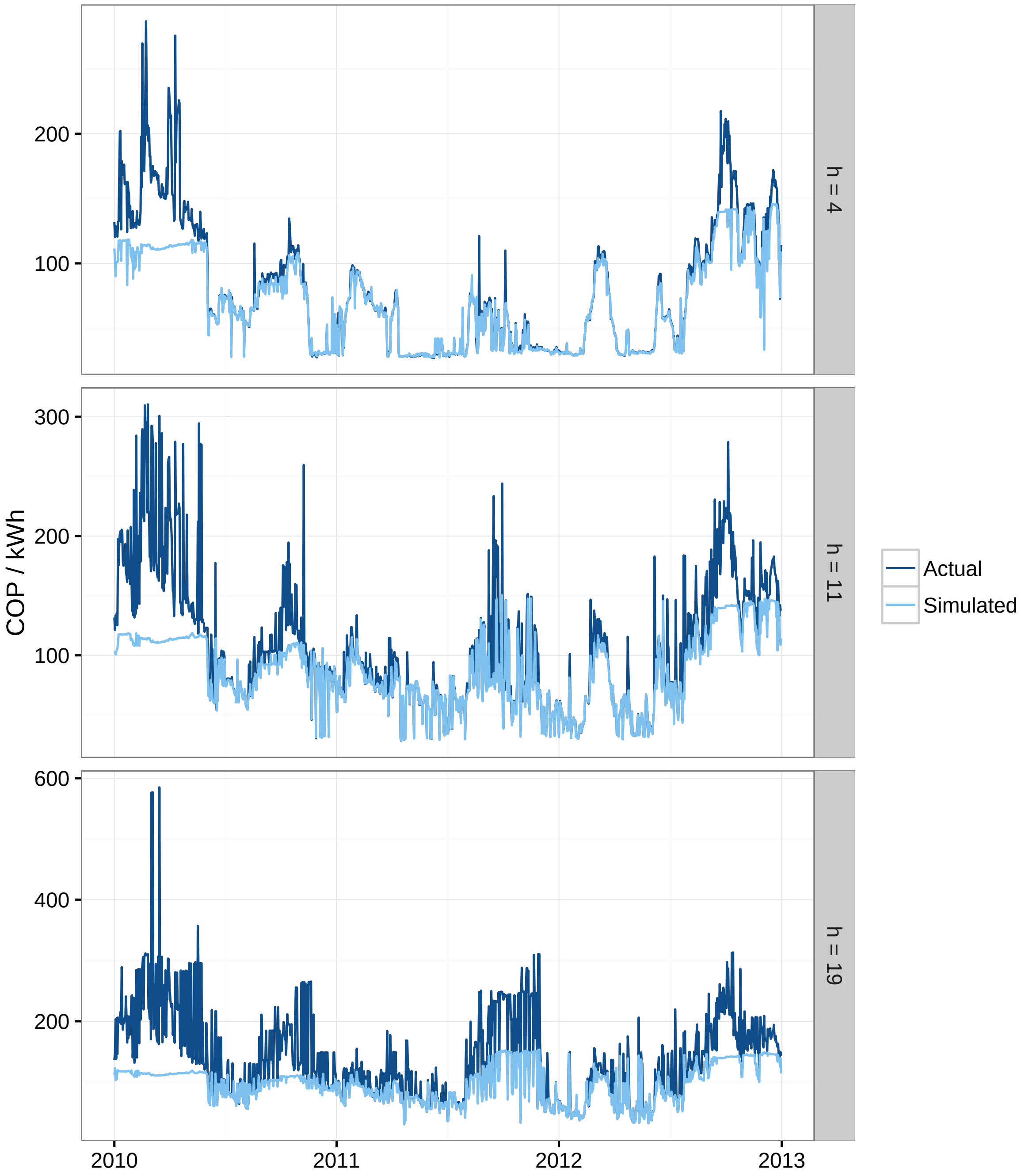
$$z_{jh} + d_{jh} \leq 1 \tag{46}$$

A.2 Simulation exercise

In this subsection we perform a small simulation exercise to illustrate the goodness of fit of this dispatch model compared with the observed ideal dispatch computed by XM.

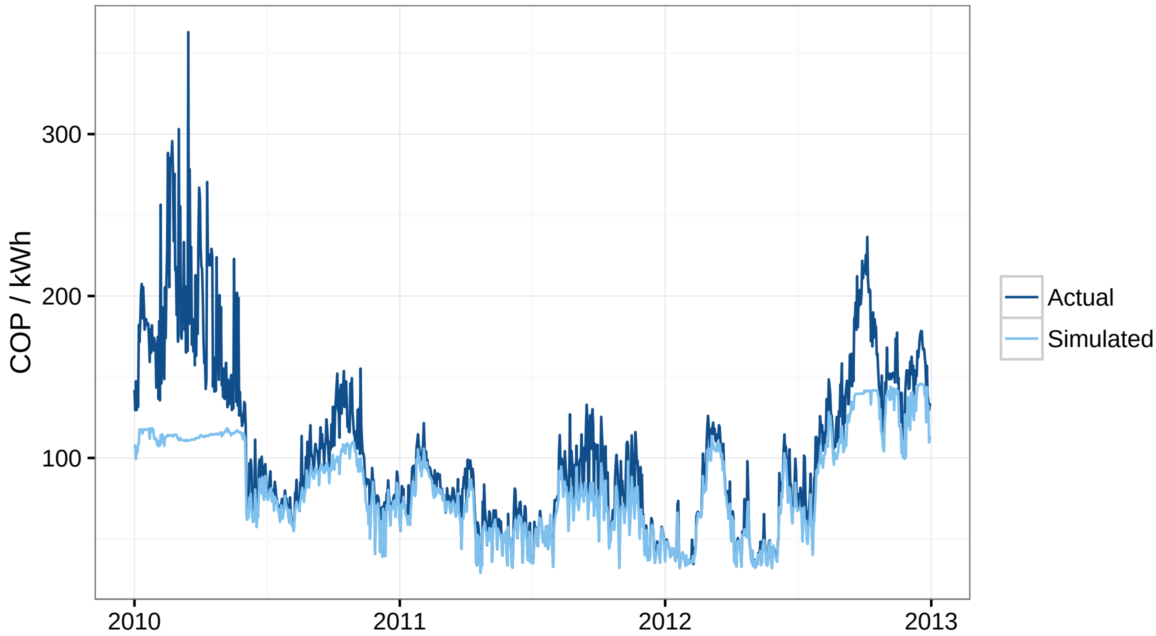
To test the validity of our model, we simulate the period from June 2010 to October 2012 using real start-up costs and bids. Then, we compare the simulated market price with the real one, as reported by XM. Below, Figure 7 shows the actual versus the sumulated market prices for three hourly periods, including the peak hour $h = 19$. On the other hand, Figure 8 shows the same comparison but between the daily averages of the real versus the simulated market price.

Figure 7: Comparison between actual and simulated market prices by hourly periods



Source: Own calculations based on data from XM.

Figure 8: Comparison between actual and simulated average daily market prices



Source: Own calculations based on data from XM.

As the plots show, except for the highest peaks, the model has a good fit for the market price. In Table 6 we present a comparison between some summary statistics between real and simulated market prices.

Table 7: Summary statistics for actual and simulated hourly market prices

	Actual	Simulated
Min	26.97	27.54
Quantile 5	30.71	30.73
Quantile 10	33.32	32.72
Quantile 20	52.21	51.58
Quantile 50	87.73	79.17
Quantile 80	148.74	113.72
Quantile 90	181.76	123.85
Quantile 95	215.79	141.49
Max	1889.15	153.44

Notice that our computational model underestimates actual market prices, specially for peak hours. One of the reasons for this discrepancy could be that in the actual dispatch performed by the exchange there are a number of complex rules which exclude generators deemed inflexible from participation in the price setting.

In hour theoretical model we assume that firms cannot fully anticipate the meeting of such additional restrictions and that the implied differences in the market outcomes can be summarized in the random component of the demand ε_{ht}.

This computational model for the dispatch is used to generate the bootstrapped moments that allows us to approximate each firm's expectation terms that are implied in the optimality conditions of the model. In other words we use the optimization algorithm to simulate several equilibrium to get a distribution of different market outcomes that will empirically approximate firm i's beliefs about the realization of its own profits, which will subsequently used to construct the empirical moment conditions defined in (23).

B Indentification of marginal costs of hydro plants

B.1 Markup composition

To estimate the components of the hydro plants' pricing equation, we follow the s identification strategy proposed by Martin (2015), Hence, we begin with the first-order necessary conditions when strategy, $q^*_{ij}(p)$, is optimal

$$p_{ij} = C'(q^*_{ij}(p)) + \Theta\big(p, q^*_{ij}(p); \mathbf{w}\big) + \Psi\big(q^*_{ij}(p), \boldsymbol{\omega}_{ij}\big)\,, \tag{47}$$

where $\Theta(\cdot)$ and $\Psi(\cdot)$ are defined as the static and dynamic component of the markup, respectively.

Notice that $\Psi_i \equiv \Psi\Big(q^*_{ij}(p), \boldsymbol{\omega}_{ij}\Big)$ is nonngeative and can be interpreted as firm i's intertemporal opportunity cost of water.

Assuming that Ψ_i is a nonincreasing function of firm i's own current stock and own future inflows, whenever i's current stock is full and its expected future inflows are positive, the firm's opportunity cost will be equal to its minimum, that is, $\Psi_i = 0$.

Given the assumptions, we employ the following strategy for identifying both markup terms using the available bidding data.

1. For every day t in the data, find the day t^* such that $\mathbf{w}_{t^*} \neq \mathbf{w}_t$ and $\boldsymbol{\omega}_{t^*} \to \boldsymbol{\omega}_t$. Then, since $C'(\cdot) = \lambda_{ij}$ is constant on q for hydro plants, $(p_{it} - p_{it^*}) \to (\Theta_{it} - \Theta_{it^*}) \neq 0$.
2. By construction, $\Delta\Theta_t \equiv (\Theta_{it} - \Theta_{it^*})$ can be expressed as the difference of two econometric equations. Therefore, Θ_t can be inferred, up to a constant, by estimating the following expression:
$$\Delta\Theta_t = f_t(\mathbf{x}_{it}) - f_{t^*}(\mathbf{x}_{it^*}) + (\mu_{it} - \mu_{it^*}), \tag{48}$$
where $f_t(\cdot)$ and $f_{t^*}(\cdot)$ are parametric or nonparametric functions to be estimated, $\mathbf{x}_{it}$ is a vector of covariates that includes $\mathbf{w}_t$ and $\mu_{it} - \mu_{it^*}$ is a zero mean stochastic error.
3. Given the estimates of f_t and f_{t^*}, the dynamic markup term can also be inferred, up to a constant,
$$p_{ijt} = \hat{\lambda}_{ij} + (k + \hat{f}_t(\cdot)) + \hat{\Psi}_{it}, \tag{49}$$
where k is a constant and $\hat{\lambda}_{ij}$ is estimated using the bootstrapping algorithm.
4. Finally, the constant can be identified from the observations when $w_{it} = \max\{w_{it}\}$.

C Estimation results

C.1 Parameter estimates by generator

In this section we present the parameter estimates associated to the marginal costs of all the thermal units in our sample data. It is worth to mention that these coefficients by themselves lack of economic interpretation since the constant and variable part of the marginal cost function, as well as the ramping cost part depend on the fuel prices.

Table 8: Coefficient estimates of the marginal cost function for units using diesel

Unit	γ_1^{cons}	γ_1^{Pfuel}	γ_1^{Foil6}	γ_1^{TRM}	γ_1^{CERE}	γ_1^{FAZN}	γ_2^{cons}	γ_2^{Pfuel}	γ_2^{Foil6}	γ_2^{TRM}	γ_3^{cons}	γ_3^{Pfuel}	γ_3^{Foil6}	γ_3^{TRM}
TERMOCANDELARIA 1	−16076.01*	−766.00*	−167.51*	3421.85*	−310.90*	4233.60*	551.30	−36.82	14.38	−45.56	79.53	1.99	−9.06	−2.97
	(2976.14)	(163.41)	(85.63)	(289.02)	(101.16)	(1559.66)	(5027.92)	(505.18)	(27.17)	(190.94)	(1666.43)	(67.15)	(17.63)	(166.31)
TERMOCANDELARIA 2	−7781.39*	−903.72*	−10.87	2304.32*	−158.11	1506.57*	33521.69*	−1080.89*	538.97*	−3778.37*	252.73	−3.02	−4.77	−24.84
	(3459.67)	(132.75)	(79.11)	(316.29)	(87.59)	(776.78)	(58373.82)	(6349.19)	(139.01)	(986.55)	(182.81)	(7.01)	(3.40)	(19.25)
TERMOEMCALI 1	−37948.75*	5045.31*	−404.00*	176.44*	−983.22*	−7263.78*	−385.99*	14.17*	15.43*	17.53*	119.61	−3.45	−7.03	−4.04
	(838.75)	(57.93)	(21.74)	(63.81)	(43.10)	(106.12)	(72.58)	(3.87)	(1.84)	(10.27)	(172.02)	(8.61)	(4.60)	(17.44)
FLORES 1	3998.19*	−27.78	−239.22*	−234.69*	28.38*	550.32*	−12.50*	−0.80*	3.49*	−1.28*	0.41	0.69	−1.82*	1.17
	(634.76)	(74.16)	(12.93)	(21.72)	(13.62)	(115.07)	(6.45)	(0.33)	(0.22)	(0.43)	(19.34)	(0.69)	(0.55)	(1.55)
TERMOSIERRAB	−17745.33*	1670.95*	55.00*	449.65*	−163.43*	−1268.96*	148.14*	−10.40*	−1.74*	−5.53*	−44.42	2.96	0.38	2.00
	(973.39)	(77.59)	(14.54)	(37.31)	(23.12)	(66.47)	(12.44)	(0.84)	(0.20)	(0.77)	(40.84)	(2.57)	(0.49)	(2.39)
TERMOVALLE 1	3623.00*	220.30*	−67.04*	−685.73*	63.46*	544.84*	1.57	−7.59*	2.31*	6.28	−9.40	1.30	−0.60	0.36
	(290.72)	(13.70)	(3.48)	(25.56)	(10.86)	(41.14)	(40.04)	(1.60)	(0.47)	(5.65)	(34.45)	(2.44)	(0.54)	(3.41)

Bootstraped standard errors are in parentheses. * Significant at 5%.

Table 9: Coefficient estimates of the marginal cost function for units using fuel Oil

Unit	γ_1^{cons}	γ_1^{Pfuel}	γ_1^{Foil6}	γ_1^{TRM}	γ_1^{CERE}	γ_1^{FAZN}	γ_2^{cons}	γ_2^{Pfuel}	γ_2^{Foil6}	γ_2^{TRM}	γ_3^{cons}	γ_3^{Pfuel}	γ_3^{Foil6}	γ_3^{TRM}
CARTAGENA 1	9035.61*	−1865.81*	965.93*	−178.18	28.45	4905.86*	−7036.72*	358.68*	−23.62	543.47*	1983.32	−139.44	8.95	−110.76
	(3940.56)	(238.31)	(62.55)	(486.94)	(109.11)	(1024.69)	(2011.41)	(72.56)	(34.12)	(196.77)	(1415.19)	(82.69)	(33.32)	(76.01)
CARTAGENA 2	18859.23*	−1921.51*	596.07*	−511.19*	−1110.88*	5656.78*	−2890.88*	244.90*	−38.67*	140.78	−231.99	15.25	32.89	−23.47
	(2168.89)	(205.01)	(46.63)	(254.83)	(78.06)	(520.28)	(721.17)	(55.91)	(19.94)	(83.24)	(747.82)	(37.93)	(21.36)	(55.21)
CARTAGENA 3	824.78	−1177.34*	613.22*	875.00*	−831.64*	5542.06*	−979.77	87.35*	−24.55*	55.42	−11.28	−12.99	8.71	6.94
	(2200.24)	(222.40)	(44.48)	(253.99)	(74.19)	(545.86)	(590.67)	(29.41)	(12.30)	(51.07)	(428.21)	(20.07)	(14.78)	(37.29)
BARRANQUILLA 3	−43301.74*	5803.52*	−416.86*	45.28	−966.46*	−5433.90*	1998.20*	−101.74*	−79.26*	−59.12*	−231.18	13.23	9.28	5.01
	(980.10)	(92.73)	(25.13)	(85.33)	(33.36)	(205.06)	(204.28)	(10.94)	(6.32)	(12.93)	(212.49)	(11.35)	(7.28)	(13.71)
BARRANQUILLA 4	−44633.65*	5088.79*	−290.12*	792.55*	−797.75*	−3238.51*	2824.83*	−189.34*	−41.52*	−109.20*	−698.38*	48.26*	9.82	25.81
	(961.92)	(113.28)	(24.67)	(103.21)	(34.29)	(268.60)	(240.30)	(13.97)	(10.31)	(14.55)	(234.78)	(14.15)	(10.89)	(14.02)

Bootstraped standard errors are in parentheses. * Significant at 5%.

Table 10: Coefficient estimates of the marginal cost function for units using coal

Unit	γ_1^{cons}	γ_1^{Pfuel}	γ_1^{Foil6}	γ_1^{TRM}	γ_1^{CERE}	γ_1^{FAZN}	γ_2^{cons}	γ_2^{Pfuel}	γ_2^{Foil6}	γ_2^{TRM}	γ_3^{cons}	γ_3^{Pfuel}	γ_3^{Foil6}	γ_3^{TRM}
PAIPA 1	2253.99*	90.25	88.40*	−663.38*	347.02*	25.23	−720.49*	27.56*	10.16*	42.23*	147.17	−1.64	−6.62	−9.61
	(765.32)	(55.71)	(10.49)	(43.57)	(22.83)	(102.42)	(53.40)	(6.10)	(2.25)	(10.69)	(91.41)	(14.10)	(5.04)	(13.82)
PAIPA 2	−7446.12*	−112.48*	244.58*	576.78*	749.71*	−90.41	−39.79	15.95*	−6.24*	−12.27*	25.55	−3.85	1.25	1.09
	(557.89)	(40.05)	(10.45)	(31.52)	(17.66)	(71.25)	(35.89)	(3.32)	(0.80)	(4.73)	(53.10)	(6.09)	(2.00)	(6.34)
PAIPA 3	8778.63*	−1235.31*	312.08*	195.60*	488.06*	−2147.85*	−209.51*	44.32*	−6.22*	−32.22*	63.94	−9.33*	0.45	5.10
	(533.50)	(40.49)	(8.27)	(35.51)	(15.75)	(73.03)	(17.15)	(1.65)	(0.54)	(2.83)	(36.73)	(4.10)	(2.20)	(5.35)
PAIPA 4	−801.38	−630.66*	343.08*	467.87*	502.61*	28.15	0.60	3.66*	−1.80*	−3.67*	24.11	−3.18	1.37	0.11
	(522.47)	(37.68)	(9.93)	(29.42)	(10.59)	(75.03)	(7.29)	(0.44)	(0.16)	(0.74)	(24.59)	(1.81)	(1.13)	(3.00)
GUAJIRA 1	1035.91*	−70.75*	0.76	−0.37	−5.49	−264.51*	−25.99*	−2.99*	1.25*	6.57*	6.28	1.82*	−0.58*	−2.93*
	(140.83)	(11.25)	(2.50)	(8.51)	(5.16)	(22.81)	(3.10)	(0.34)	(0.14)	(0.52)	(4.18)	(0.48)	(0.22)	(0.62)
GUAJIRA 2	−308.36*	86.93*	−14.31*	−32.48*	−33.43*	−106.96*	−28.06*	−4.16*	1.40*	8.44*	8.38*	2.34*	−0.68*	−3.87*
	(162.92)	(13.51)	(2.58)	(10.18)	(4.97)	(24.20)	(3.13)	(0.46)	(0.10)	(0.59)	(3.92)	(0.58)	(0.16)	(0.71)
TASAJERO 1	1321.49*	−53.61*	0.40	−90.74*	47.07*	−218.27*	−17.39*	1.99*	−0.08*	−0.61*	10.72*	−1.24*	0.06	0.39
	(68.67)	(4.34)	(1.11)	(3.40)	(1.69)	(9.70)	(0.47)	(0.12)	(0.04)	(0.19)	(1.09)	(0.20)	(0.08)	(0.26)
ZIPAEMG 2	3581.06*	−180.07*	−21.26*	−145.07*	−54.77*	390.52*	−278.30*	−1.72	−5.87*	46.26*	185.94	3.00	2.65	−32.25
	(222.62)	(16.14)	(3.47)	(13.06)	(8.91)	(33.45)	(58.32)	(1.78)	(1.77)	(7.40)	(367.27)	(10.03)	(10.07)	(41.90)
ZIPAEMG 3	5352.35*	−383.41*	−112.76*	−23.76	69.31*	−94.56*	−0.47	−4.11*	9.40*	−4.15*	−6.57	2.78	−3.56	0.63
	(241.01)	(18.63)	(5.13)	(14.89)	(10.26)	(36.68)	(10.96)	(0.83)	(0.79)	(1.86)	(25.50)	(2.81)	(2.22)	(4.27)
ZIPAEMG 4	3747.15*	−308.08*	−86.69*	92.17*	−41.14*	151.65*	118.22*	−5.28*	−1.84*	−5.68*	−65.31*	2.13	2.24	2.98
	(254.13)	(18.69)	(4.93)	(15.65)	(10.43)	(38.12)	(6.99)	(0.60)	(0.49)	(0.99)	(28.57)	(3.11)	(1.83)	(4.00)
ZIPAEMG 5	6696.89*	−324.36*	−139.08*	−256.85*	73.03*	−453.92*	41.32*	−11.61*	1.85*	9.96*	−31.76	5.31	−0.56	−3.16
	(236.29)	(18.15)	(5.17)	(15.92)	(10.85)	(35.92)	(8.32)	(1.68)	(0.66)	(2.57)	(36.05)	(8.44)	(2.34)	(12.13)

Bootstraped standard errors are in parentheses. * Significant at 5%.

Table 11: Coefficient estimates of the marginal cost function for units using gas

Unit	γ_1^{cons}	γ_1^{Pfuel}	γ_1^{Foil6}	γ_1^{TRM}	γ_1^{CERE}	γ_1^{FAZN}	γ_2^{cons}	γ_2^{Pfuel}	γ_2^{Foil6}	γ_2^{TRM}	γ_3^{cons}	γ_3^{Pfuel}	γ_3^{Foil6}	γ_3^{TRM}
MERILECTRICA 1	−5616.88*	310.29*	268.05*	−169.77*	521.16*	3009.55*	120.78*	−4.66*	−18.42*	9.72*	23.60	0.96*	0.75	−5.07*
	(345.45)	(6.95)	(15.39)	(30.19)	(21.90)	(80.21)	(24.14)	(0.53)	(2.39)	(2.05)	(17.49)	(0.26)	(1.25)	(2.18)
PROELECTRICA 1	−724.61*	15.53*	10.28*	61.99*	63.64*	415.41*	−117.31*	−3.92*	−5.42*	26.31*	1.51	0.00	−0.04	−0.16
	(30.53)	(0.36)	(0.54)	(4.21)	(1.44)	(5.13)	(29.24)	(0.51)	(0.95)	(4.33)	(3.95)	(0.06)	(0.11)	(0.54)
PROELECTRICA 2	−843.14*	20.16*	14.20*	68.11*	59.98*	485.22*	−79.19	14.24*	20.91*	−28.80*	2.99	−0.08	−0.15	−0.14
	(31.40)	(0.29)	(0.54)	(4.23)	(1.42)	(5.18)	(40.54)	(1.32)	(2.20)	(6.45)	(2.47)	(0.06)	(0.11)	(0.42)
TEBSAB	−1129.40*	0.70	12.33*	164.30*	−9.02*	−37.31*	1.86*	−0.02*	0.13*	−0.37*	−1.41*	0.03*	−0.07*	0.23*
	(57.21)	(1.19)	(2.43)	(7.62)	(4.62)	(11.65)	(0.33)	(0.01)	(0.02)	(0.04)	(0.55)	(0.01)	(0.04)	(0.07)
FLORES 4B	−2402.80*	15.43*	210.39*	34.51	63.90*	1377.08*	−5.29*	0.37*	−0.89*	1.25*	3.44	−0.15*	0.40	−0.72
	(336.81)	(3.75)	(18.99)	(44.95)	(8.25)	(51.14)	(1.26)	(0.03)	(0.13)	(0.26)	(2.37)	(0.07)	(0.27)	(0.52)
TERMOCENTRO CC	−6139.71*	205.01*	521.58*	−232.72*	452.36*	2357.86*	−57.51*	−5.47*	−9.35*	24.25*	23.65*	1.48*	3.18*	−8.36*
	(618.47)	(14.66)	(37.47)	(27.33)	(19.00)	(119.28)	(4.38)	(0.30)	(0.58)	(1.02)	(8.33)	(0.22)	(0.50)	(1.24)
TERMOYOPAL 2	6503.54*	23.40*	29.71*	−988.54*	199.57*	−810.41*	−968.81*	−6.96*	−2.84*	139.84*	124.76*	2.21*	3.00*	−22.36*
	(157.86)	(2.74)	(6.08)	(20.27)	(6.04)	(33.71)	(26.41)	(0.45)	(0.87)	(3.38)	(46.88)	(0.57)	(1.04)	(6.99)

Bootstraped standard errors are in parentheses. * Significant at 5%.

C.2 Figures of estimated marginal costs

In this section we present the estimated series of daily average marginal costs implied by the model specification (7).

In particular, figures 9-13 compare our estimated series with those implied by equation (25) introduced by de Castro et al. (2014). Notice that the estimated series implied by specification (7) have a pattern of steeper peaks which is directly associated with the technical inflexibilities faced by the marginal thermal units within a day. This structure of the marginal costs allows us to better identify whether peaks in the market spot price are caused by technological issues or by the exercise of unilateral market power exercised by the generating firms.

Figure 9: Estimated vs. engeneering marginal costs of diesel units

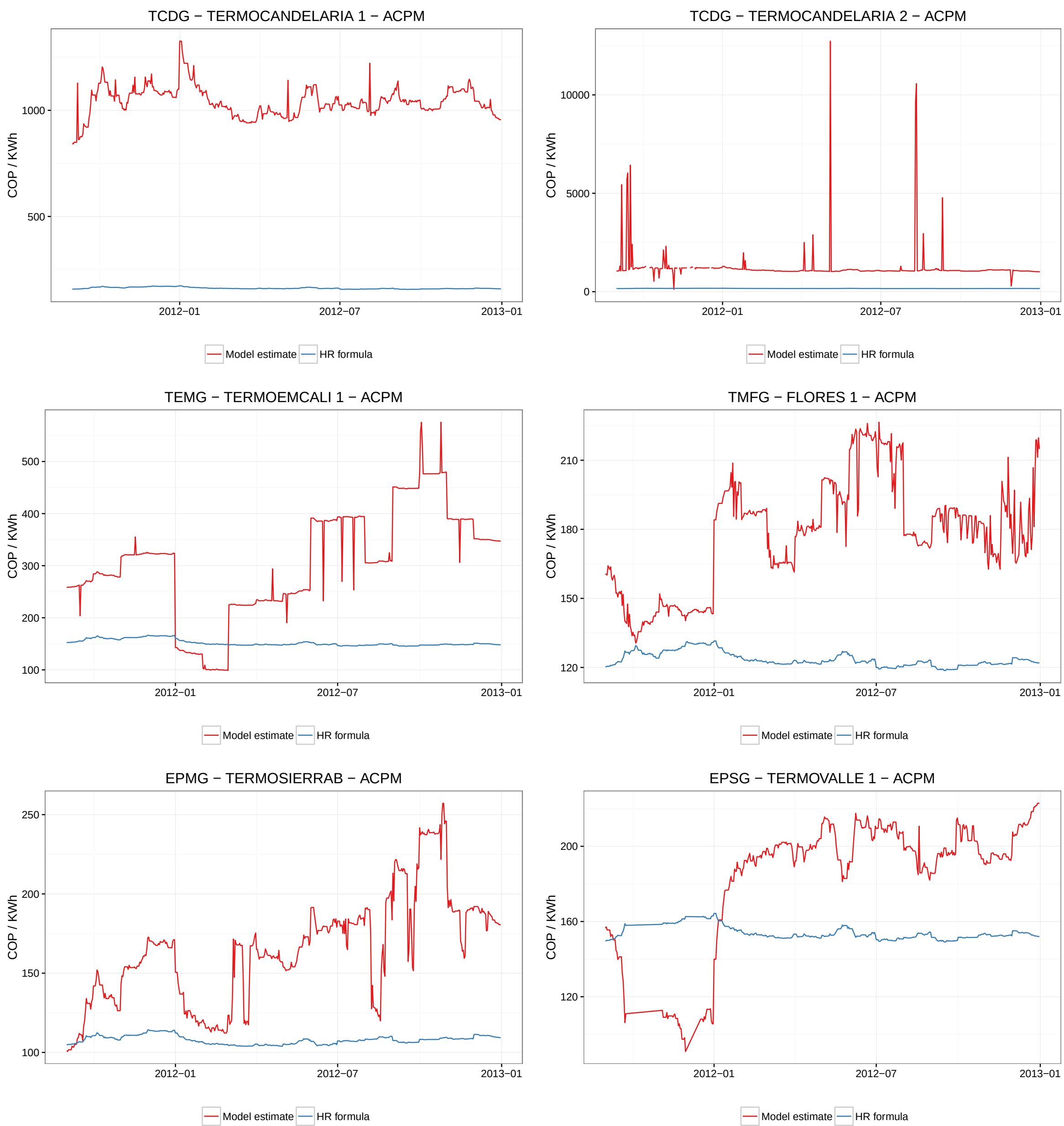


Figure 10: Estimated vs. engeneering marginal costs of coal units, 1 of 2

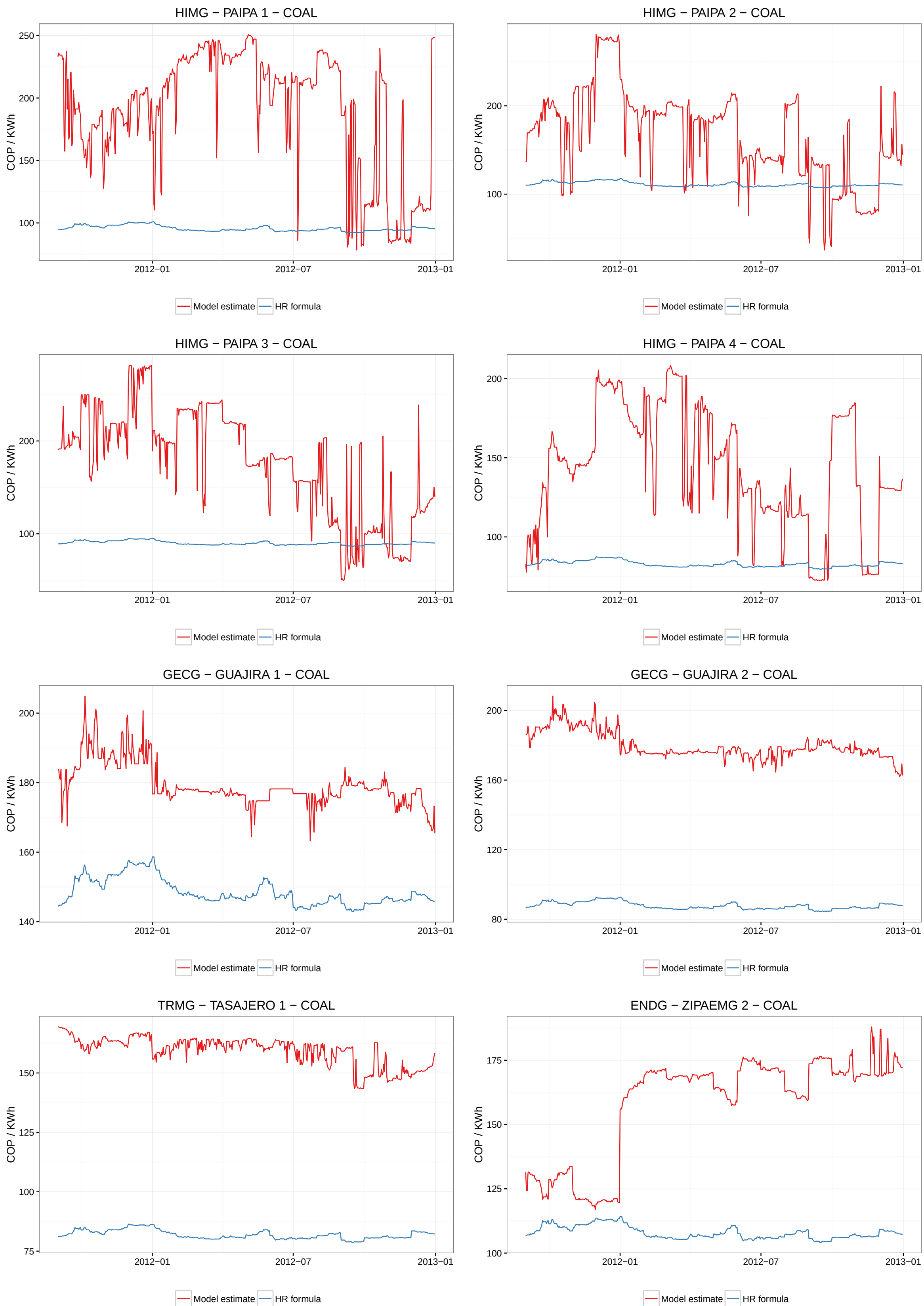


Figure 11: Estimated vs. engeneering marginal costs of coal units, 2 of 2

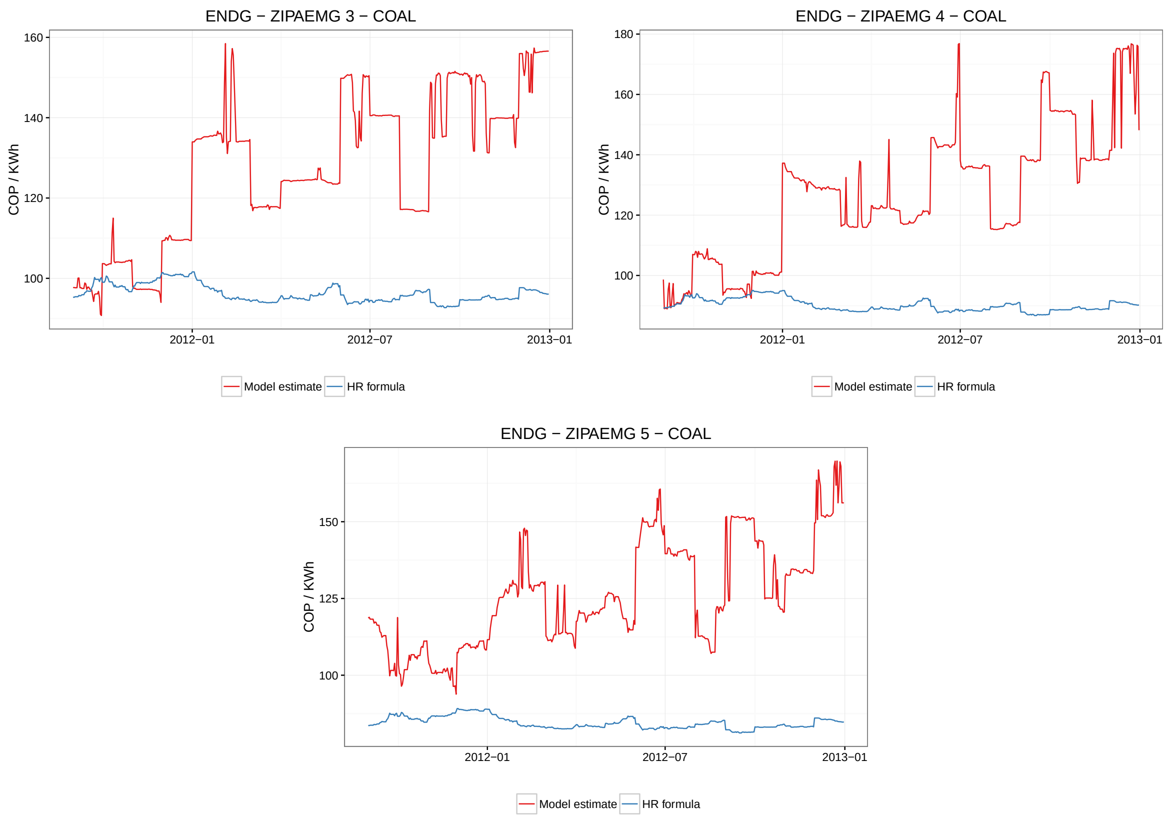


Figure 12: Estimated vs. engeneering marginal costs of fuel oil units

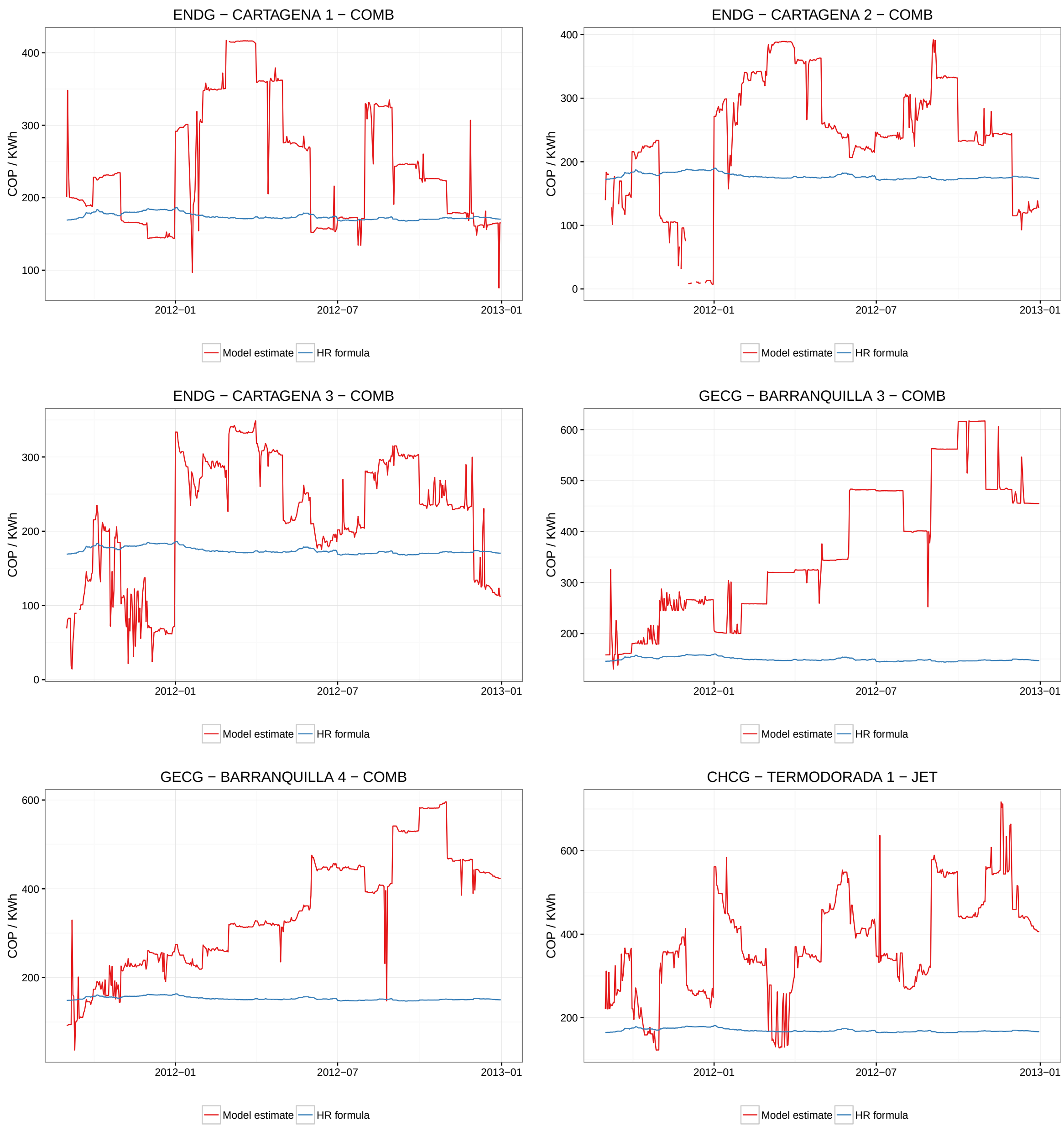
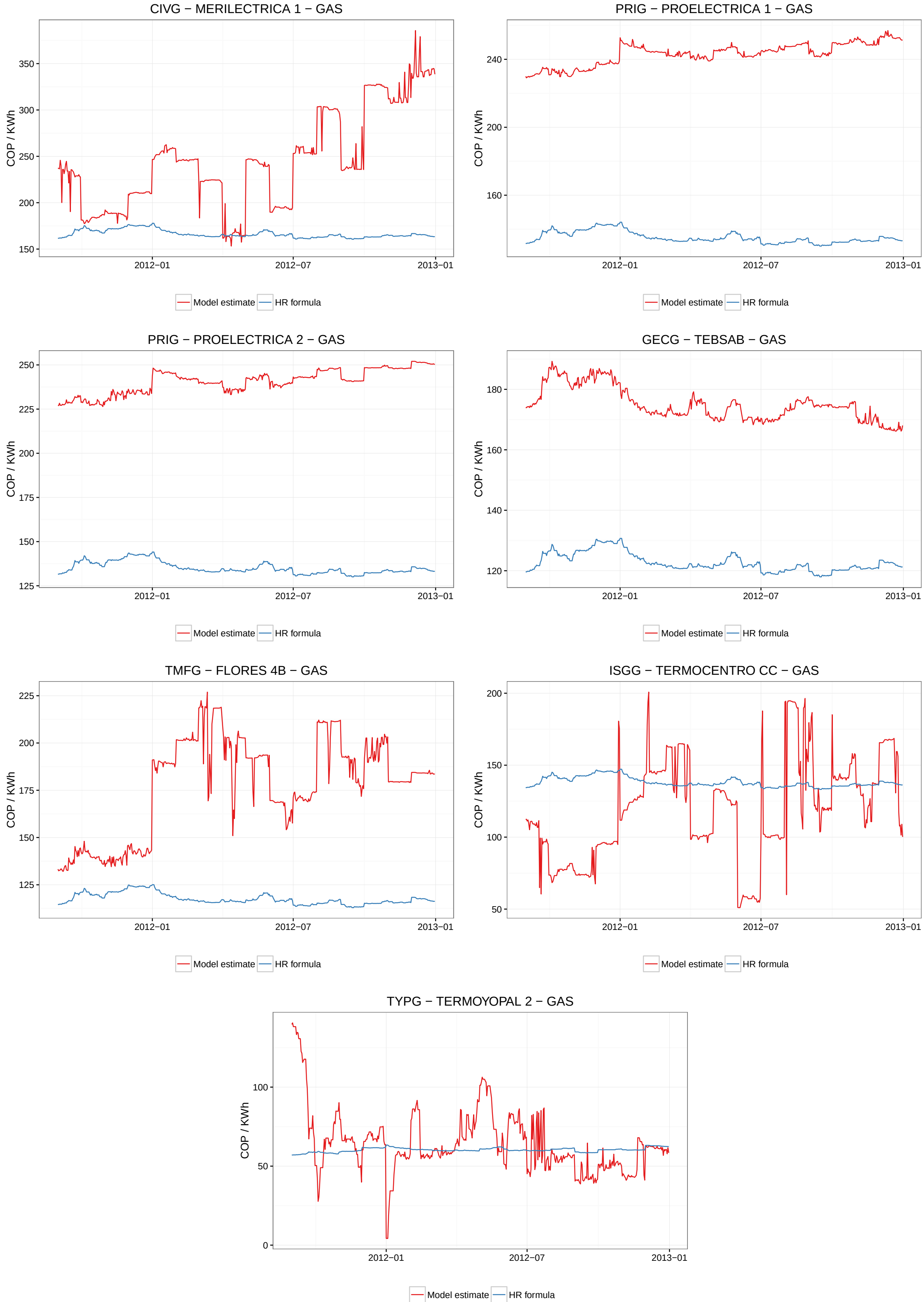


Figure 13: Estimated vs. engeneering marginal costs of natural gas units



At the same time, below figures .... compare the series of the daily average estimated marginal costs with the corresponding daily series of the observed price bid made by each unit. Notice that for several days, the estimated markups are negative. Such events occur on days when the firm's supply function at the respective unit's bid price is lower than its aggregate energy sold in the bilateral contract market, $S_i(p_{ij}) < v_i$. This is consistent with literature regarding the bilateral contracts in electricity markets (Hortacsu & Puller, 2008; Wolak, 2003).

Figure 14: Price bids and marginal costs of diesel units

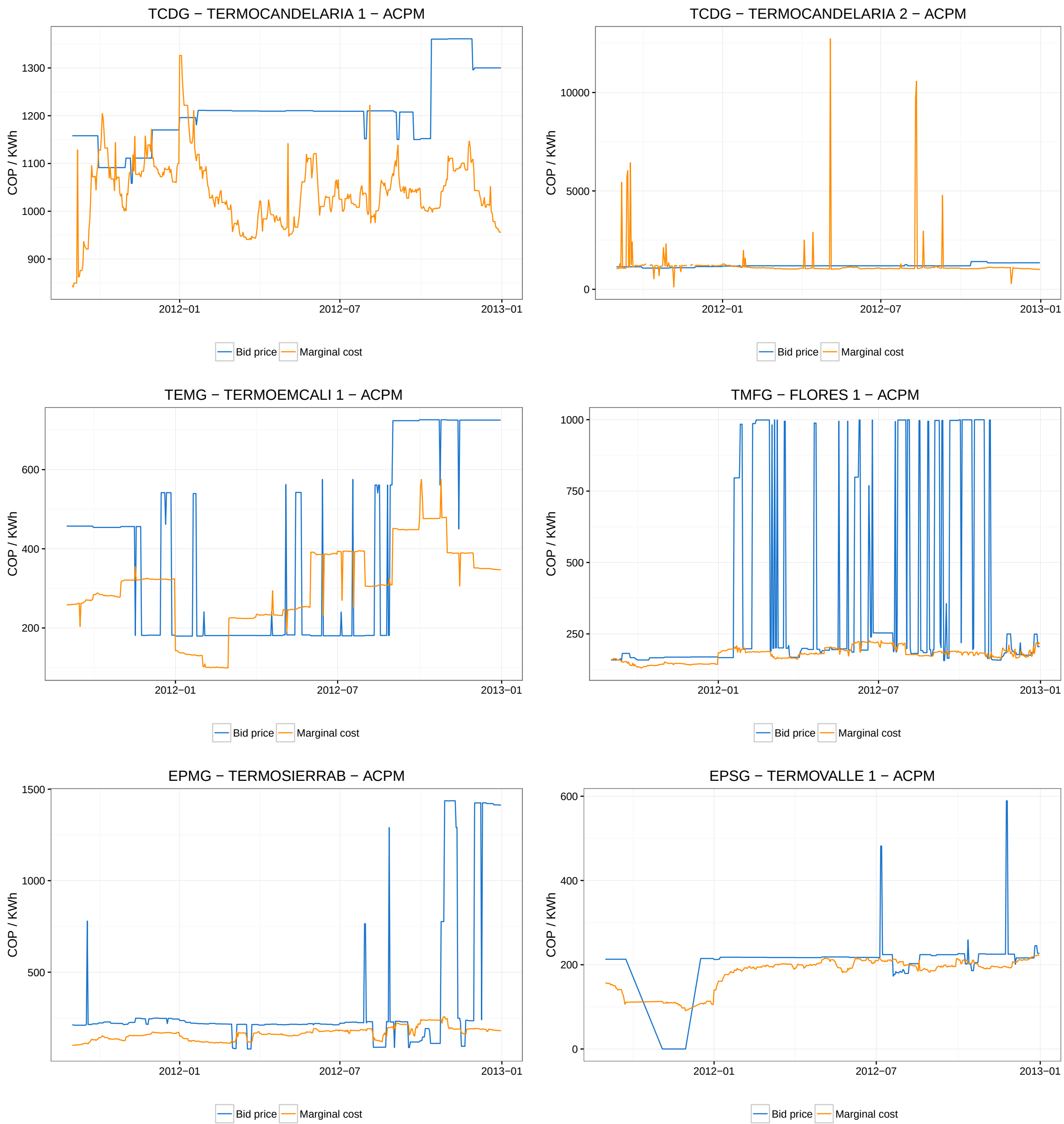


Figure 15: Price bids and marginal costs of coal units, 1 of 2

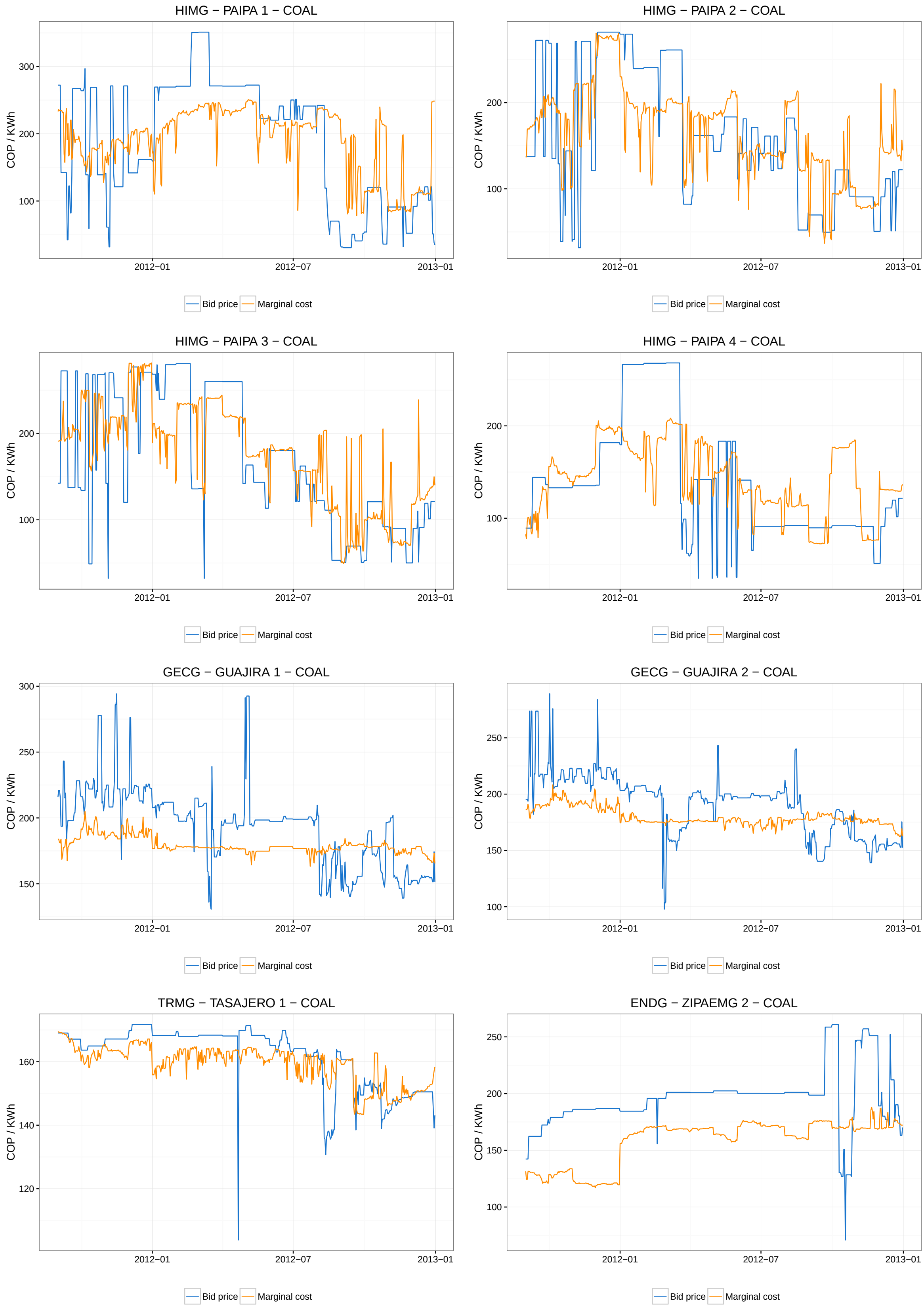
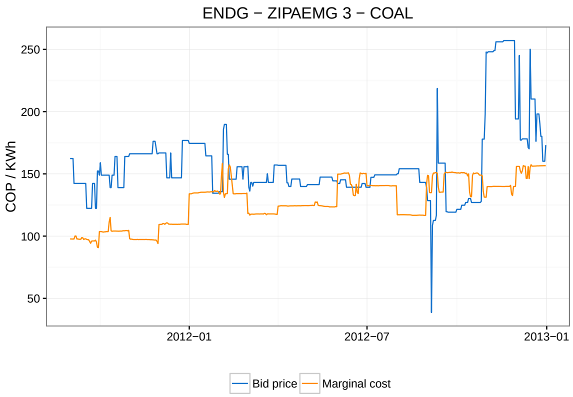
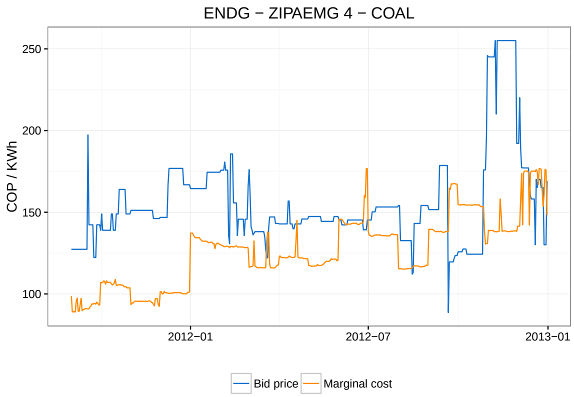


Figure 16: Price bids and marginal costs of coal units, 2 of 2





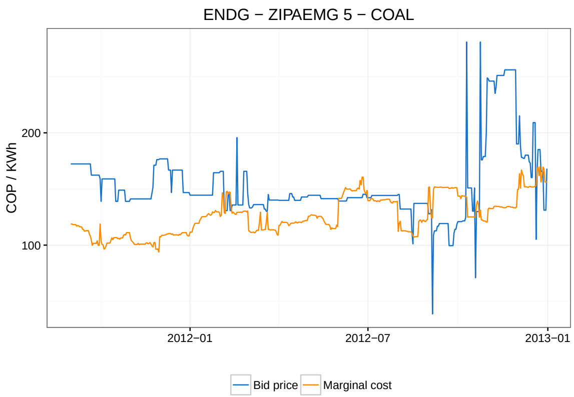


Figure 17: Price bids and marginal costs of fuel oil units

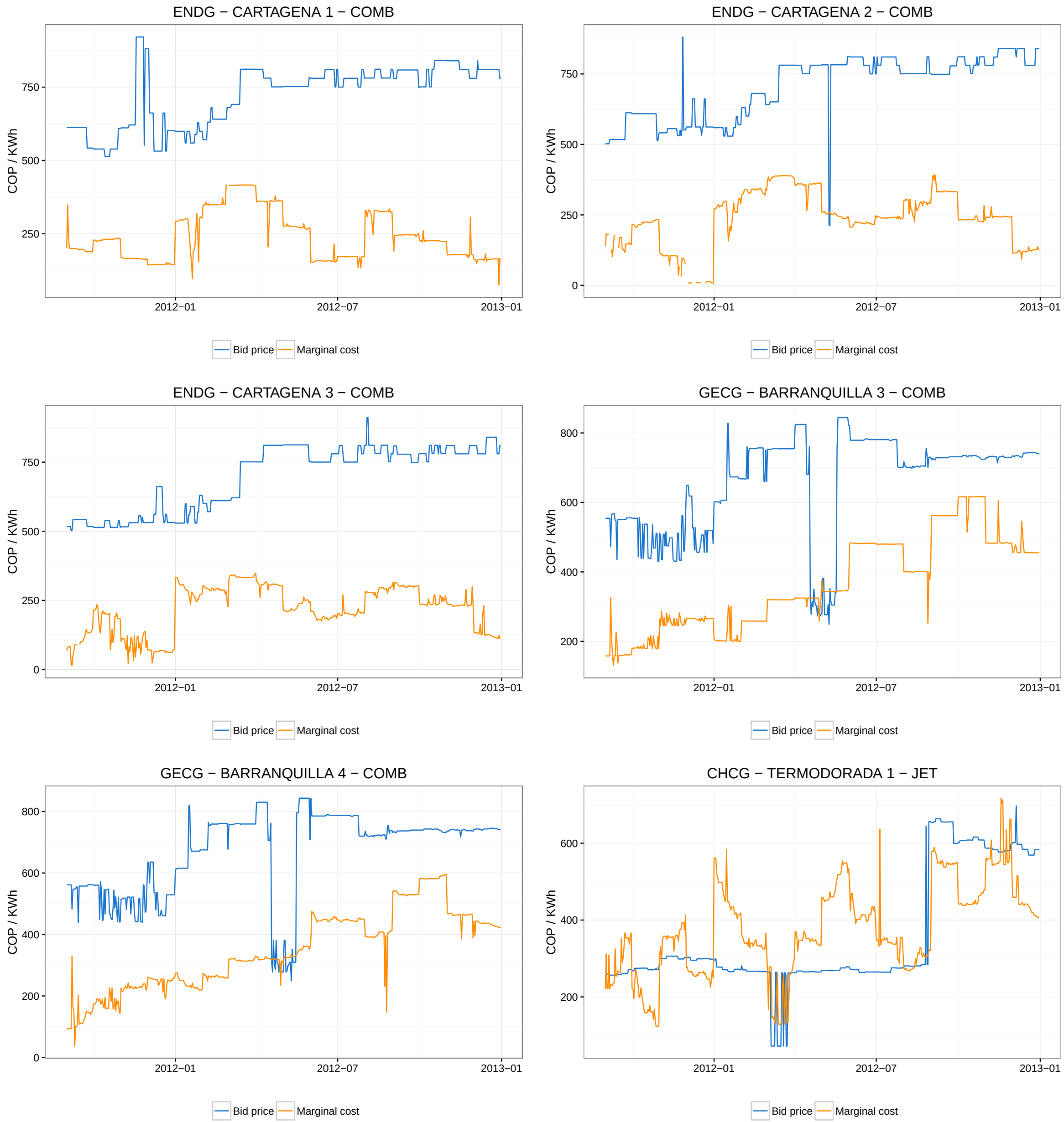
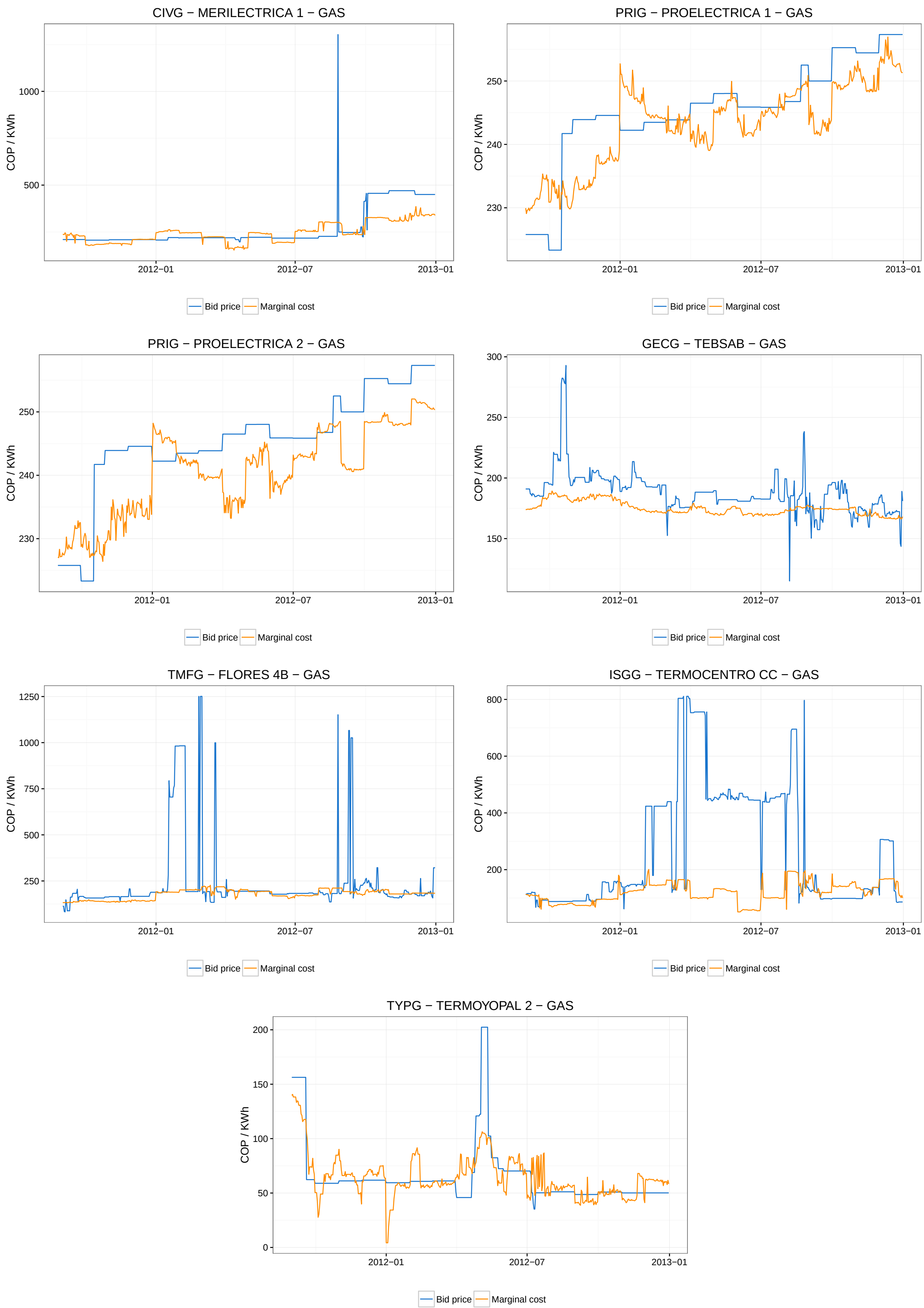


Figure 18: Price bids and marginal costs of natural gas units

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