Market Power in Electricity Storage: Evidence from the Iberian Market

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Abstract

I study empirically the bidding behavior of Pumped Hydro Storage (PHS) in the Iberian Electricity Market. I solve a simplified Cournot model for an arbitrary number of players, and apply an instrumental-variable strategy to identify potential exercise of market power from PHS in the Iberian market. I find that following the predictions of the theoretical model, a steeper residual demand curve causes PHS operators to withhold capacity on the purchasing side of the market. This behavior leads to increased wholesale prices, lower integration of renewable output and supports the case for TSO-operated PHS capacities. However, although I detect evidence of capacity withholding on the sell-side too, my results suggest that Cournot competition might not be the most appropriate model to describe the strategy of the PHS on the sell side. I report the results from a different empirical strategy which suggests that PHS might exploit their market power in a supply-function equilibrium setting when they enter the market as sellers.

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Introduction

The increasing penetration of variable renewable energy (VRE) in energy systems around the world contributes to the required reduction in carbon emissions, but brings about important challenges for power systems. One of them is balance: as electricity is difficult to store at scale, and because the power system operates continuously at the same frequence, there needs to be a constant equivalence between supply and demand on the market. VRE generation, although clean, is not dispatchable, meaning meteorological conditions greatly influence their output. Moreover, wind and solar can increase their output very quickly, which threatens the balance of the system if the transmission lines get congested, or if demand does not match the increased generation.

One of the solutions to this problem is electricity storage. It comes in different forms: grid-scale batteries are a recent technology, yet to be deployed in most electricity markets. Pumped-Hydro Storage (PHS) however, is common in some markets. PHS rely on the ability to store water in reservoirs, that can come from partly from other bodies of water (lakes, rivers) for open-loop PHS (OLPHS) or are exclusively pumped directly from another reservoir downhill for closed-loop PHS (CLPHS). The electricity is pumped at times of low demand, when prices are low, and is released at times of high demand, when prices increase. This allows to partially smooth prices across times of high and low demand, which reduces generation costs.

However, electricity storage is not the only solution to balance the system: similar benefits could be achieved from increasing the number of transmission lines, reinforcing and upgrading them, or building new interconnections with neighboring countries. These infrastructure projects are costly, and the decision to build them is always the result of a cost-benefit analysis. When performing these calculations, all factors must be taken into account, among which the potential inefficiencies induced by market structures. Several engineering studies have shown that storage providers could profitably exercise market power, and recent work in economic theory underlines the fact that under specific market structures, large inefficiencies could arise and potentially diminish the case for investing in storage. This is the topic explored in this paper. Slightly expanding on the basis of a model developed by Natalia Fabra and David Andrés-Cerezo, I build an empirical strategy to identify the exercise of market power in the Iberian market. Under a simplified model structure that assumes an arbitrary number of symmetric generation firms and PHS operators, I examine how the market structure affects the optimal strategies of the PHS.

I find that the degree of market power in the market for generation positively influences how much withholding of storage is done by the storage operator. In the model chosen, the degree of market power manifests through the steepness of the residual demand curve faced by the storage operators. When the dominant producer withholds output, the gap in demand is satisfied along the fringe's supply curve, which raises prices in the product market. This steepness in the residual demand curve manifests in the optimal decision of the storage operator, who strategically withholds charging (discharging) to avoid increasing (decreasing) prices too much when it purchases (sells) on the market. As in a traditional Cournot problem, the analytical solution of the quantity that maximizes profits is a function of the steepness of the residual demand curve. However, since those strategies are the outcomes of strategic games, we need to instrument this incentive to exercise market power (IEMP) to properly identify the reactivity of the strategic players to the variations in the competitive environment.

The rest of the paper proceeds as follows. Section 1 describes the literature. Section 2 describes the Iberian power market, its rules and the generation and storage fleet it uses. Section 3 outlines the model and states the main results regarding the optimal bidding strategies of the different market participants. Section 4 describes the data and its main features. Section 5 summarizes the empirical strategy I use to identify the effect of market structure on the exercise of market power. Section 6 describes the practical implementation of the empirical strategy, the challenges and the methods used. Section 7 describes and discusses results. Section 8 reports an exercise aiming at explaining regularities in the data uncovered in Section 7. Section 9 concludes.

1 Literature review

"Production technologies in the electricity industry are straightforward and well understood." In the first few lines of her paper, Wolfram (1999) outlines one of the main advantages of the electricity industry when it came to performing empirical analysis of profit-maximization behavior: most of the generation fleet was gas-based, its marginal costs were easy to model, and a wealth of paper developed at the time aimed at analyzing whether the price bids were significantly departing from marginal costs, evidencing the exercise of market power. First proposed by Wolak (2003), the residual demand framework allows to understand profit-maximization decisions in a context where the expectation of a firm about the supply of its competitors gives her information about her opportunity to exercise market power. The realized inelastic demand, from which the competitors willingness-to-supply bids are subtracted at every price, offers a downward sloping residual demand curve. The inverse semi-elasticity of this residual demand curve represents a strategic incentive to exercise market power, since the potential profit that can be made from withholding a MWh of generation is an increasing function of this inverse semi-elasticity. This method is applied by Mcrae & Wolak (2009) to analyze competition in the New Zealand Electricity market. They find significant correlation between market-clearing prices and the half-hourly incentive to exercise market power for the main suppliers, as well as a reduced-form positive effect of the inverse semi-elasticity of residual demand on optimal bidding prices. However, this analysis is restricted to gas-fired generators since, "estimating [hydro resources'] no-market-power opportunity cost of supplying energy is a massively complex computation problem related to the actual opportunity cost of stored water"(Mcrae & Wolak, 2009). Woerman (2018) exploits another exogenous variation in competitive environment through studying the Texan market. When transmission lines get congested, the market splits in two submarkets. He finds that in a residual demand context, this exogenous event leads to large increases in markups. He estimates range of values for the implied deadweight loss and the additional transfers induced by those markups, which raises the question of welfare and surplus sharing in electricity markets.

This problem is also outlined by Suarez (2023)who reproduces this analysis in the Colombian energy market, attempting to show that publicly and privately held firms react differently to the IEMP. His estimation yields similar results whether he includes hydro units or not, hinting at the fact that the opportunity cost of water might be approximated by the opportunity cost of gas. Peña (2024) takes this hypothesis into consideration when brushing a global picture of the behavior of hydropower as a marginal price setter in the Iberian market. However, he finds that prices set by hydropower are up to ~10% higher than they should be, based on gas-fired generation costs. This reinforces the idea that modelling the cost curves of hydro generators is a problem that is not so well understood, which bars us from analyzing the behavior of PHS in a supply-function equilibrium fashion (Klemperer & Meyer, 1989). Puu & Norin (2003) analyze Cournot competition in a duopoly under capacity constraint, but still rely on explicit cost functions.

Ito & Reguant (2016) document the patterns of arbitrage across day-ahead and intraday markets for dominant and fringe firms in the Iberian market. They derive theoretical results that point to the fact that dominant firms withhold energy in the day-ahead market and follow a method that incorporates a regression of the price-premium in the day-ahead market on the slope of residual demand to identify the exercise of arbitrage between the day-ahead and the intraday markets across technologies. My method differs in three important dimensions: first, I focus on studying the quantities bid rather than on the price premium. Second, I single out pumped hydro storage for which profit maximization does not depend only on the slope of the residual demand, but also on the time of the day and gaps between demand and average demand during the day, whereas their estimates group the entire hydro sector together. I leverage a model to estimate an equation that incorporates more parameters. Finally, my IV strategy relies on shocks to both demand and supply that are directly interpretable in the context of my model.

Most of the studies that have attempted to model the optimal operation rules of the PHS belong to the engineering literature. Lamp & Samano (2022) document the patterns of behavior of battery storage in the Californian market. Problems of cost-benefit analyses are also raised by Newbery (2018), who reminds that interconnectors and conventional peakers might be more cost-efficient than energy storage (including PHS), which reinforces the need for competitive assessment. The value of storage is also studied in a context that compares them to peaking generators: McConnell *et al.* (2015) finds that storage has an edge over peaking generators because it can earn revenue from various other markets, such as ancillary services or capacity mechanisms. Most closely related to the model I use in this paper, Schill & Kemfert (2011) apply a game-theoretic Cournot model to analyze the German market. They find that electricity storage can have adverse welfare effects if its owners exercise market power, in particular by under-utilizing their storage capacities. They perform simulations in the German market under different capacity expansion scenarios. The same conclusions are reached by Williams & Green (2022) who perform Cournot simulations in a model of the British Electricity market, under a different generation portfolio. Andrés-Cerezo & Fabra (2023), from which I draw the theoretical inspiration for this paper, arrive to the same conclusion with their model of PHS operation. Schill and Kemfert find that an integrated storage monopolist, that also engages in generation, yields the worst welfare consequences for consumers, a conclusion shared by Fabra and Andrés-Cerezo. However, their results suggest that when the storage capacity is distributed across strategic storage operators, under-utilization is unlikely and might therefore not be a welfare concern. Briefly mentioned by Fabra and Andrés-Cerezo, Ambec & Crampes (2019) and Schmalensee (2019) propose models of PHS operation that closely resemble the one I use, but which assume perfect competition in storage. Schmalensee equally makes the assumption that the PHS operates over a daily cycle. On the empirical side, Karaduman (2021) models the intervention of storage operators as a shock to net demand and computes a new equilibrium in which generators and storage operators iteratively adjust their best responses. He subsequently performs counterfactuals and concludes similarly that a monopolist yields the worst possible outcome. He also finds that competitive storage has better outcomes than monopolistic storage, but do not reach the efficiency of consumer-operated batteries. My modelling assumptions slightly differ: I model profit-maximizing PHS who are owned by a generation firm but do not internalize their complementarity with the generation firms' portfolio[1]. Bjørndal *et al.* (2023) extends the complexity of this calculation by incorporating different market designs: zonal, nodal and uniform pricing systems.

This paper contributes to this literature by bringing empirical evidence of the exercise of market power in the PHS segment in the Iberian day-ahead market. To my knowledge, my paper is the first paper to focus on analyzing the behavior of PHS in a retrospective manner. Most of the literature has focused on estimating the impact of storage under various ownership structure under different scenarios, without analyzing which behavior we currently observe in power markets. Furthermore, I bring evidence of an asymmetry in behavior across the buy side and the sell side, and I evidence the sensitivity of PHS to the price IEMP in a McRae and Wolak fashion.

2 The Spanish power market

The Spanish power market is a liberalized power market in which generating firms and purchasing firms submit bids to sell or buy electricity. A bid is characterized by a quantity and a price, and they form blocks. On the sell side, all the generation bids are ordered in ascending price order, forming a "merit-order" curve. On the sell side, bids are sorted in descending price order, which yields a downward sloping demand curve. This process takes place once for every hour of the day, 12 hours before the day begins. The equilibrium price and quantities are determined at the intersection of the supply and demand curves. On the supply side, demand comes mostly from suppliers, that is, large buyers who in turn serve residential or industrial customers. On the supply-side, generating firms are firms who operate a portfolio of generation assets. The Spanish market is highly concentrated: in 2021, the three largest firms served 64% of total demand. The Spanish market is composed of several large firms, and a multitude of little firms, which motivates our approach (a competitive fringe and several oligopolists).

[1] I derived the optimal PHS behavior under a third market structure (vertical integration with a generation oligopolist), in complement of the two I present in my paper. Given that my empirical results invalidated this third market structure, I chose to not report it, and instead perform the exercise reported in Section 8.

Name	Owner	Capacity (MW)	Storage (MWh)	Cycle
IP	ACCIONA	84	4,900	SEASONAL
SALLENTE	ENDESA	446	900	DAILY
MORALETS	ENDESA	221.4	27,000	WEEKLY
GUILLENA	ENDESA	210	1,300	DAILY
TAJO ENCANTADA	ENDESA	360	1,000	DAILY
LA MUELA	IBERDROLA	1,506.2	24,500	WEEKLY
BOLARQUE	NATURGY	215	1,400	DAILY
AGUAYO	REPSOL	360.6	3,700	WEEKLY

Sources: OMIE, Geth *et al.* (2015), Red Eléctrica de Espana (2009)

Table 1: PHS units in the Spanish market

As regards the portfolio of generation assets, Spain has a large share of renewable energy: wind represents 26% of its installed capacity, solar 20% and hydro 14.5%. Wind and solar capacities are not controllable, hydro is dispatchable and very flexible but in the limit of its stock of water, which can be scarce in Spain. Spain still has some nuclear plants (6% of installed capacity), which are dispatchable but not very flexible. Spain has natural gas plants which account for 25% of its installed capacity, which are highly flexible and efficient. Finally, PHS account for roughly 3% of the total generation capacity, with 8 "pure" PHS plants and 6 pump-back units**?**. I present the pure PHS plants in Table 1, which are those on which this master thesis focuses.

I then discuss the model.

3 The model

3.1 The setup

I start from a model similar to the one of Andrés-Cerezo & Fabra (2023), which accurately describes the Spanish power market. I extend their model to account for several PHS operators with symmetric storing and unloading capacities.

Demand The demand $\theta \in (\underline{\theta}, \bar{\theta})$ is assumed perfectly inelastic in the day-ahead market, and symmetrically distributed according to the load duration curve $G(\theta)$, around its expectation $\mathbb{E}[\theta]$. A load duration curve describes the number of hours in a day where demand is below a certain point, therefore behaves similarly to the CDF of a function. The load duration curve describes the demand in a day and allows the agents to form expectations regarding the levels of the demand throughout the day.

In reality, the demand in the Spanish market is elastic: as described in the previous sections, market participants submit bids both to sell and purchase in the auction. However, assuming a perfectly inelastic demand is particularly appealing for two reasons: first, it allows to easily characterize periods of high and low demand, which resonates empirically with the sinusoidal demand cycles that we observe in the Spanish market. Secondly, the agents rely on day-ahead forecasts of total demand for electricity, and not every firm is able to forecast the elasticity of demand in the same way. Lastly, the demand θ is electricity demand net of non-dispatchable demand, that is, net of solar and wind production. In addition to the necessary cycles in demand throughout the day, this motivates the assumption that demand is symmetrical around its expectation, up to small deviations. It is reasonable to assume that all market players form conditional expectations regarding the type of day they are going to operate in. Therefore, I omit the condition in the expectation operator, but it should be understood that agents adjust their expectations reasonably to the seasons.

The players The market is composed of three types of agents. The first agent is a dominant firm who operates a large dispatchable fleet with increasing marginal costs. The "dominant sector" operates a portion $\alpha \in (0, 1)$ of the market. At each period of the game, the dominant players offer each a quantity q_D, determined strategically.

The second group is a fringe of competitive producers, who operate a portion $(1 - \alpha)$ of the gas-fired generators. They are understood as a continuum of firms, and are not able to operate strategically. As such, they take prices as given, and offer their output at marginal cost. At each stage, we subtract their supply curve from the inelastic demand, which gives us a downward sloping residual demand curve.

The last group of players is a set of m PHS, indexed by j, who each operate a PHS plant. The PHS are symmetric, which means that they all have the same storage tank capacity, and the same hourly constraint. In each period, the storage operator chooses quantities $q_{B,j}(\theta)$ to purchase from the market, and quantities $q_{S,j}(\theta)$ to sell in the market. The PHS can charge up to a capacity K_j, and is limited by its pumping capacity, therefore can only charge quantities up to k_j in each period.

The timing of the game Because the fringe is competitive, it offers its output at marginal cost and is not strategic in the production. Regardless of who among the dominant firm or the PHS operator moves first (or if they move together), the fringe always offers all the necessary output to satisfy the market clearing condition stated below. The set of dominant firms sets the price, anticipating the strategies of the set of PHS. The PHS formulates strategies, taking into account the strategy of the dominant firm. The participants compete therefore in a traditional multi-firm Cournot setting, without capacity constraints for the producers. This is motivated by the market clearing condition stated below: in electricity systems, the supply and the demand coincide at each period. Although prices in the Iberian electricity market are constrained to remain below EUR 3,000/MWh, we assume prices that prices can raise up to the value of lost load (the value at which the demand prefers to disconnect). In reality, the ceiling on prices keep this from happening, which requires putting in place a capacity mechanism, a mechanism whereby generators are paid to remain idle, and are called to generate only if a scarcity event puts the system in jeopardy. This is important because PHS is the ideal candidate for a capacity mechanism: this might explain their idleness in a large portion of hours, as I explain it below.

The cost The cost function of the competitive industry is non-linear and convex. The assumed cost function is quadratic, with linear marginal costs. This is both reasonable regarding the modern gas-fired technology and buys the model a lot of tractability.

$$c'(q) = q$$
$$c(q) = \frac{q^2}{2}$$

Therefore, we can model the marginal costs of the dominant sector and of the fringe in this way:

$$c'_D(q) = \frac{q}{\alpha}$$
$$c'_F(q) = \frac{q}{(1-\alpha)}$$

Although the Spanish market has three-four dominant firms, I normalize the number of oligopolists to 1 in the theoretical model, because it never varies in the data.

As explained in the first section, because of the characteristics of electricity, the market must clears in every period, that is the following equation always hold with equality:

$$\theta = q_D(\theta) + q_F(\theta) + q_S(\theta) - q_B(\theta) \tag{1}$$

3.2 The market structures

I will restrict my attention to two market structures. First, I will characterize the second-best[2], i.e. the optimal storage and generation from the dominant producer when the storage operator operates competitively, or in a way that aims to fully flatten the prices across demand levels (which would be comparable to an outcome in which the TSO could operate the PHS). Then, I will analyze the optimal storage and the optimal generation of the dominant producer in a market where the storage facilities are operated by a separate storage oligopolist that maximizes profits and internalizes the effects of its own position on market prices.

[2]The first-best structure is one where the welfare planner has control over the dominant producer as well as over the PHS. This is never a case that arises in reality in Spain.

3.2.1 The first-best

Under the second-best, the PHS operator acts competitively and solves the following problem:

$$\max_{q_{S,j}(\theta),q_{B,j}(\theta)} \int_{\Theta} p(\theta)\left(q_{S,j}(\theta) - q_{B,j}(\theta)\right) g(\theta) d\theta$$

w.r.t.

$$\begin{aligned}
\int_{\Theta} q_{S,j}(\theta) g(\theta) d\theta \leq \int_{\Theta} q_{B,j}(\theta) g(\theta) d\theta \\
K_j \geq \int_{\Theta} q_{B,j}(\theta) g(\theta) d\theta \\
k_j \geq q_{S,j}(\theta), q_{B,j}(\theta)
\end{aligned}$$

To solve this problem, we need to characterize first the pricing rule of the strategic firms.

Lemma 1. *The competitive fringe offers a quantity $q_F = (1-\alpha)p(\theta)$, which yields the following inverse residual demand curve*

$$p(\theta, q_B(\theta), q_S(\theta), q_D(\theta)) = \frac{\theta + q_B(\theta) - q_S(\theta) - q_D(\theta)}{(1-\theta)}$$

and the following optimal quantity for the dominant sector

$$q_D = \frac{\alpha}{1+\alpha}\left(\theta - q_S(\theta) + q_B(\theta)\right)$$

The proof is provided in the appendix.

Intuitively, we see that the quantity served by the individual strategic firm is increasing in the percentage of capacity it operates, but we still see some capacity withholding. In an extreme case where the monopolist operates $\alpha = 1-\epsilon$ of the capacity, the quantity it produces will be just below half of the necessary generation, leaving the fringe meet the remainder of the demand.

We can now solve the problem of the PHS. As explicit in the formulation of the problem, the PHS faces an exogenous price $p(\theta)$. The first constraint states that the quantities discharged across hours and demand levels should be the same as the quantities charged. It follows immediately that this constraint should be binding: otherwise, it would be possible to increase by an amount $\epsilon > 0$ the quantity discharged and make more profit. The second constraint states that the quantity charged should be less or equal to the reservoir capacity. Finally, the third constraint states that the quantity charged or dischard in an hour should be less than the pumping and generating capacity of the PHS (k_j).

Lemma 2. *The optimal loading and unloading quantities are given by*

$$\begin{cases} q_B(\theta) = \min\left\{\max\left\{\frac{\theta_1-\theta}{m},0\right\},k_j\right\} & \textit{if}\, \theta<\theta_1 \\ q_S(\theta) = \min\left\{\max\left\{\frac{\theta-\theta_2}{m},0\right\},k_j\right\} & \textit{if}\, \theta>\theta_2 \end{cases}$$

where

$$\theta_j^1 = \mathbb{E}\left[\theta\right] - \mu_j \frac{(1-\alpha^2)}{2}$$
$$\theta_j^2 = \mathbb{E}\left[\theta\right] + \mu_j \frac{(1-\alpha^2)}{2}$$

The proof is provided in the appendix.

First, we notice that the quantity charged by the operator is limited by its capacity k_j. Second, the optimal charging quantity is decreasing in m, the number of pumps in the market. Third, there is a region of idleness where the PHS does not charge or discharge anything, that is the time of the day when demand is comprised between θ_j^1 and θ_j^2. As outlined in the proof of the Lemma 1, this region of idleness arises from the fact that the PHS schedules its operations so that in expectation, he will fill up his tank across the low-demand periods of the day and empty it across the higher demand levels of the day, but she can only do so in the limit of her reservoir capacity K_j. The width of this idleness area corresponds to the levels of demand between θ_j^1 and θ_j^2. Intuitively, μ_j corresponds to the strength with which the capacity constraint binds: it will be larger for smaller operators, because they want to charge larger quantities to smooth the price as much as they can, but they cannot do it.

The values θ_j^1 and θ_j^2 are uniquely defined by

$$\int_{\underline{\theta}}^{\theta_j^1} \min\left\{\frac{\theta_j^1-\theta}{m},k_j\right\} g(\theta)d\theta = \int_{\theta_j^2}^{\bar{\theta}} \min\left\{\frac{\theta-\theta_j^2}{m},k_j\right\} g(\theta)d\theta = K_j$$

In this formulation, the values of the Lagrange multipliers are equal for all PHS. The calculation of the thresholds value depend ultimately on the total storage capacity present in the market.

3.2.2 The strategic PHS operator

Now, the PHS operator internalizes the effect of its decisions on market prices and acts strategically. The main difference between this situation and the one in the previous subpart is that the price (i.e. the inverse residual demand $p(\theta; q_S(\theta), q_B(\theta), q_D(\theta)))$ is no longer taken as given by the PHS. It is now solving a similar problem, using the new expression for the inverse residual demand.

$$\max_{q_S(\theta),q_B(\theta)} \int_{\Theta} p(\theta; q_S(\theta), q_B(\theta), q_D(\theta)) \left(q_{S,j}(\theta) - q_{B,j}(\theta)\right) g(\theta) d\theta$$

w.r.t.

$$\begin{aligned}\int_{\Theta} q_{S,j}(\theta) g(\theta) d\theta \leq & \int_{\Theta} q_{B,j}(\theta) g(\theta) d\theta \\ K_j \geq & \int_{\Theta} q_{B,j}(\theta) g(\theta) d\theta \\ k_j \geq & q_{S,j}(\theta), q_{B,j}(\theta)\end{aligned}$$

The functional that is maximized by the PHS operator can then be re-expressed in this way:

$$\max_{q_S(\theta),q_B(\theta)} \int_{\Theta} \frac{\theta - q_S(\theta) + q_B(\theta) - q_D(\theta)}{(1-\alpha)} \left(q_{S,j}(\theta) - q_{B,j}(\theta)\right) g(\theta) d\theta$$

subject to the constraints previously outlined.

Lemma 3. *The optimal loading and unloading quantities are given by*

$$\begin{cases} q_B^O(\theta) = \min\left\{\max\left\{\frac{\theta_1 - \theta}{m+1+\alpha}, 0\right\}, k_j\right\} & \textit{if}\, \theta < \theta_1 \\ q_S^O(\theta) = \min\left\{\max\left\{\frac{\theta - \theta_2}{m+1+\alpha}, 0\right\}, k_j\right\} & \textit{if}\, \theta > \theta_2 \end{cases} \tag{2}$$

where

$$\begin{aligned}\theta_j^1 &= \mathbb{E}\left[\theta\right] - \mu_j \frac{(1-\alpha^2)}{2} \\ \theta_j^2 &= \mathbb{E}\left[\theta\right] + \mu_j \frac{(1-\alpha^2)}{2}\end{aligned}$$

The proof is provided in the appendix.

Here, we see that the storage oligopolist departs from the competitive benchmark and reduces the quantities it is storing and unloading for each demand level. This reduction in quantities purchased is akin to a standard monopolist problem: the strategic operators internalize the interaction between their strategy and the steepness of the residual demand they face. This leads to storage smoothing: the oligopolist does not charge too much per hour for low demand levels, so as to avoid a sharp increase of the price at which it buys, and does not unload too much per hour at high demand levels, so as to avoid a sharp decrease of the price at which it buys.

Interestingly in this case, it is not obvious whether the quantities are lower than under the competitive benchmark. Because of the following implicit definition:

$$\int_{\underline{\theta}}^{\theta_1^1} \min\left\{\frac{\theta_1^1-\theta}{m+1+\alpha}, k_j\right\} g(\theta)d\theta = \int_{\theta_1^2}^{\bar{\theta}} \min\left\{\frac{\theta-\theta_1^2}{m+1+\alpha}, k_j\right\} g(\theta)d\theta = K_j$$

We have here two countervailing forces: the quantity that is integrated over demand levels is lower than in the competitive case, but the storage monopolist will store across more demand levels than it was in the competitive benchmark. The direction of the change depends on the shape of the distribution. This is likely to represent a decrease in efficiency: a MWh stored in high demand levels is more costly than a MWh stored under low demand levels, which increases the overall cost of generation. This theoretical insight is absent in models that model marginal cost as constant up to a certain capacity and it is closer to reality.

Additionally and more interestingly for my empirical strategy, we see that the quantity stored is sensitive to α, the degree of market power in the generation segment. The reason behind this fact lies with the strategic component: a larger degree of market power means a steeper residual demand curve, resulting from the combined supply of the fringe and the dominant firm. It means that when the PHS makes its strategic decisions, it faces a steeper price schedule, which increases its incentive to exercise market power: a small reduction in output yields large price increases, leading to more profit for the PHS.

3.3 Testable implications

The conclusion of the model is therefore that when the PHS acts strategically, it will tend to underutilize its storage and generation capacities. Fabra and Andrés-Cerezo find that such behavior causes the quantity-weighted price to increase for customers, which reduces overall welfare. Therefore, my empirical strategy will aim to evaluate whether we observe such capacity withholding in the Iberian Market. A modified form of equation (2) can be empirically evaluated with a two-stage least squares regression and potentially identify a causal effect of the opportunities to exercise market power for the PHS.

4 The data

I constituted a dataset that comprises all supply and demand bids for every hour of 2023, which were matched with technology types, and their owner. All data has been obtained from OMIE (from their website or from contacting them), the Iberian market operator. Each row corresponds to a bid, with the quantity committed and the price per MWh as well as the maximum power the unit can deliver. Each row also includes a “Fixed term” and a “Variable term” which are minimum quantities that need to be recovered for a plant to remain in the market. These bids are called “complex bids” because they come with revenue conditions: if an operator does not achieve the expected revenue in the day-ahead market, it is taken out by OMIE when dispatching the energy. The richness of the dataset allows me to construct supply and demand curves for each hour, at the unit level. This dataset allows me to calculate the numerical approximation of the incentive to exercise market power.

Realized demand comes in the form of a series of blocks, similarly to supply. However, demand is assumed inelastic in the model, and the calculation of the arbitrage component in the day-ahead market relies on a forecast of total demand. I extract these figures from the website of ENTSO-E, the European association of TSO (Transmission System Operators).

As regards the instrumental variables, I extracted from the website of OMIE the data regarding hourly unavailabilities of generation units. The data on the hourly unavailabilities comes disaggregated at the physical unit level, which means that for a given gas-fired or hydro plant, only one turbine can be unavailable, which gives reduced availability, but not full unavailability. The variable "unavailability" is the total unavailable capacity, in MW, of the competitors of a given firm. Since one Excel file is published per day, that details current and future unavailabilities, we can find conflicting information between days (for example, the file from October 12 might indicate that a coal plant might be only 50% unavailable on December 3rd, whereas the file from October 13 states the coal plant will be completely available). To construct the variable, I only considered the information in the file that was edited on the day of the corresponding row.

To obtain the filling rate of the hydro reservoirs of competitors, I relied on several data sources. The weekly report from the MITECO called *Boletín hidrológico peninsular* gives me the filling rate of the relevant reservoirs in Spain. Since not all reservoirs are used for power generation purposes, nor all managed by the power companies, I matched by hand the reservoirs with bidding units, which allowed me in turn to match them with the relevant company. I relied for this on a variety of sources, including the websites of the generation firms, and a document from the MITECO. For portuguese reservoirs, I extracted monthly data from the *Boletim de Armazenamento nas Albufeiras de Portugal Continental*, the Portuguese equivalent of the hydrologic bulletin. I relied on linear interpolation between each month to calculate hourly filling rates for Portuguese reservoirs. Once I obtained the hourly filling rate for each bidding unit, I calculated an average filling rate for each competitor, weighting each filling rate by the total power of the unit it feeds. Each competitor operates reservoirs and units both in Spain and in Portugal, which gives significant daily variation in filling rates for each competitor. This gives me a hourly weighted filling rate for each competitor, that covers more than 85% of the hydro generation capacity of the Iberian market.

To calculate the IEMP, the steepness of the supply curves matter. Therefore, it is important to take out the gas- or coal-fired generators that might not meet their revenue goals in the day-ahead market. The conventional method, used by the matching algorithm that performs the market-clearing operations, consists in including all the blocks in the first matching process, then identify the plants that do not meet their revenue goals. Those plants are ordered from the least-close to meet their revenue goal to the closest, and the least close is taken out. The matching is performed again, until all plants meet their revenue goal. Out of efficiency concern, I chose to discard the bids of generators that did not meet their revenue goal in the actual day-ahead market, using day-ahead prices from ENTSO-E. This method yields approximately the same result as performing the iterative procedure, and permitted considerable time savings.

5 The empirical strategy

With the results from the theoretical model in mind, I turn to specifying the statistical model I will estimate. The main dependent variable for which I wish to identify an effect is the optimal storing and unloading quantity, which I call Q^*_{it}.

Leveraging the theoretical model, I assume that the optimal quantities can be expressed in this way:

$$Q^*_{it} = A_t^{\beta^A} \cdot \epsilon_{it} \cdot \text{IEMP}_{it}^{\beta^{MP}} \cdot \psi_{it} \tag{3}$$

where the stars indicate that the quantity is the result of profit-maximization, i indexes the unit and t indexes time. A_t is the arbitrage term in the equation, which represents the gap between the demand in period t and the average demand during the day. It provides an approximation of how much should be stored or released in a given hour and broadly corresponds to the difference $\theta^1_j - \theta$ on the buy-side ($\theta - \theta^2_j$ on the sell-side). IEMP_{it} is a composite term comprising the decrease in optimal generation implied by the presence of competing PHS, and of the incentive for the PHS to exercise market power in hour t. ϵ and ψ are errors terms that are company-specific: they can for example represent an error in the forecast of such quantities, or be correlated to prudence in the behavior of a company: a smaller company can probably move less the market than a large company, resulting in less careful bidding behavior, or less agressive market power exercise. Additionally, as mentioned above, PHS can be managed in strategic ways that do not depend entirely on the day-ahead market: some PHS participate in ancillary services markets (frequency regulation, spinning reserves, etc...) or capacity markets and might be forced to withhold more or less energy than the model would suggest, or even to remain completely idle.

The model is non-linear (multiplicative), following the insights of the theoretical model. I take the logarithm of the equation (3) and re-express it in a linear form, that corresponds to the modified version of equation (2):

$$q^*_{it} = \beta^A \cdot \underbrace{a_{jt}}_{\ln(\theta^1_j - \theta)} + \beta^{MP} \cdot \underbrace{\text{iemp}_{jt}}_{\ln(m+1+\alpha n)} + \eta_{jt}$$

where $a_{it} = \ln(A_{it}) = \ln(\theta^1_j - \theta)$ on the buy-side and $\ln(\theta - \theta^2_j)$ on the sell-side, $\text{iemp}_{it} = \ln(\text{IEMP}_{it}) = \ln(m + 1 + \alpha n)$ and $\eta_{it} = \ln(\epsilon_{it}) + \ln(\psi_{it})$.

5.1 The arbitrage term

The arbitrage term a_t is simply the logarithm of the incentive to arbitrage for the PHS. It can be simply calculated using the empirical analogs of θ, θ^1 and θ^2. Note that the incentive to arbitrage is equivalent to the quantity that a welfare-maximizing PHS monopolist (case where $m = 1$) would load (unload) if it were to act as a price taker in period of low (high) demand. PHS are also constrained by their hourly pumping/generation capacity k_j. I calculated for each PHS an empirical θ^1_j by solving the following problem, using the empirical distribution of θ taken from OMIE:

$$\min_{\theta^1} \int_{\underline{\theta}}^{\theta^1_1} \left\{ \frac{\theta^1_1 - \theta}{m} \right\} \mathrm{d}G(\theta) - K_1$$

which yielded values $\theta^1 > \mathbb{E}[\theta]$ for all PHS. This points to the fact that theoretically, all pumps are supposed to never reach their full capacity K_j even if they bid the largest quantities they could – the competitive quantities. Coming back to the mathematical formulation of the optimization problem in Lemma 4.

$$\theta^1_j = \mathbb{E}\left[\theta\right] - \mu_j \frac{(1-\alpha^2)}{2}$$
$$\theta^2_j = \mathbb{E}\left[\theta\right] + \mu_j \frac{(1-\alpha^2)}{2}$$

Recall that μ_j is the Lagrange multiplier on the storage tank constraint K_j. If the constraint slacks, then the value of μ_j is 0. This allows us to reformulate θ^1 and θ^2 in a similar way for all pumps, which greatly simplifies the calculations:

$$\theta^1 = \theta^2 = \mathbb{E}\left[\theta\right]$$

Note also that $\mathbb{E}[\theta]$ is not an expectation in the probabilistic sense: it is the average demand net of renewable generation in a day. Of course, when using the actual data, its empirical analog is the average demand in a specific subset of hours in a specific subset of days. For example, it is important that realized demand in summer is not compared with demand during spring. I obtained one distribution for each season, which are all different from each other according to Kolmogorov-Smirnov tests, and to an Anderson-Darling test that all empirical vectors of demands come from the same distribution.

5.2 The IEMP

As stated before, the IEMP is highly related to the degree of market power in the electricity generation market. In the model, this manifests through the steepness of the residual demand curve faced by the storage oligopolist. Re-stating the theoretical formula for the denominator of the optimal quantity, we can decompose it in two parts: the effect of the number of pumps competing in the market, and the IEMP.

$$\mathrm{IEMP}_{it} = \ln\left(\underbrace{m}_{\text{shift effect (related to pumps)}} + \underbrace{1+\alpha}_{\text{steepness effect (related to steepness of the offer)}} \right)$$

However, the α parameter results from a simplification necessary to make the model tractable. We have no guarantee that in the real market, the fringe has a supply curve much steeper than the dominant firm, much less do we have a guarantee on the shape of the supply and demand curves in that hour. In fact, as evidenced by Figure 1, the elasticity of the residual demand is highly dependent on where the supply curve of the marginal firm crosses it. We see that the blue curve, which could theoretically happen in a period of low VRE generation or high inelastic demand, crosses the offer curve at a steeper point than the red curve, despite the curves the same, only one of them was shifted. This evidences a larger problem that we face when using the data from the day-ahead market: the curves are not smooth, and we cannot make a general statement on the degree of market power in a hour only by using α, the percentage of the generation fleet owned by the dominant firm. We therefore need a better empirical proxy to calculate the IEMP of the PHS operator, that is still motivated by economic theory.

There are several ways the PHS can exercise market power in the product market. It can attempt to be marginal, and artificially raise its price above marginal cost. As evidenced by Suarez (2023), gas-fired generators attempt to exercise market power in the Colombian market when the availability of hydro resources is low, and they have a larger probability to be marginal. However, I first conjecture that this method would not be appropriate for PHS operators[3], since they provide a small portion of demand. However, through quantity withholding, PHS are able to pull the supply curve to the left, potentially leading to a large raise in the prices if the residual demand is particularly steep in a given hour. This is evidenced by Figure 1 too: if the black curve were to shift to the left, for example because its first step were to be reduced, it would meet the red curve on one of its higher and steeper portion.

Therefore, a more convenient approximation of the IEMP is the absolute value of the slope of the residual demand curve faced by the marginal firm, that we can use to derive an empirical parameter α. Formally, if this derivative was a continuous and smooth function, we could approximate the IEMP as follows:

$$\text{IEMP}_{it} \equiv \left(1 + n \cdot \frac{\partial p_i(\theta; q_{B-i}, q_{S-i}, q_{D-i})}{\partial q_{Di}(\theta)}\right)^{-1}$$

where

$$p(\theta) = \frac{\theta - q_S(\theta) + q_B(\theta) - q_D(\theta)}{(1-\alpha)} = \frac{\theta - q_S(\theta) + q_B(\theta)}{(1-\alpha^2)}$$

However, as mentioned above, the inverse residual demand curve is not smooth, but piecewise linear. Therefore, the slope is always null or indeterminate along the curve. To address this issue, I apply a smoothing procedure to calculate the derivative locally where the residual demand crosses the supply curve of the generator who owns the PHS. I follow an idea similar to Wolak (2003) who uses a method to calculate the slope of the residual demand curve. The method relies on using the steps of the bids that are closest - above and below - to the equilibrium market price. Formally, the formula for the approximation

[3]PHS were marginal in 13% of hours in 2022Peña (2024), which is disproportionate given the fact they represent merely 3% of installed capacity. This motivates Section 8.

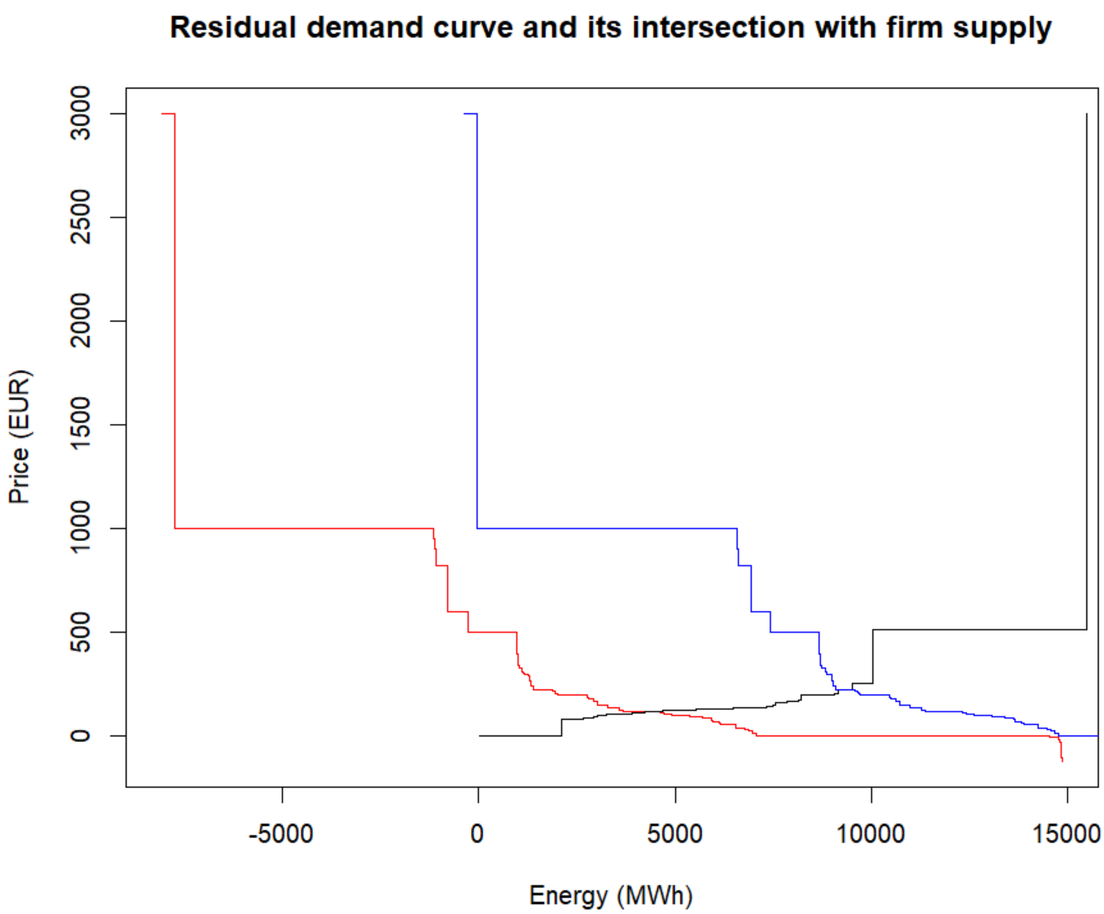

Figure 1: Two examples of intersection between residual demand in low-demand hour (red) and high-demand hour (blue) and the offer curve of a firm (in black)

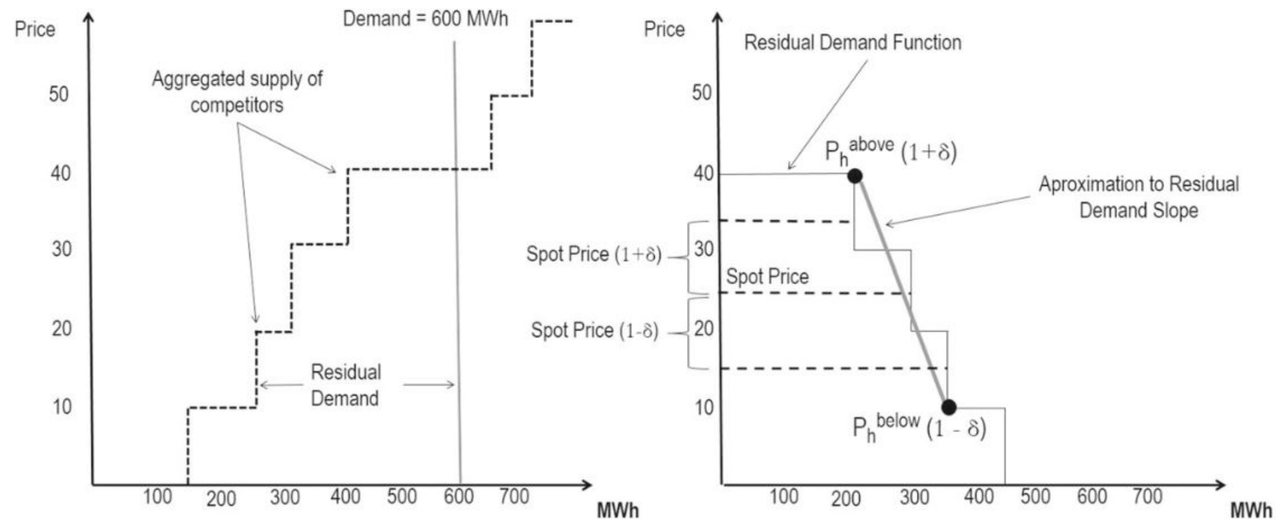

Figure 2: Illustration of the calculation of the IEMP (source Suarez (2023))

is as follows:

$$\text{slope}_{it} = \frac{P_t(\text{high}) - P_t(\text{low})}{\text{DR}_{itk}(P_t(\text{high})) - \text{DR}_{it}(P_t(\text{low}))}$$

The technique is sketched in Figure 2.

However, this theoretical estimation of the IEMP is not sufficient to detect a true causal effect. In fact, the IEMP likely suffers from endogeneity. Indeed, all market participants form their strategies as a function of their expectations of their competitors' strategies. For example, when the PHS operator chooses to withhold quantity to increase prices, the efficacy of the process might be compounded or reduced by the strategies of other PHS operators or by other dominant producers. This is influenced by different abilities to forecast market power due to the size of the firm or different willingness to engage in profit maximization, as evidenced by Hortaçsu & Puller (2008).

5.3 Instrumenting the IEMP

Following Suarez (2023), I will model the stochastic component of the IEMP as a function of three main components, which will allow me to instrument the IEMP. I select a set of instrumental variables who satisfy both the first-stage condition (i.e. who are correlated with the IEMP) and who satisfy the exclusion restriction (i.e. are uncorrelated with η_{itk}). I chose instrumental variables that are correlated to the supply function of the firm's competitors or to the inelastic demand forecast, but are not related to the strategic management error term mentioned above. This amounts to considering variables that are correlated with increased opportunities to exercise market power for the firms who operate the PHS, but which are not correlated with the opportunity cost of generating for the firm for which we instrument the IEMP.

The instrumental variables that I selected to instrument the residual demand are the following:

1. *Availability of commercial units*: currently, the law requires firms who are registered to bid in the Spanish market to submit one bid per unit available to generate. However, generation units must be stopped sometimes and declared unavailable for many possible reasons (maintenance, forced outages, nuclear refueling, etc...). This is known in advance by competitors and it modifies the shape of the supply curve of companies who must declare their units available, and the shape of the inverse residual demand for their competitors. Theoretically, removing an increasing supply curve from the aggregate supply curve of a company is akin to making the supply curve steeper. Therefore, when firm $-i$ declares its units unavailable, it renders the inverse residual demand of all firms i steeper. As regards the exclusion restriction, it is unlikely that maintenance of the units of firm i modify the opportunity cost of generation for firms i through another channel than the steepness of the residual demand.

2. *The filling rate of the hydro reservoirs*: as noted by Peña (2024), conventional hydropower (which groups regular hydropower plants and OLPHS) is an important player in the Spanish market, setting prices in more than half of hours in 2021 and early 2022. It has been noted that conventional hydropower plants bid prices that consistently exceed the benchmarks based on the opportunity cost of gas-fired generation, hinting at the fact that reservoir filling rate might be a better approximation to the opportunity cost of water. This motivates a first-stage in which variations in the filling rate of the reservoirs would cause a change in the steepness of the residual demand curve, since this would cause a change in the marginal cost curves of competing firms. As regards the exclusion restriction, there is no reason that the filling rate of the reservoirs of firms $-i$ lead to a change in the cost function of firm i, except in the case in which we observe large correlations across the reservoir filling rate of several firms. This is likely to not be a big concern, given the large number of dams in the country. The geographical repartition of the dam reservoirs is available in Annex .

3. *A weekday dummy:* the days of the week provide a positive shock to electricity demand. This shifts the residual demand, provoking variations in the IEMP, which are uncorrelated with the strategy of either competing firms.

With this identification strategy in mind, I turn to the empirical implementation.

6 Implementation

6.1 Calculating the arbitrage term

I assume no losses due to round-trip efficiency, nor storage capacity constraints, but the bidding units are limited in their hourly bids by the hourly capacity constraint[4]. This assumption is grounded on the theoretical results obtained above. I calculated for each pump the optimal thresholds θ^1 and θ^2, and found that under the hourly capacity constraint, as well as the optimal bidding behavior, there should be no hours in which the pump is supposed to remain idle. We see however in the data that the PHS who operate on a daily cycle are operating only in 34% of hours in a year. This could be caused by several factors that are not taken into account in the modelling exercise. First, the PHS could be selling power in the ancillary services market or in a capacity, which would mean that she must reserve her capacity and not bid it directly in the day-ahead market. It is also documented by Fratto Oyler & Parsons (2020) that the pattern of pumping and generation of the PHS approximately doubles in the intra-day market, which is in accordance with the idea that the PHS can serve as an emergency storage/generator and react swiftly to variations in the intra-day market.

Therefore, we can calculate the arbitrage term A_t in the following way for each PHS:

$$A_t = \begin{cases} \mathbb{E}[\theta] - \theta & \text{if } \theta > \mathbb{E}[\theta] \\ \theta - \mathbb{E}[\theta] & \text{if } \theta < \mathbb{E}[\theta] \end{cases}$$

I plot the histogram of different values in Figure X.

An interesting pattern is that quantities bid in the sell-side are often much larger than quantities purchased. This is of course not coherent with the predictions of our model, but could be caused by several factors, among which the settlement of differentials in the intra-day market.

6.2 Calculating the IEMP

All pumps who operate on a daily cycle in the Iberian market are owned by a generation firm. Therefore, I calculate the IEMP at the neighboorhood of the intersection of the residual demand and the supply of each of these four generation firms. To do so, I follow the procedure outlined in part 4: I filter out the generators who do not meet their revenue criteria under the day-ahead prices from ENTSO-E. These generators form a supply curve, which I subtract from the inelastic demand forecast, equally obtained from ENTSO-E. This gives me a downward sloping residual demand curve, of which I calculate the intersection with the supply of the given competitor. At the intersection, I calculate one price “above” (respectively “below”)

[4]The size of the reservoir, K is referred to as the storage capacity constraint, whereas the installed capacity k is referred to as hourly capacity constraint.

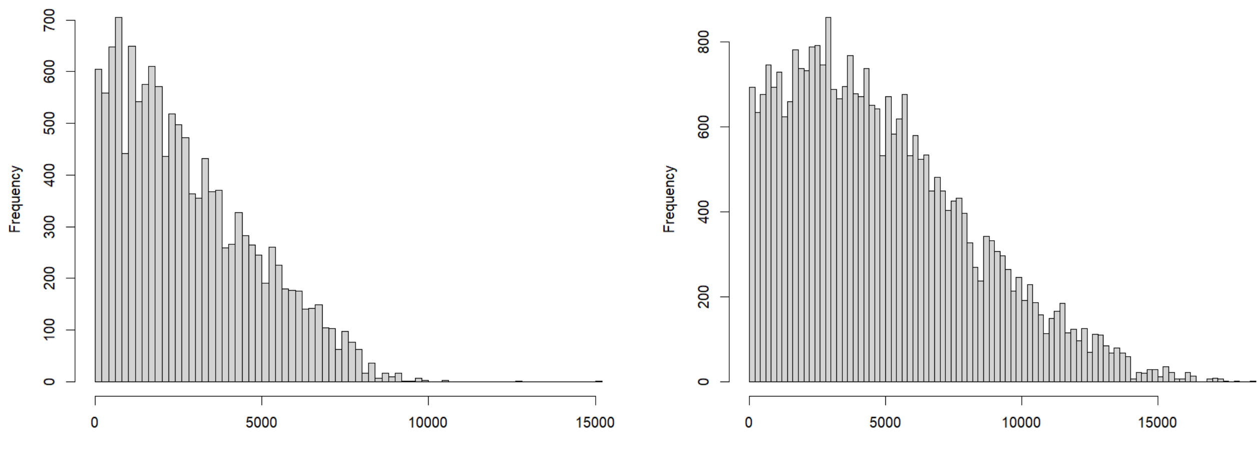

Figure 3: Histogram of arbitrage terms A_t (buy-side on the left, sell-side on the right)

using the following formula:

$$-\frac{1}{(1-\alpha^2)} = \text{slope}_{it} = \frac{P_t(\text{high}) - P_t(\text{low})}{\text{DR}_{it}(P_t(\text{high})) - \text{DR}_{it}(P_t(\text{low}))} = \frac{(1+\delta)P_t - (1-\delta)P_t}{\text{DR}_{it}((1+\delta)P_t) - \text{DR}_{it}((1-\delta)P_t)}$$

where I chose $\delta = 0.1$. Once the slope is calculated, we can back out α_{it}. We have established earlier that the formula for the IEMP is the following.

$$\text{IEMP}_{it} = \ln\left(\underbrace{m_t}_{\text{shift effect (related to pumps)}} + \underbrace{1+\alpha_{it}}_{\text{steepness effect (related to steepness of the offer)}} \right)$$

6.2.1 First model

However, this simplifies when we take the model to the data. The first term in the above expression, m, is the effect of increasing the number of pumps in the market. However, as we outlined earlier, in our model, all pumps are supposed to always be active. Therefore, theoretically, all the variation in the IEMP comes from the variation in the steepness of the curve, induced by the degree of market power exercised by the dominant firms. This leads me to construct the variable "fixed" IEMP (F-IEMP) in this way:

$$\text{F-IEMP}_{it} = \ln(m + 1 + \alpha_{it})$$

where $m = 4$ is the constant number of PHS who operate in the market.

6.2.2 Second model

However, as mentioned above, PHS are often idle. This could be because of unmodelled opportunities outside of the day-ahead market (PHS can earn revenue from diverse sources: ancillary services such as frequency regulation or spinning reserve, back-up capacity, etc...) or because PHS realize a large part of their activity in the intraday market, as mentioned before.

However, similarly to the IEMP, the number of PHS active is an endogenous variable. Indeed, it is greatly linked to the strategic management factor (the error term of the regression) and needs to be instrumented.

First, we can rewrite the IEMP in equation X to reflect the impact of the variable PHS presence throughout the day.

$$\begin{aligned}\text{IEMP}_{it} &= \ln\left(m + 1 + \alpha_{it}\right) \\ &= \underbrace{\ln(m)}_{\text{"Pure" PHS effect}} + \underbrace{\ln\left(1 + \frac{(1+\alpha_{it})}{m}\right)}_{\text{"scaled" IEMP effect}}\end{aligned}$$

This new expression for the IEMP has an economic interpretation that relates to the log-log formulation of the equation. The first term captures the pure effect of seeing a new PHS bid in the market. The second term captures the effect of the IEMP, scaled down by the effect of a new pump. This term has the following interpretation: when many PHS already bid in the market, the decrease in quantity induced by the IEMP is proportionally less than it would be if the PHS was a monopolist. The theoretical model predicts a negative coefficient on both terms; however, as we will see below, although the regression on the buy side seems to confirm the predictions of the theoretical model, the sell-side seems to exhibit a positive correlation between the pure effect of introducing a PHS and the quantity of energy bid.

6.2.3 Instrumentation

We therefore have three variables to instrument. First, the F-IEMP outlined in the first model, where the entire variation is explained by the variation in α_{it}. Then, we need to instrument the pure PHS effect (PPE, $\ln(m)$) in the second model. Finally, we need to instrument the scaled IEMP effect (S-IEMP, $\ln\left(1 + \frac{(1+\alpha_{it})}{m}\right)$) in the second regression. For all three variables, the first stage regression I estimate is the following:

$$Y_{it} = \pi_0 + \pi^F Z_{it}^F + \pi^U Z_{it}^U + \Psi_{\text{weekday}} + \chi_{it}$$

where $Y_{it} \in \{\text{F-IEMP}, \text{PPE}, \text{S-IEMP}\}$, π are the coefficients on the value of the instrumental variables, Z_{it}^F and Z_{it}^U correspond respectively to the filling rate of competitor's hydro reservoirs and unavailabilities of competitors' commercial units, and Ψ_{weekday} is the weekday dummy.

6.3 Calculating the energy bids of the PHS

Lastly, we need to calculate the energy bids of the PHS. Whereas the model outlined in the first part is a Cournot model (one quantity for every price), this is not the behavior we observe for all PHS. While some PHS compete in a form close to Cournot, some others exhibit increasing supply curves, similar to what we could expect from a gas-fired generator. Figure 4 presents the histogram of the price range of each PHS' bidding curve and the differences we observe. We see that in the overwhelming majority of hours, the PHS behave "à la Cournot" and bid one quantity at one price. However, for the remainder of hours, we need to take into account the fact that it is unlikely that the PHS wants to bid its entire curve, regardless of the price of the steps.

To calculate the energy bid of a PHS, we could sum all the steps of its bidding curve. However, this is not going to be a quantity for all prices, given the fact that different levels of demand would yield different quantities, all else equal. To better approximate this quantity, we leverage the residual demand approach adopted to calculate the IEMP and assume each PHS expect the price in hour t to be the intersection between its supply and the residual demand curve it faces. Therefore, the quantity bid by the PHS below this price can be interpreted as one quantity for the expected price in this hour. The existence of more expensive bids can be rationalized by the idea of expectation: the PHS faces uncertainty towards the realization of the residual demand curve and hedges its bets by providing additional steps in case a higher inelastic demand realizes itself, or if the residual demand curve is shifted outwards, resulting in a higher price.

7 Results

I formulate two hypotheses that rely on the assumption that the theoretical model accurately explains the behavior of PHS in the Iberian market.

1. *The PHS operates competitively.* An insignificant coefficient on F-IEMP or S-IEMP would lead me to conclude that the PHS do not react to changes in their competitive environment. This would allow us to reject the validity of the second theoretical model.

2. *The PHS reacts to the IEMP.* A positive and significant coefficient on F-IEMP and/or S-IEMP would lead me to reject the first hypothesis and is the sign that the PHS is sensitive to the IEMP. If the PHS exploits his opportunity to exercise market power, we should see a negative coefficient on the IEMP. To the opposite, if the PHS reacts to changes in the competitive environment through an increase in the quantity provided, we should see a positive coefficient on the IEMP, which would not be predicted by the model.

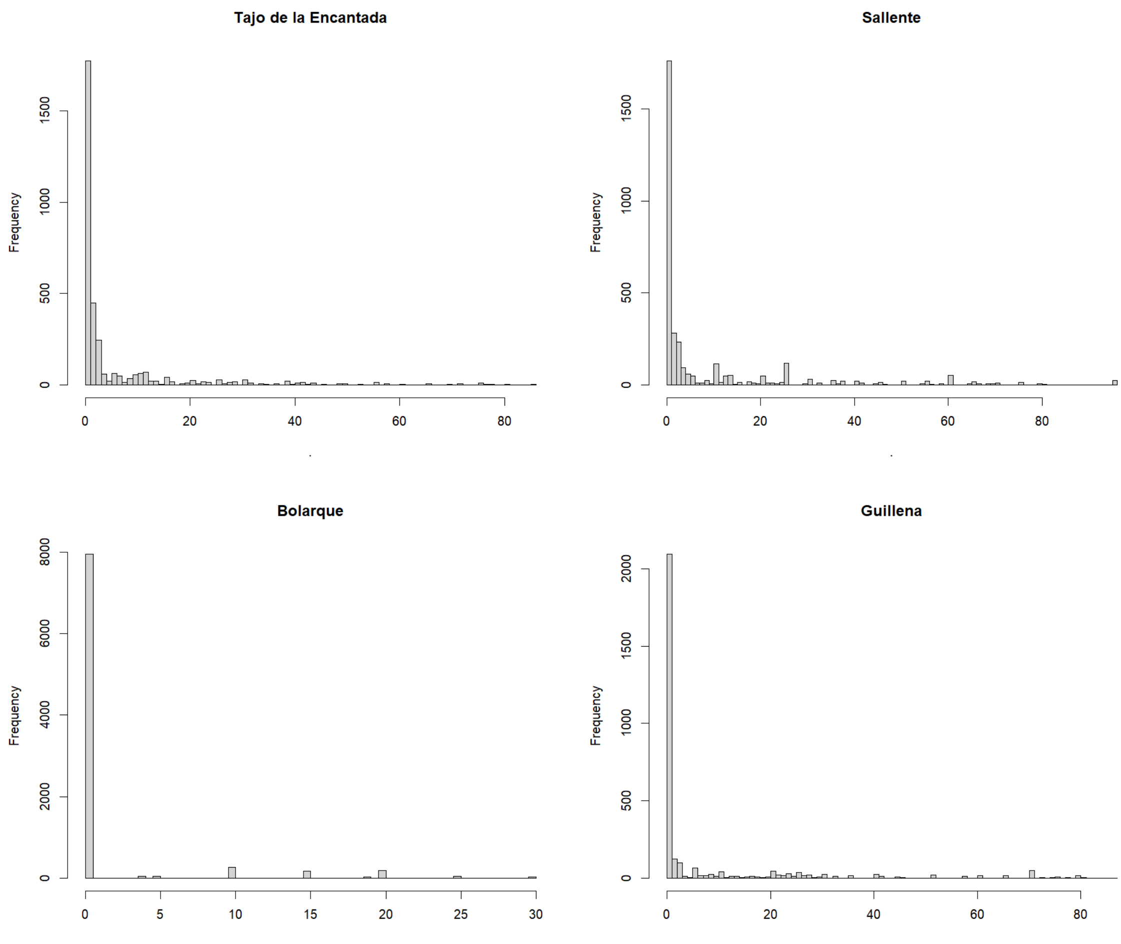

Figure 4: Price range (price of most expensive step - price of least expensive step) per PHS who operates on a daily cycle

	Dependent variable:	
	log(Energy bid (MW))	
	(1)	(2)
log(Arbitrage term)	0.565^{***}	-0.090^{***}
	(0.014)	(0.013)
log(F-IEMP)	-1.119^{***}	
	(0.064)	
log(Number of PHS)		2.516^{***}
		(0.050)
log(S-IEMP)		-0.057
		(0.094)
Observations	30,961	30,961
R^2	0.489	0.599
Adjusted R^2	0.489	0.599
Residual Std. Error	2.718 (df = 30959)	2.409 (df = 30958)
F Statistic	$14{,}840.180^{***}$ (df = 2; 30959)	$15{,}401.790^{***}$ (df = 3; 30958)
Note:		*p<0.1; **p<0.05; ***p<0.01

Table 2: Naive model results (sell side)

7.1 Naive model

To gain a first idea of the direction of correlations, I first specify a naive model with regular OLS, without instrumentation. I report the results of those regressions in Table 2 on the sell side, and in Table 3 on the buy side. The estimates in the first columns correspond to the model with a fixed number of pumps, whereas the second column incorporates the pure PHS effect and the scaled term.

I first focus on the buy-side. In the naive model (Table 3), the coefficients on arbitrage term vary sharply across specifications. Whereas the natural logarithm of the fixed IEMP is negatively significant in the first model, both the logarithm of the number of active PHS and the scaled IEMP have positive significant coefficients in the second column. This hints at the endogeneity of the variables in the second specification and motivates my instrumental variables strategy.

On the sell-side, the results are equally inconsistent across the fixed model and the extended model.

	Dependent variable:	
	log(Energy bid (MW))	
	(1)	(2)
log(Arbitrage term)	0.566^{***}	-0.058^{***}
	(0.017)	(0.010)
log(F-IEMP)	-1.751^{***}	
	(0.070)	
log(Number of PHS)		2.433^{***}
		(0.040)
log(S-IEMP)		0.314^{***}
		(0.069)
Observations	13,632	13,632
R^2	0.262	0.666
Adjusted R^2	0.262	0.665
Residual Std. Error	2.205 (df = 13630)	1.485 (df = 13629)
F Statistic	$2{,}423.972^{***}$ (df = 2; 13630)	$9{,}039.939^{***}$ (df = 3; 13629)
Note:		*p<0.1; **p<0.05; ***p<0.01

Table 3: Naive model results (buy side)

The fixed model exhibits a positive significant coefficient on the arbitrage term and a negative significant coefficient on the fixed IEMP. However, the extended model sees a reversion in the coefficient of the arbitrage term and more importantly, a positive coefficient on the number of PHS in the market. This is the first evidence of a pattern that contradicts the predictions of the theoretical model: the number of PHS seems to be positively correlated with the quantity bid on the sell side. In line with the predictions of the theoretical model, the coefficient on the scaled IEMP is negative significant.

I now turn to the causal instrumented model.

7.2 Causal model

I estimate the Two-stage least squares and report the results of the model in Table 4 for the sell side, and in Table 5 for the buy side.

I first focus on the buy side to interpret the results. The instrumented model (Table 4) offers results that are consistent across specifications and corroborate the theoretical predictions of the model. The arbitrage term is positive significant across specifications. The fixed IEMP is negatively significant, which hints at the exercise of market power. It is confirmed by the extended model: both number of PHS in the market and an increase in the scaled IEMP have negative significant coefficients. I report the p-value for the F-statistic of the first stage regression for both instrumented variables. I do not report R^2 since it has no meaning in the context of an instrumental variables regression. I estimate the model only on 13,301 observations, which is a third of the number of observations I use on the sell-side. This is related to several filters I applied on the dataset before estimating the regressions. First, I discarded all hours in which there was no scope to exercise market power, that is all hours in which the slope of the residual demand curve was less than 1, due to a lower inelastic demand forecast, or to a high renewable output. By design, all hours in which the PHS choose to store power are hours below a certain level of demand, which makes this situation more common.

On the sell side, the instrumented model exhibits consistently positive significant coefficients on the arbitrage term across specifications. Both the fixed IEMP and the scaled IEMP exhibit negative significant coefficients. However, the coefficient on the number of PHS is positive significant, which confirms the insights of the naive OLS model. This is inconsistent with the predictions of the theoretical model and hints at a misspecification of the equation, and at a potential asymmetry between the buy side and the sell side, which I discuss below. I report the p-value for the F-statistic of the first stage regression for both instrumented variables. I do not report R^2 in this model either for the same reason outlined above. I estimate my regressions on 30,242 observations, which correspond to approximately 50% of the hours of the year. I apply the same filters as mentioned above on the sell side, but it affects many less rows.

Both models were tested with a Sargan test of over-identifying restrictions. The buy-side extended model is the only model to successfully pass the test, indicating that the sell-side models are misspecified, and that the model that includes the F-IEMP is likely wrong too. Following the conclusions of Abadie *et al.* (2023), I do not cluster my standard errors. Indeed, the population of PHS is most likely clustered

	Dependent variable:	
	log(Energy bid (MW))	
	(1)	(2)
log(Arbitrage term)	0.567***	0.308***
	(0.014)	(0.042)
log(F-IEMP)	$-$1.128***	
	(0.066)	
log(Number of PHS)		0.604***
		(0.221)
log(S-IEMP)		$-$1.590***
		(0.134)
F first stage (log(Number of PHS))	0***	0***
F first stage (log(S-IEMP))		0***
Wu-Hausman test	1.70	0***
Sargan test	0***	0***
Observations	30,242	30,242
Residual Std. Error	2.719 (df = 30240)	2.501 (df = 30239)
Note:		*p<0.1; **p<0.05; ***p<0.01

The F-statistic for the first stage of both instrumented variable is reported. H0 : instruments are weak. The retained instruments are the natural logarithm of the filling rate of competitors and of the unavailability of competitors and a weekday dummy.

Table 4: Model results (sell side)

by their operating cycle, but within this cluster, there is no reason to believe that some PHS might be more intensively exposed to the IEMP, or that any of those would have more chance to internalize it. Luckily, all pure PHS plants who operate on a daily cycle belong to large generation firms, which reduces the scope for strategic incentive mismeasurement.

7.3 Discussion

My empirical analyses allow me to draw two main conclusions:

1. Cournot competition is a relevant model to understand the dynamics of competition on the buy side. My analyses suggest that PHS operators exercise market power on the buy-side, potentially under-utilizing their capacity, which allows them to decrease their costs of charging and might have adverse consequences for welfare.

2. The "true model" is probably not symmetric. My result on the sell-side, although pointing at the exercise of market power, is an inconclusive one, given the fact that the restricted model fails the Wu-Hausman test and both model fail to pass the Sargan test. Whereas it is ambiguous whether the problem lies in the instrumental variables themselves or in the specification of the equation, the fact that the coefficient on the number of PHS is positive seems to imply that the model is clearly misspecified.

This could be due to several factors. One possible explanation, which would be broadly coherent with the previous results on gas-fired generation in the literature is that rather than withholding capacity, PHS operators bid in the day ahead market to attempt to be marginal and set a price above their marginal cost. In that context, bidding larger quantities de facto raises the probability of being marginal, therefore giving more scope to raise unilaterally the market-clearing price.

8 How do PHS really compete on the sell side?

As outlined in the first section of this master thesis, the design of the Spanish electricity market allows firms to submit an increasing supply function as their bid, therefore allowing them to compete neither in a Cournot nor in a Bertrand fashion. This motivates an empirical strategy in which the PHS are understood to be part of a generating firm's increasing supply curve. In this section, I follow closely the model and the method proposed by McRae and Wolak, which I instrument and estimate following the method of Suarez.

	Dependent variable:	
	log(Energy bid (MW))	
	(1)	(2)
log(Arbitrage term)	0.553***	1.332***
	(0.017)	(0.440)
log(F-IEMP)	−1.689***	
	(0.071)	
log(Number of PHS)		−6.173**
		(2.766)
log(S-IEMP)		−6.670***
		(2.176)
F first stage (log(Number of PHS))	0***	0***
F first stage (log(S-IEMP))		0***
Wu-Hausman test	0***	0***
Sargan test	0.00**	0.89
Observations	13,301	13,301
Residual Std. Error	2.205 (df = 13299)	4.231 (df = 13298)
Note:		*p<0.1; **p<0.05; ***p<0.01

The F-statistic for the first stage of both instrumented variable is reported. H0 : instruments are weak. The retained instruments are the natural logarithm of the filling rate of competitors and of the unavailability of competitors and a weekday dummy.

Table 5: Model results (buy side)

8.1 The profit function

Following the model of Mcrae & Wolak (2009), we can specify the profit function of a firm that engage in profit maximization as the following

$$\pi_{it} = p(DR_{it})(DR_{it} - q_t^c) + P_{it}^c q_{it}^c - C_i(DR_{it}) \tag{4}$$

where $p(\cdot)$ is the inverse residual demand, DR_{it} is the residual demand faced by competitor i in hour t, $C_i(DR_{it})$ is the marginal cost function evaluated at the generation quantity DR_{it} required to clear the market. q_{it}^c is the quantity of energy sold through forward contracts and P_{it}^c is the price at which this energy is sold. A seminal article from Allaz & Vila (1993) shows that a Cournot oligopolist who sells in the forward market has less incentive to exercise market power in the spot market. This effect is noticeable in the equation and needs to be taken into account. In the case of power markets, this becomes evident when we take the first-order condition of equation 3. We differentiate the profit with respect to the quantity sold and obtain the following expression for the optimal price-setting rule for the oligopolist:

$$P_t(DR_{it}) = \underbrace{\frac{\partial C_i(DR_{it})}{\partial DR_{it}}}_{\text{Marginal cost}} - \underbrace{\frac{\partial P_t(DR_{it})}{\partial DR_{it}}(DR_{it} - q_{it}^c)}_{\text{Strategic element}}$$

We see that under the assumption that the derivative of the residual demand curve is negative, the optimal price set by the oligopolist in the day-ahead market corresponds to its marginal cost added to a strategic element that depends on the slope of the residual demand curve, scaled by the quantity sold by the oligopolist. Here, we see that this quantity is decreased by the amount of energy sold through forward contracts: indeed, part of the energy the oligopolist bids in the market has already been sold at a pre-determined price, and does not incrementally increase his payoff from raising the spot price. More details on the theory can be found in Mcrae & Wolak (2009).

8.2 The identification

I assume that in a given hour t, the price of the marginal bid of the oligopolist is given by the following equation

$$p_{it}^* = \beta_0 + \beta_1 c_{it} + \beta_2 \text{P-IEMP}_{it} + \epsilon_{it} \tag{5}$$

where c_{it} is the marginal cost of the oligopolist, P-IEMP is the "price" incentive to exercise market power (as opposed to the IEMPs derived in the previous sections, that were influencing the quantities) and ϵ_{it} is an error term. Under this assumption, I am able to empirically analyze whether the firms who bid in the day-ahead market use their PHS to increase the spot price when they are marginal. In the same spirit as Pena who identifies a sur-representation of hydropower in setting marginal prices in the Iberian market in 2022, I find that a PHS plant is the marginal unit in 23% of hours across all four dominant generation firms, whereas installed PHS capacity represents only 5.5% of total dispatchable capacity[5]. This suggests that dominant firms purposefully use their PHS capacity to clear the market. By estimating equation 3 through TSLS, I can potentially detect whether generation firms exercise market power by increasing the spot price when PHS are marginal rather than by withholding capacity. Admittedly, when the residual demand curve is shallow enough, increasing the spot price will result in a reduction in generation, since the demand is downward sloping. However, when the demand is inelastic enough (when the P-IEMP is particularly high), this exercise of market power does not induce a large reduction in generation for the PHS, therefore it would not be captured by the empirical analyses I carried out in the first part of the paper.

The P-IEMP suffers from the same endogeneity problem as the IEMP in the first part of the paper; I therefore use the same set of instruments to carry out the TSLS estimation.

The only variable left to identify is the marginal cost. As mentioned above, the marginal cost of a PHS is the opportunity cost of water, that depends on a multitude of factor. For a large hydro generator that relies on inflows from rivers and rainfall, the calculation of this opportunity cost is in essence a wheather forecast exercise. However, in the case of PHS, who only depends on an upstream and a downstream reservoir, who do not suffer from evaporation, the wheather plays no role besides to shifts in the residual demand. Additionally, for PHS who operate on a daily cycle, the opportunity cost of water is entirely described by the gaps between demand in hour t and average demand in the day, as well as the size of the storage tank of the PHS. Therefore, including fixed effects at the day, hour and PHS level should be sufficient to capture all the variation in the opportunity cost of water[6]. I therefore estimate the following equation:

$$p^*_{it} = \beta_0 + \psi_i + \gamma^h_t + \gamma^d_t + \beta_1 \text{P-IEMP}_{it} + \epsilon_{it}$$

where ψ_i is a PHS fixed-effect, γ^h_t is an hour fixed effect and γ^d_t is a day fixed-effect.

8.3 Results

Similarly to the first part of the paper, I formulate two hypotheses.

1. *The PHS operates competitively.* An insignificant coefficient on P-IEMP would lead me to conclude that the PHS do not react to changes in the IEMP. I am not only concerned with hours in which the PHS has an incentive to raise the spot price: if the firm who owns the PHS has sold more energy in the long-term forward market than it can afford to generate, the PHS have the incentive to lower

[5]This does not mean that PHS clear the market in 23% of hours, rather that the firms schedule their PHS units to clear the market in 23% of hours in the year 2023.

[6]Suarez reports this exercise for gas-fired units, by replacing its model of marginal cost by monthly and unit-level fixed effect to take into account variations in the price of gas and heat rates across firms and units. He finds those estimates to be in line with its estimates from specifications which included marginal costs. Furthermore, once fixed effects at the unit and month level were added to those models, the coefficient on marginal cost became insignificant.

the spot price, so that the firm can repurchase energy to meet its contractual commitments. More details can be found in the theoretical part of Ito & Reguant (2016)[7].

2. *The PHS reacts to the IEMP.* A positive and significant coefficient on the P-IEMP would lead me to reject the first hypothesis and would signal that PHS are sensitive to the P-IEMP. This result would be broadly consistent with previous results from Ito & Reguant (2016), Suarez (2023) and Mcrae & Wolak (2009).

I report results from the TSLS estimation in Table 6.

In the first column, I report the results of the regression including only PHS who operate on a daily cycle. We see that the coefficient on the P-IEMP is positively significant, which indicates that firms use them in a manner that is reactive to the P-IEMP, and which leads to increased market prices. In the second column, I report the estimates from the same regression, adding pumps who operate on a weekly cycle, for which I add day of the week fixed-effects. In both cases, we see statistically and economically significant coefficients: an increase of EUR1/MWh in the inverse semi-elasticity of residual demand leads to a EUR5/MWh increase in the price of the marginal bid when we include the PHS who operate on a daily cycle. Furthermore, both models pass the Sargan test with success. Whereas the result of this test should be interpreted with caution, it represents suggestive evidence that the PHS mimick the gas-fired generators in competing in supply-function equilibrium on the sell-side. When comparing the results of this estimation to the results obtained from my previous model, it is possible to rationalize the negative coefficient on S-IEMP in the misspecified model: attempting to rise unilaterally the market clearing price can result in the PHS units being displaced by less agressive units, yielding this predicted decrease in the quantity of energy bid.

9 Conclusion, limitations and future research

My master thesis builds on a Cournot model of interactions between a dominant producer, a fringe of competitive firms and a fleet of symmetrical storage operators. This set-up closely reproduces the Iberian market and allows me to simply outline the dynamics of the model. I then take advantage of the functional form of the supply functions of market participants to characterize the parameter α and empirically calculate it from a rich dataset obtained from the Iberian Market Operator, OMIE. This allows me to test the predictions of the model using an instrumental variables, testing both that the model is correctly specified and whether we observe market power exercise.

I conclude that the buy-side is accurately described by a Cournot model in which I detect the exercise of market power in the day-ahead market. This corroborates the idea that private operation of the PHS,

[7] Ito and Reguant describe a market setting in which the day-ahead market is the forward market and the intraday the spot market. However, forward contracting extends beyond the day-ahead market: suppliers who hedge their portfolio contract more than a day in advance with producers. In this context, the day-ahead market is akin to a forward market in which predictable gap between contracted demand and expected generation capacity can be closed.

	Dependent variable:	
	price_eur_per_MWh	
	(1)	(2)
P-IEMP	3.880***	5.186***
	(0.550)	(0.987)
Constant	124.286***	189.610***
	(12.639)	(17.721)
F first stage (P-IEMP)	0***	0***
Wu-Hausman	0***	0***
Sargan test	0.12	0.09
Observations	1,462	7,412
Day FE	NO	YES
Hour FE	YES	YES
Unit FE	YES	YES
Residual Std. Error	63.871 (df = 1434)	189.059 (df = 7351)
Note:		*p<0.1; **p<0.05; ***p<0.01

The F-statistic for the first stage of P-IEMP is reported. H0 : instruments are weak. The retained instruments are the unavailability of competitors, filling rate of competitor's hydro reservoirs and a weekday dummy.

Table 6: Alternative model results

as is currently favored by the European jurisprudence, is unlikely to yield consequences that maximize welfare. I equally conclude that the Cournot model Fabra and Andrés-Cerezo developed, and that I slightly extend, inaccurately describes the sell-side, both because the sign of coefficients is not in line with the theoretical predictions, and because the failed Sargan test of overidentifying restrictions seems to suggest that the variables I used for instrumentation might in fact be regressors. In any case, the statistical model seems to suffer from omitted variable bias. I took into account the potential sensitivity of the model to the choice I made regarding parameters, particularly when calculating the IEMP. I performed a robustness check exercise, increasing δ to 15% and 20%, which caused a reduction in the number of hours for which the IEMP was well-defined, leaving the main results unchanged.

Based on the summary exercise I report in Section 8, I also conclude that supply-function equilibrium conditions accurately describe the pricing strategy of the PHS. Although this model is not particularly informative on the correlation between the entry of PHS and the increased energy bids detected in Section 7, it allows me to formulate hypotheses that are worth exploring in future research, namely that this increased generation is an attempt to increase the probability to be marginal.

Of course, this master thesis is limited in its scope. First, the effects I identify should be tested in a structural model that incorporates the asymmetry mentioned above in the bidding strategies, comparable to the model developed by Karaduman (2021). Such a model is necessary to identify the magnitude of the effects and reach policy-relevant conclusions. Second, this master thesis is too limited in scope to fully understand the action of PHS operators. The intra-day market, which is more complicated to analyze, is the market in which PHS realize roughly 50% of their purchases and generation. Furthermore, Ito & Reguant (2016) find differentiated arbitrage strategies across firms size and technology portfolios. It would be interesting to apply their methodology to the case of PHS operators and use the structural model they develop to build counterfactuals that integrate the strategy of PHS operators on the intraday market. A full analysis of PHS behavior cannot be restricted to the day-ahead market and needs to incorporate the dynamics of the intra-day market to reach relevant conclusions.

10 Appendix

10.1 Proofs of mathematical results

10.1.1 Proof of Lemma 1

Proof. The competitive fringe solves the following problem:

$$\max_{q_F(\theta)} \pi_F(\theta) = \int_\Theta p(\theta)q_F(\theta) - \frac{q_F(\theta)^2}{2(1-\alpha)}\mathrm{d}G(\theta)$$

Pointwise optimality implies:

$$p(\theta) = \frac{q_F(\theta)}{(1-\alpha)} \Rightarrow q_F(\theta) = (1-\alpha)p(\theta)$$

Then, using the market clearing condition (1):

$$\begin{aligned}\theta =& q_D(\theta) + q_F(\theta) + q_S(\theta) - q_B(\theta)\\ =& q_D(\theta) + (1-\alpha)p(\theta) + q_S(\theta) - q_B(\theta)\\ p(\theta) =& \frac{\theta - q_S(\theta) + q_B(\theta) - q_D(\theta)}{(1-\alpha)}\end{aligned}$$

We can now formulate the problem of the strategic firm i.

$$\max_{q_{D,i}(\theta)} \pi_{D,i}(\theta) = \int_\Theta p\left(\theta, q_S(\theta), q_B(\theta), q_D(\theta)\right) q_D(\theta) - \frac{q_D(\theta)^2}{2\alpha}\mathrm{d}G(\theta)$$

Replacing the formula for the residual demand curve in the formula, we obtain

$$\max_{q_{D,i}(\theta)} \pi_{D,i}(\theta) = \int_\Theta \left(\frac{\theta - q_S(\theta) + q_B(\theta) - q_D(\theta)}{(1-\alpha)}\right) q_D(\theta) - \frac{q_D(\theta)^2}{2\alpha}\mathrm{d}G(\theta)$$

We obtain the first-order condition:

$$\frac{1}{(1-\alpha)}\left(\theta - q_S(\theta) + q_B(\theta) - 2q_D(\theta)\right) - \frac{1}{\alpha}q_D(\theta) = 0$$

Solving for $q_D(\theta)$, we obtain the final expression

$$q_D(\theta) = \frac{\alpha}{(1+\alpha)}\left(\theta - q_S(\theta) + q_B(\theta)\right)$$

Plugging this quantity in the formula for the price, we retrieve the full residual demand curve:

$$p(\theta) = \frac{1}{(1-\alpha^2)}(\theta - q_s(\theta) + q_B(\theta))$$

QED. □

10.1.2 Proof of Lemma 2

Proof. The competitive PHS operator chooses quantities so as to solve the problem outlined in subsection 3.2.1. We can write the Lagrangian:

$$\begin{aligned}\mathcal{L}\left(q_{S,j}(\theta), q_{B,j}(\theta)\right) = &\int_{\Theta} p(\theta)\left(q_{S,j}(\theta) - q_{B,j}(\theta)\right) g(\theta) d\theta + \mu_j \left(K_j - \int_{\Theta} q_{B,j}(\theta) \mathrm{d}G(\theta)\right) \\ &+ \lambda_j \left(\int_{\Theta} \left\{q_{B,j}(\theta) - q_{S,j}(\theta)\right\} \mathrm{d}G(\theta)\right)\end{aligned}$$

We are dealing with a convex optimization problem, the Karush-Kuhn-Tucker conditions are therefore necessary and sufficient. Taking the derivatives yield the following KKT conditions:

$$\begin{aligned}\frac{\partial \mathcal{L}}{\partial q_{S,j}(\theta)} =& p(\theta) - \lambda_j = 0 \\ \frac{\partial \mathcal{L}}{\partial q_{B,j}(\theta)} =& - p(\theta) + \lambda_j + \mu_j = 0\end{aligned}$$

Which in turn yields the two first order conditions.

$$\begin{cases} p(\theta) = \lambda_j & \text{when } \theta > \theta_j^2 \\ p(\theta) = \lambda_j - \mu_j & \text{when } \theta < \theta_j^1 \end{cases}$$

Without loss of generality, we consider cases in which $q_{B,j}(\theta) > 0 \Rightarrow q_{S,j}(\theta) = 0$ and plug in the formula for the price derived in the proof of Lemma 1.

$$\begin{aligned}\frac{1}{(1-\alpha^2)}\left(\theta + q_B(\theta)\right) =& \lambda_j - \mu_j \\ q_B(\theta) =& (\lambda_j - \mu_j)(1-\alpha^2) - \theta \\ q_{B,j}(\theta) =& \frac{(\lambda_j - \mu_j)(1-\alpha^2) - \theta}{m}\end{aligned}$$

Without loss of generality, we consider cases in which $q_{B,j}(\theta) = 0 \Rightarrow q_{S,j}(\theta) > 0$ and plug in the formula for the full residual price curve.

$$\begin{aligned}\frac{1}{(1-\alpha^2)}\left(\theta - q_S(\theta)\right) =& \lambda_j \\ -q_S(\theta) =& \lambda_j(1-\alpha^2) - \theta \\ q_{S,j}(\theta) =& \frac{\theta - \lambda_j(1-\alpha^2)}{m}\end{aligned}$$

I conjecture there exists two values θ_j^1 and θ_j^2 such that (1) $\theta_j^1 < \theta_j^2$, (2) that $\theta < \theta_j^1$ implies that $q_{S,j}(\theta) = 0$ and $q_{B,j}(\theta) > 0$ and (3) that $\theta > \theta_j^2$ implies that $q_{S,j}(\theta) > 0$ and $q_{B,j}(\theta) = 0$. Then, we check under which conditions the four values $\theta_j^1, \theta_j^2, q_{S,j}(\theta), q_{B,j}(\theta)$ satisfy all the KKT conditions. First, we note that λ_j is always positive, since otherwise, the PHS would have unsold energy in its tank, going to waste. More details on the uniqueness of μ_j can be found in the original paper from Fabra and Andrés-Cerezo.

We check the value of θ_j^2 when $q_{S,j}(\theta) = 0$.

$$q_{S,j}(\theta) = 0 \Rightarrow \theta = \lambda_j(1-\alpha^2) \Rightarrow \theta_j^2 = \lambda_j(1-\alpha^2)$$

Similarly, we check the value of θ_j^1 when $q_{B,j}(\theta) = 0$

$$q_{B,j}(\theta) = 0 \Rightarrow \theta = (\lambda_j - \mu_j)(1-\alpha^2) \Rightarrow \theta_j^1 = (\lambda_j - \mu_j)(1-\alpha^2)$$

We can therefore write

$$\begin{aligned} q_{S,j}(\theta) =& \frac{\theta - \theta_j^2}{m} \\ q_{B,j}(\theta) =& \frac{\theta_j^1 - \theta}{m} \end{aligned}$$

To obtain an analytic form for θ_j^1 and θ_j^2, we calculate the width of the region of idleness as $\theta_j^2 - \theta_j^1$.

$$\theta_j^2 - \theta_j^1 = \mu_j(1-\alpha^2)$$

Therefore, using the fact that the thresholds are necessarily symmetric around $\mathbb{E}[\theta]$, we get

$$\begin{aligned} \theta_j^1 &= \mathbb{E}\left[\theta\right] - \mu_j \frac{(1-\alpha^2)}{2} \\ \theta_j^2 &= \mathbb{E}\left[\theta\right] + \mu_j \frac{(1-\alpha^2)}{2} \end{aligned}$$

QED. □

10.1.3 Proof of Lemma 3

Proof. The strategic PHS operator chooses quantities so as to solve the problem outlined in subsection 3.2.2. We are now facing the downward sloping inverse residual demand curve, which means that the PHS is internalizing the effect of its positions on the market price. We can write the Lagrangian:

$$
\begin{aligned}
\mathcal{L}\left(q_{S,j}(\theta), q_{B,j}(\theta)\right) = & \int_{\Theta} \left(\frac{\theta - q_S(\theta) + q_B(\theta) - q_D(\theta)}{(1-\alpha)}\right) \left(q_{S,j}(\theta) - q_{B,j}(\theta)\right) g(\theta) d\theta \\
& + \mu_j \left(K_j - \int_{\Theta} q_{B,j}(\theta) \mathrm{d}G(\theta)\right) \\
& + \lambda_j \left(\int_{\Theta} \left\{q_{B,j}(\theta) - q_{S,j}(\theta)\right\} \mathrm{d}G(\theta)\right)
\end{aligned}
$$

We are dealing with a convex optimization problem, the Karush-Kuhn-Tucker conditions are therefore necessary and sufficient. Taking the derivatives yield the following KKT conditions:

$$
\begin{aligned}
\frac{\partial \mathcal{L}}{\partial q_{S,j}(\theta)} = & \frac{1}{(1-\alpha)} \left(\theta + q_B(\theta) - \sum_{l \neq j}^{m-1} q_{S,l}(\theta) - 2q_{S,j}(\theta) - q_D(\theta)\right) - \lambda_j = 0 \\
\frac{\partial \mathcal{L}}{\partial q_{B,j}(\theta)} = & \frac{1}{(1-\alpha)} \left(\theta + 2q_B(\theta) + \sum_{l \neq j}^{m-1} q_{B,l}(\theta) - q_{S,j}(\theta) - q_D(\theta)\right) - \lambda_j + \lambda_j - \mu_j = 0
\end{aligned}
$$

Taking advantage of the symmetry of the PHS, we can rewrite

$$
\begin{aligned}
\frac{\partial \mathcal{L}}{\partial q_{S,j}(\theta)} = & \frac{1}{(1-\alpha)} \left(\theta + q_B(\theta) - (m+1)q_{S,j}(\theta) - q_D(\theta)\right) - \lambda_j = 0 \\
\frac{\partial \mathcal{L}}{\partial q_{B,j}(\theta)} = & \frac{1}{(1-\alpha)} \left(\theta + (m+1)q_{B,l}(\theta) - q_{S,j}(\theta) - q_D(\theta)\right) - \lambda_j + \lambda_j - \mu_j = 0
\end{aligned}
$$

Without loss of generality, we can focus on cases where $q_{B,j}(\theta) > 0 \Rightarrow q_{S,j}(\theta) = 0$ and rearrange to obtain

$$
q_{B,j}(\theta) = \frac{(1-\alpha)}{(m+1)}(\theta - q_D(\theta)) - (\mu_j - \lambda_j)\frac{(1-\alpha)}{(m+1)}
$$

Then, without loss of generality, we can focus on cases where $q_{B,j}(\theta) = 0 \Rightarrow q_{S,j}(\theta) > 0$ and rearrange to obtain:

$$
q_{S,j}(\theta) = \frac{(\theta - q_D)}{(m+1)} - \lambda\frac{(1-\alpha)}{(m+1)}
$$

We obtain finally the three following reaction functions:

$$\begin{cases} q_{B,j}(\theta) = \frac{(1-\alpha)}{(m+1)}(\mu_j - \lambda_j) - \frac{(\theta - q_D(\theta))}{(m+1)} & \text{if } \theta < \theta_j^1 \\ q_{S,j}(\theta) = \frac{(\theta - q_D)}{(m+1)} - \lambda\frac{(1-\alpha)}{(m+1)} & \text{if } \theta > \theta_j^2 \\ q_D(\theta) = \frac{\alpha}{(1+\alpha)}\left(\theta - q_S(\theta) + q_B(\theta)\right) & \forall\theta \end{cases}$$

We can finally solve for the expressions of $q_{B,j}(\theta)$ and $q_{S,j}(\theta)$. I follow the same logic as above to determine the values of θ_j^1 and θ_j^2.

$$\begin{cases} q_{B,j}(\theta) = \frac{\theta - \overbrace{\lambda_j(1-\alpha^2)}^{\theta_j^1}}{m+1+\alpha} & \text{if } \theta < \theta_j^1 \\ q_{S,j}(\theta) = \frac{\overbrace{(\lambda_j - \mu_j)(1-\alpha^2)}^{\theta_j^2} - \theta}{m+1+\alpha} & \text{if } \theta > \theta_j^2 \end{cases}$$

To obtain an analytic form for θ_j^1 and θ_j^2, we calculate the width of the region of idleness as $\theta_j^2 - \theta_j^1$.

$$\theta_j^2 - \theta_j^1 = \mu_j(1-\alpha^2)$$

Therefore, using the fact that the thresholds are necessarily symmetric around $\mathbb{E}[\theta]$, we get

$$\theta_j^1 = \mathbb{E}\left[\theta\right] - \mu_j\frac{(1-\alpha^2)}{2}$$
$$\theta_j^2 = \mathbb{E}\left[\theta\right] + \mu_j\frac{(1-\alpha^2)}{2}$$

QED. □

10.2 Geographical repartition of hydro reservoirs

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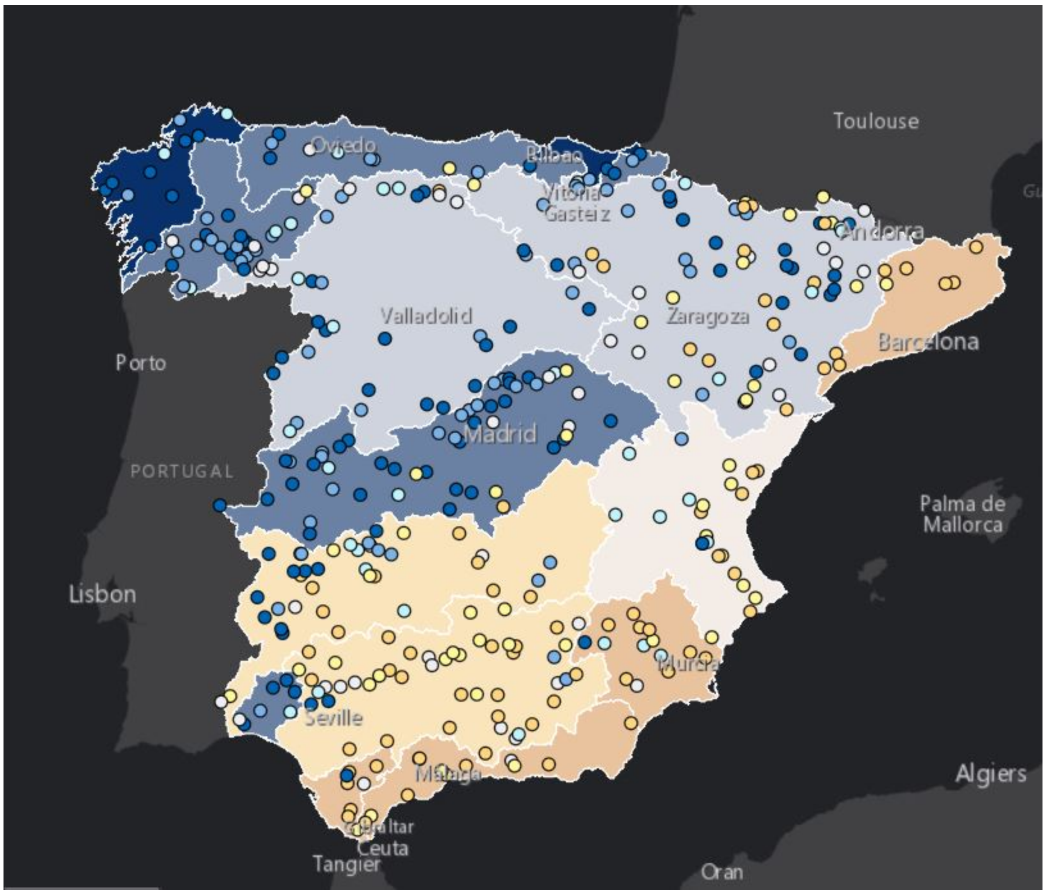

Figure 5: Geographical repartition of hydro reservoirs in Spain (source: MITECO)

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