Strategic Ability and Corporate Carbon Emissions

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Abstract

We measure the ability of firms to play oligopoly games, and the consequences for market efficiency and carbon emissions if firms lack strategic ability and deviate from Nash-equilibrium outcomes. Making use of rich micro-level data from the Spanish electricity market, we show that large incumbent firms approximately offer optimal output and charge optimal prices. Smaller firms lack strategic ability and tend to "price their production out of the market". We show that this heterogeneity in strategic ability deteriorates the efficiency of carbon pricing, because the allocation of carbon abatement across firms is not optimal. We find that large and strategically able firms with high shares of low-carbon generation are pivotal for efficient abatement and for decreasing the sector's carbon intensity. We compute counterfactual merger cases that allow for higher carbon prices and decrease the sector's carbon intensity, at no costs for consumers.

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1 Introduction

Recent findings in the behavioral industrial organization literature suggest that differences in firm characteristics can lead to heterogeneity in firms' strategic sophistication, e.g., in their ability to play oligopoly games (Hortaçsu et al., 2019). An immediate implication is that, whenever firms deviate from expected equilibrium play, they can cause damage to the intended market outcomes that policymakers aimed to achieve when imposing new regulation and incentive mechanisms.

Carbon pricing is one of the most ubiquitous mechanisms that policymakers have put into practice, with the goal to reduce carbon emissions at lowest cost. However, carbon-intensive sectors are often dominated by large strategic companies, so the efficiency of carbon prices, too, is subject to the ability of firms to adjust their output and pricing strategies accordingly.

In this paper, we ask how heterogeneity in strategic ability affects market efficiency and, in particular, market externalities. We focus on electricity markets and investigate the impact of strategic sophistication on firms' optimal pricing decisions, their carbon-dioxide (CO2) emissions, and the efficiency of CO2 abatement.

To study the effects of strategic ability on market externalities, we exploit rich firm-level data from the Spanish electricity market. Electricity markets represent a great example for large carbon-intensive sectors where strategic firms compete in oligopoly markets. Indeed, scholars have provided a wealth of evidence for strategic equilibrium play in this sector (e.g. Green and Newbery, 1992; Wolfram, 1999; Wolak, 2003; Reguant, 2014). The consequences of —more or less strategic— firm behavior on market externalities have however received little attention so far, although especially electricity markets are prone to significant CO2 externalities.

In efforts to decarbonize power generation, large power producers increasingly started to add wind and solar energy to their production portfolio. Yet, other firms remain operating conventional plants only, whereas small market entrants often rely exclusively on low-carbon production from wind and solar assets. Furthermore, power generating companies often differ in their size; and some operate specialized strategy departments that other firms lack. This heterogeneity can lead to differences in firms' ability to efficiently price and sell their "clean or less clean" output to the market, with large consequences on market efficiency and overall CO2 emissions. Prior research started exploring differences in strategic ability, proposed ways to rationalize deviations from Nash equilibria, and found strong impact of strategic sophistication on market efficiency (e.g. Hortaçsu and Puller, 2008; Hortaçsu et al., 2019).

The equilibrium framework we apply to measure firms' strategic ability follows canonical multi-unit auction models (Wilson, 1979; Klemperer and Meyer, 1989) that scholars have refined to match electricity market environments (Green and Newbery, 1992). Nearly all electricity wholesale markets operate as multi-unit uniform price auctions. To sell their output, firms have to form expectations on overall market demand and on the aggressiveness of their competitor's bidding strategies. In practice, firms have to submit supply functions to the market operator that specify their willingness to sell a certain amount of power at any given price. In addition, electricity wholesale markets usually clear at high frequency, e.g., at hourly granularity, so that firms have the possibility to learn from prior strategies. As such, electricity markets present an ideal setting to study the impact of strategic sophistication and strategic pricing on market externalities.

Deviations from optimal bidding strategies and their impact on market performance have been investigated before. Wolfram (1999) compares prices in the UK electricity market to theoretical oligopoly models and finds that prices were not as high as theory predicts, attributing deviations, amongst others, to financial contracts between suppliers and their customers. Hortaçsu and Puller (2008) use data on the Texas power market and show that especially smaller firms deviate from optimal supply functions, and forgo significant amounts of profit. Using a similar framework, Ciarreta and Espinosa (2010) focus on the Spanish power market and show that firms do not exploit the full potential of their pricing power. We draw from this approach to identify sub-optimal pricing in electricity markets, and investigate implications of potential deviations on the sector's CO2 emissions and the carbon intensity of producers.

For our empirical setup, we exploit detailed supply and demand bids in the Spanish wholesale market for electricity, which has been extensively researched to show how electricity generating firms formulate bidding strategies (Reguant, 2014; Fabra and Reguant, 2014; Ito and Reguant, 2016). Given that we observe each firm's biddding strategy, i.e., their supply functions, we can compare the observed supply to counterfactual optimal supply schedules to assess each firm's strategic ability.

As we seek to understand the impact of strategic pricing on CO2 emissions, we focus on all companies that hold fossil fueled power plants in their portfolio. We therefore investigate the strategies of eight relatively large companies, which together own all fossil production capacity and are responsible for the bulk of CO2 emissions in the Spanish market. When computing optimal supply functions and "optimal" counterfactual CO2 emissions, we also account for the forward positions of each firm. As indicated by Wolfram (1999) and shown in Wolak (2003), Mansur (2007), and Bushnell et al. (2008), forward commitments change optimal bidding strategies. As we do not observe firms' forward positions, we follow common approaches to first infer forward positions from the data (Hortaçsu and Puller, 2008; Reguant, 2014; Brown and Eckert, 2021).

Our results show that market participants, irrespective of their size, submit supply schedules which are steeper than the profit maximizing supply schedules. This is, firms' supply functions should be more aggressive to maximize profit. However, this effect is more pronounced for smaller firms. This finding confirms earlier results in Hortaçsu and Puller (2008) and Hortaçsu et al. (2019). The excessively steep supply schedules lead to higher prices than profit maximizing behavior would suggest and, given elastic demand, less electricity sold in the market.

Our counterfactual optimal supply functions therefore predominantly lead to higher output and consequently higher carbon emissions. In short, our findings suggest that the lack of strategic sophistication favors conservation and reduces CO2 emissions, although abatement is not strategic and not optimal. We also observe that the composition of a firm's production portfolio moderates this effect. Deviations from relatively cleaner firms can lead to an overall increase in emissions. This is because firms tend to submit too steep supply functions and, when having low-carbon supply, price their clean output out of the market. As a consequence, when relatively clean firms lack sophistication, overall market emission levels rise. Our findings hence show that, from a policy perspective, firms with clean production that lack strategic ability can be costly in terms of externalities.

To compute policy counterfactuals that can increase strategic sophistication, we estimate the impact of a merger between a sophisticated large firm and a less sophisticated but relatively "clean" firm. We assume that the merged company adopts the bidding behavior of the more sophisticated firm. First, our findings suggest that mergers between heterogeneous firms may have a pro-competitive effect. This is because sophistication increases and pricing becomes more aggressive. Second, we find that this increase in efficiency does not come at a significant cost of increased emissions. This is because the merger led the small but clean firm to more efficiently price its low-carbon output in the market, hence decreasing the overall CO2 intensity. This finding suggests that there are benefits to merger policy when accounting for firms' strategic abilities and the consequences on the utilization of low-carbon production.

Our findings contribute to the large literature on bidding behavior in multi-unit auctions (Wilson, 1979; Klemperer and Meyer, 1989) and, in particular, in electricity markets. The literature on bidding behavior in electricity markets has been mostly confined to understanding the impact of strategic bidding on market efficiency (Green and Newbery, 1992; von der Fehr and Harbord, 1993; Wolfram, 1999; Borenstein et al., 2002; Baldick et al., 2004), with less emphasis on how bidding behavior impacts CO2 externalities. Previous works have instead focused on the impact of cost pass-through (Fabra and Reguant, 2014), complex cost structures (Reguant, 2014), discrete bids (Fabra et al., 2006; Holmberg et al., 2013), arbitrage in sequential markets (Ito and Reguant, 2016), and the impact of forward contracts (Wolak, 2003; Mansur, 2007; Bushnell et al., 2008).

More broadly, we also contribute to the growing field of behavioral industrial organization, in particular on firm behavior in auction markets. Previous works in this field have embedded cognitive hierarchy models into oligopoly pricing frameworks (Hortaçsu et al., 2019), and studied the role of learning for converging towards Nash-equilibrium bidding (Doraszelski et al., 2018). In line with our study, both latter works exploit rich firm level data from electricity markets. We add to this literature by quantifying the impact of strategic sophistication on market externalities.

The remainder of this paper is organized as follows. In section 2, we provide an overview of the market environment and introduce our empirical setup. In section 3, we present our model framework. Section 4 outlines how we proceed empirically, while section 5 illustrates our data. In 6, we present our results and robustness checks, and compute policy counterfactuals. Section 7 concludes.

2 Market environment and empirical setup

Our empirical setup exploits rich firm level data from the Iberian electricity market. The Iberian electricity market, Mercado Ibrico de la Electricidad (MIBEL), is the main market place for electricity in Spain and Portugal.[1] Market participants can trade on several consecutive markets. The centralized wholesale market is organized by OMI-Polo español S.A. (OMIE) and includes a day-ahead market place, six intraday markets, as well as a continuous intraday market for last-minute adjustments prior to delivery. Before the centralized wholesale markets clear, market actors can engage in bilateral or exchange-based forward trading.

[1]The formerly distinct Spanish and Portuguese markets were officially coupled in July 2007 and form one pricing zone. Market prices in both countries only differ when transmission capacity does not allow for the electricity flows as determined by the market.

2.1 The day-ahead market

Our empirical analysis focuses on the day-ahead market, where the bulk of electricity is traded. The market opens at 12 a.m. on the day prior to delivery and clears simultaneously for all 24 hours of the consecutive delivery day. The regulator obliges suppliers to submit bids for all of their available capacity. To give suppliers more opportunity to smoothen their supply schedules, they can submit up to 25 distinct bids of price quantity combinations per production unit. In addition to these simple bids, that reflect a firm's willingness to sell electricity at or above this bid, suppliers can make use of complex bids. Firms use complex bids to flag additional cost components for the auction clearing mechanism, such as start-up or ramping costs of power plants. If a supplier makes use of a complex bid (usually in the form of a minimum income condition or a condition on indivisibility), the production unit is only called if the condition stated in the complex bid is met. If the condition is not met, the clearing process neglects all bids submitted for this production unit.

On the demand side, bids can be submitted by retail firms, vertically integrated generation companies, or large consumers who directly participate in the wholesale market. Both supply and demand bids are submitted to the market operator (OMIE), where bids are sorted in increasing (supply-side) and decreasing order (demand-side). After controlling for complex bids, the market clears as a uniform price auction, where the last supply bid needed to satisfy demand determines the market clearing price. This price consequently applies for all the electricity bought and sold in the market at that particular hour.

2.2 Market structure

The wholesale market structure is characterized by few large firms and several fringe firms. Fringe firms mainly are small renewable producers. The dominant large Spanish companies in our sample are Endesa, Iberdrola, and Naturgy, who control the majority of fossil, nuclear, and large-scale hydro capacity, i.e., those technologies which are setting the clearing price most of the time. In the Portuguese market region, EDP controls nearly 80% of the market. Overall, the market equilibrium hence is determined by the strategies of the large power producers.[2]

[2]During our period of observation, i.e., the year 2017, average market prices in both trading zones differed only by 0.24 €/MWh, (52.24 €/MWh in the Spanish zone and 52.48 €/MWh in the Portuguese zone) indicating that interconnection capacities where largely sufficient to enable a common price in both trading zones.

2.3 Production technologies and CO2 emissions

Renewable technologies, such as wind power, bio-energy, small-scale hydro, and concentrated solar power (CSP) meanwhile dominate the market and represented approximately 43% of sales in the day-ahead market in 2017. Energy from nuclear (19%), coal (18%), natural gas (11%), and hydro power plants (9%) made up the rest of production.

Table 1: Production technologies by firm.

	EDP	Iberdr.	Endesa	Naturgy	Viesgo	Engie	REN	Cepsa	All
Coal	31.2	11.4	61.0	39.4	25.5	0.0	56.1	0.0	22.4
Natural Gas	18.6	25.0	22.0	36.2	3.8	45.4	43.9	47.7	16.8
Renewable	37.5	22.4	9.6	8.4	38.5	54.6	0.0	52.3	16.2
Nuclear	0.0	12.8	4.4	8.2	0.0	0.0	0.0	0.0	3.2
Hydro	12.7	24.1	3.0	6.1	16.8	0.0	0.0	0.0	9.2
Residual	0.1	4.4	0.0	1.7	15.4	0.0	0.0	0.0	1.5

Notes: Sample from 01/10/2017 to 31/12/2017 for hours 17, 18, and 19. Hydro comprises pumped hydro, residual includes co-generation as well as production from unknown sources.

Table 1 presents the composition of production technologies for the firms in our sample. We focus on the eight largest firms in the wholesale market, who taken together own all fossil fuel units that operate in the market. The firms in Table 1 hence are responsible for 100 percent of the market's CO2 emissions. The last column reflects overall technology shares across all eight firms. As can be seen, several companies employ coal-fired plants, which carry the highest carbon intensity among all generation technologies. Also gas-fired plants are deployed to a significant extent. Depending on the plant efficiencies, gas-fired units typically only emit about half the CO2 emissions when compared to coal-fired units.

Because firms hold diverse production portfolios that differ in their carbon intensity, firms' pricing strategies will impact overall carbon emissions in the market. For instance, aggressive bidding behavior by Endesa will result in relatively more coal-fired generation and thus entail increased overall carbon emissions.

3 Model

This section presents a model for strategic bidding in multi-unit uniform price auctions, the clearing mechanism used in the Iberian electricity wholesale market.[3] We use the model to investigate the impact of firms' strategic pricing behavior on their equilibrium output and carbon emissions. In particular, we outline a supply function equilibrium as in Hortaçsu and Puller (2008). The model allows to account for the firms' forward positions, which have been shown to have a large impact on strategic pricing (Allaz and Vila, 1993; Bushnell et al., 2008).

Each firm i submits a supply function $S_i(p)$ that specifies its supply S_i at each market price p. Demand is stochastic and denoted as $\tilde{D}(p) = D(p) + \varepsilon$, where ε is a random component of power demand. Market clearing at the equilibrium price p^* requires

$$\sum_i S_i(p^*) = \tilde{D}(p^*). \tag{1}$$

Firms submit their supply schedules before knowing realized demand and consequently face randomness on the equilibrium market price, which depends on the realized level of power demand. Firms hence must maximize expected profits and to this end require a prior on the demand distribution and the resulting range of possible market prices.

We follow Hortaçsu and Puller (2008) who map randomness from demand to price and write expected firm profits as

$$E[\pi_i] = \int_{\underline{p}}^{\bar{p}} \pi_i(S_i(p))dH_i(p\ |S_i), \tag{2}$$

where $H_i(p)$ is the cumulative distribution function of the market price, given firm i's supply at this price.

Firms can sell on forward markets or participate in the spot market for electricity. Profits of firm i therefore include revenues from sales in the day-ahead spot market and in the forward market. Firm i's realized profits at any market price p can be written as

$$\pi_i(S_i(p)) = S_i(p, F_i)p - C_i(S_i(p)) - (p - p^F)F_i, \tag{3}$$

where $S_i(p, F_i)$ is the supply of firm i at price p, F_i is the firm's forward position, C_i

[3] Most power exchanges around the globe clear as multi-unit uniform price auctions (see, e.g., Wilson, 2002).

denotes the cost function, and p^F is the forward price. The first two terms capture a firm's revenue and production cost. The last term adjusts profits for price differences between the spot market price p and prices realized for the firm's forward sales p^F. This is, for its forward sales firm i receives the price p^F instead of the spot market price p.

The way forward contracts change optimal supply schedules is more apparent to see after rearranging equation (3) to

$$\pi_i(S_i(p)) = (S_i(p, F_i) - F_i)p - C_i(S_i(p)) + p^F F_i. \tag{4}$$

As can be seen, revenues from forward sales $p^F F_i$ are sunk and disregarded in the optimal pricing decision. In addition, as shown in the first term, forward sales F_i decrease the quantity of firm i that receives the spot market price and hence reduce incentives to charge high prices (Wolak, 2000; Mansur, 2007; Bushnell et al., 2008).

To determine firm i's optimal supply, $S_i^*(p)$, we substitute profits in equation (4) into the expected profits in equation (2) and derive the first-order condition with respect to $S_i(p)$. The resulting Euler-Lagrange optimality condition for the optimal supply function yields

$$p - C_i'(S_i^*(p)) = (S_i^*(p) - F_i)\,\frac{H_S(p, S^*(p))}{H_p(p, S^*(p))}, \tag{5}$$

where $S_i^*(p)$ is firm i's optimal supply function, C_i' marginal costs, and H_S and H_p are derivatives of H_i with respect to supply and price, respectively. The left hand side represents the firm's mark-up at its supply of $S_i^*(p)$. The right hand side shows that the mark-up depends on overall output, net of forward commitments. Appendix A presents more details on the derivation of the optimality condition.

To interpret the optimality condition, note that H_p is the probability density function of price and must be positive. Also H_S must be positive because additional supply increases the likelihood that price is below any given value. Vice versa, withholding supply decreases the likelihood that the equilibrium price is below a certain value. The right hand side consequently is positive and determines a non-zero mark-up, unless the supply effect of firm i on the price distribution is infinitely small.[4]

To compute equation (5), one needs to either derive or estimate H_S and H_p. As Hortaçsu and Puller (2008) show, the analytical derivation simplifies when restricting the uncertainty to be additively separable, i.e., uncertainty shifts demand but does not rotate it. We hence

[4] As discussed in Wolak (2003) and Hortaçsu and Puller (2008), the strategies that follow equation (5) are also ex-post optimal, as long as shocks to supply or demand are additive.

continue with the assumption below:

Assumption 1 *Uncertainty ε causes parallel shifts in the demand function but does not rotate the demand curve.*

Using this assumption, as shown in Appendix A, the optimal pricing rule greatly simplifies and yields the standard inverse elasticity mark-up rule:

$$p^* - C_i'(S_i^*(p^*)) = \frac{S_i^*(p^*) - F_i}{-RD_i'(p^*)}. \tag{6}$$

The price cost margin on the left-hand side of the equation is a function of the firms net-position in the market, $S_i^*(p^*) - F_i$, and its ability to affect the equilibrium price. The latter is reflected by the slope of the firm's residual demand curve $RD_i'(p^*)$.[5] As $RD_i'(p^*)$ is negative, the denominator on the right-hand side becomes positive. If a firm thus has a lot of market power, the residual demand function is flat and optimal mark-ups are large. In contrast, a steep residual demand function signifies that the firm is not able to raise equilibrium prices as reductions in quantity only lead to neglectable price increases.

Equation (6) at the same time clearly demonstrates that positive mark-ups will only be realized as long as net-sales, $S_i^*(p^*) - F_i$, are positive. Intuitively, the firm is only interested in achieving higher equilibrium market prices as long as it is a net seller in the market. Should the optimal quantity for a given equilibrium price turn out to be smaller than the forward obligations of the firm, incentives revolve and the firm prefers to use its market power to decrease the equilibrium price. In this case, the firm acts as a net-buyer and bids below marginal cost such as to decrease the price it needs to pay to meet its forward obligations.

4 Empirical strategy

The aim of our analysis is to estimate firms' strategic ability to maximize expected profits, and to show what heterogeneity in strategic ability implies for the firms' overall CO2 emissions. To implement this agenda, we first quantify the strategic ability of the power producing firms in our sample. Following the extant literature (Wolfram, 1999; Hortaçsu and Puller, 2008; Ciarreta and Espinosa, 2010; Brown and Eckert, 2021), we proceed by computing the deviations between observed strategies and those resulting from optimal bidding behavior. While we can directly observe realized bidding behavior, we need to compute counterfactual optimal bidding schedules from the data.

[5] We refer to a setting with quantity on the y-axis and price on the x-axis.

4.1 Computing optimal bidding strategies

To compute optimal price-quantity combinations for the supply function of each firm, we make use of the optimality condition as stated in equation (6). Starting from equation (6), we require three central components to set up the optimal supply schedule of firm i. In particular, we construct a firm's optimal supply function for each hour t and require:

- Firm i's marginal cost curve C_i' at time t,
- Firm i's forward position F_i at time t,
- The slope of firm i's residual demand curve $RD_i'(p^*)$ at time t.

Our dataset comprises all demand and supply bids but no data on firm's production costs and their forward positions. We therefore start by estimating the marginal cost functions for each firm using engineering estimates. Specifically, we estimate marginal cost curves for each hour t and firm i using information on the marginal costs of renewable, nuclear, coal, and natural gas production units.[6] Our estimation procedure makes use of the fact that, to maximize profits, firms deploy their generation technologies in increasing order of their marginal costs. This is, we assume that firms follow the merit order when offering their production units to the market. We then use an isotonic regression to fit an upward sloping step function and assign marginal cost to each unit within the merit order.[7]

In a second step, we identify a firm's forward position, or more broadly speaking the hedging position of firm i in hour t. We make use of the optimality condition as stated in equation (6): Theory predicts that firms offer electricity below marginal cost as long as they are net-buyer, i.e. for $S_i^*(p) < F_i$. In contrast, firms price their electricity above marginal cost as soon as they are net-seller to the market, i.e. for $S_i^*(p) > F_i$. Firms consequently price electricity equal to their marginal cost when their supply $S_i^*(p)$ exactly matches their hedging position F_i.

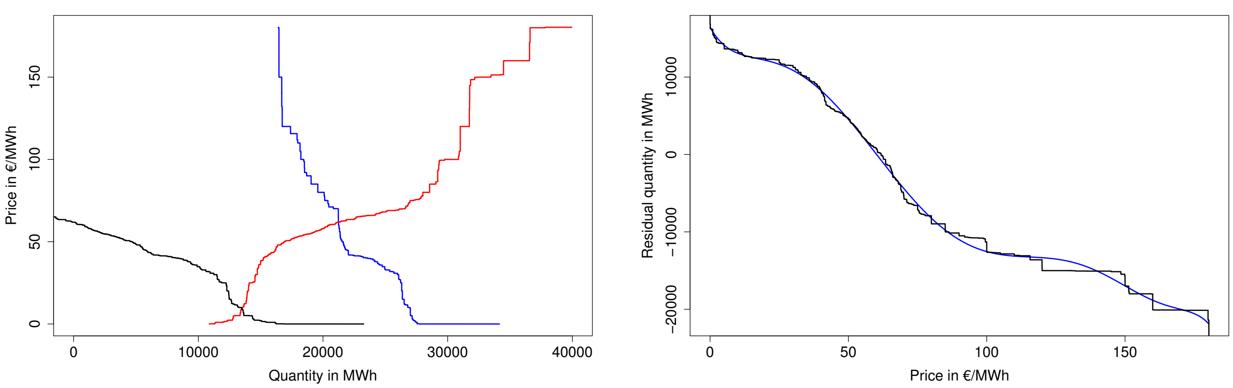
Following Hortaçsu and Puller (2008) and Reguant (2014), we exploit this condition to infer a firm's forward position. This is, we combine observed bidding schedules and the

[6] Note that our sample also includes hydro and pumped storage units, for which marginal cost parameters are hard to determine, as they depend on the opportunity costs to sell stored energy in the future. We hence use cost information on production from renewable, nuclear, coal, and natural gas power plants to fit a marginal cost curve over all types of production, including hydro and pumped storage power plants.

[7] Willems et al. (2009) follow a similar approach, but employ a cubic function to estimate marginal cost. We experimented with alternative derivations of marginal cost curves via polynomial fitting with various degrees of freedom, and by fitting non-decreasing step functions with other functional forms. However, our chosen approach yielded the best fit with bottom-up calculated and engineering based marginal cost parameters.

estimated marginal cost curves, and determine their intersection to infer a firm's hedging position F_i in each hour t. Technically, we define the cumulative sum of all bids submitted below marginal cost as hedging position. Note that this approach is contingent on the firms actually being aware of their hedging position. Yet, we believe it is fair to assume that even firms with limited strategic ability have good knowledge of their hedging position F_i, whereas they have difficulties in forming a prior on demand or their competitor's strategies.

Last, demand and supply curves are directly observable in our data and allow to construct residual demand curves for each firm. After assigning individual offers to companies, we possess all necessary information to derive residual demand curves for each firm i in our sample. Subtracting all supply curves of competitors $S_{j\neq i}$ from realized demand $D(p)$, we construct residual demand curves RD_i for each hour. Panel (a) in Figure 1 illustrates this approach. Note that residual demand becomes negative as soon as the sum of competing offers suffices to cover all demand.



(a) **(b)**

Figure 1: Panel (a) shows the residual demand for EDP, data for hour 18 on 01/11/2017. Residual demand (black) is derived by subtracting supply of all competitors $S_{j\neq i}$ (red) from demand D (blue). Panel (b) shows the estimated slope of residual demand for all potential price levels. In line with the optimality condition in equation (6), we plot residual demand on the y-axis over price on the x-axis.

Finally, to obtain the slope of residual demand, RD_i' in equation (6), we estimate the slope by fitting a polynomial with nine degrees of freedom and enforce it to be monotonically decreasing.[8] In essence, the slope is a measure for the market power of firm i. We illustrate this approach in Panel (b) of Figure 1.

[8] We use the *MonoPoly* package in R. We also considered following Ito and Reguant (2016), keeping residual demand locally linear, yet for our sample this complicates estimation for prices close to zero or the price-cap.

Given all variables computed as above, we are able to derive optimal supply functions for all suppliers using the optimality condition in equation (6). Specifically, we construct the optimal supply function by finding the optimal bid for each quantity offered. This is, we minimize the difference between the left-hand side and the right-hand side of our optimality condition as stated in equation 6. This minimization delivers an optimized bidding schedule for each firm that we can use to quantify firms' strategic ability.

4.2 Quantifying strategic ability

To quantify the strategic ability for each firm in the sample, we compare the optimal bidding schedules to the actual offer curves observed in the data. As metric for the level of strategic ability, we compare profits realized in both cases, i.e. we quantify the "money left on the table".

We compute profits for the observed bidding behavior by calculating the revenue obtained from a firm's observed supply curve, and subtracting costs using the respective estimated marginal cost curves. Note that, to measure sophistication of bidding in the day-ahead market, we only consider profits that accrue due to participation in the day-ahead market. This means we only include additional profits and neglect profits from forward sales. Extracting clearing prices p^* and offered quantities from the data, firm i's actual profits π_i^a hence are computed as

$$\pi_i^a = (S_i(p^*) - F_i)\, p^* - \sum_{j=1}^{m} C_i'(j) s_i(j). \tag{7}$$

The first term reflects revenues from net-sales of the firm, i.e all supply bids located in between the firm's forward position F_i and its total matched supply $S_i(p^*)$. Individual bids that jointly make up the net-sales of the firm are denoted by j, whereas m stands for the total number of bids j. The second term represents the cost of production for all supply bids j which are comprised of marginal cost C_i' for each bid j and the associated size of each bid $s_i(j)$.

Note that firms sometimes over-hedge. When forward sales F_i exceed the quantity $S_i(p^*)$ matched in the day-ahead market, firms become net-buyers and the profit function needs to be adjusted. Profits are now calculated as

$$\pi_i^a = (S_i(p^*) - F_i)\, p^* + \sum_{j=1}^{m} C_i'(j) s_i(j), \tag{8}$$

and the first term turns negative as it now reflects expenditures for the net-purchases of the firm. The second term adds savings from avoided production cost. As marginal cost of production $C_i'(j)$ exceed the clearing price p^*, the firm realizes profits in the market.

For our counterfactual on optimal pricing behavior, we use a firm's optimal supply function as characterized by the modeled optimality condition. In particular, we calculate a counterfactual market outcome had firm i behaved optimally, holding all other firms' strategies constant. Note that this counterfactual yields optimal firm profits and at the same time changes the clearing price, overall quantity supplied, as well as all firms' equilibrium carbon emissions.[9] We calculate counterfactual optimal firm profits as

$$\pi_i^{cf} = \left(S_i(p^{cf}) - F_i\right) p^{cf} - \sum_{j=1}^{m^*} C_i'(j) s_i(j), \tag{9}$$

where p^{*cf} is the counterfactual clearing price given firm i's optimal supply, and m^* denotes the total number of bids that make up the net sales of firm i, if the latter behaves optimally. When the firm acts as net-buyer in the market, the profit function again needs to be adjusted to

$$\pi_i^{cf} = \left(S_i(p^{cf}) - F_i\right) p^{cf} + \sum_{j=1}^{m^*} C_i'(j) s_i(j). \tag{10}$$

In line with the calculation of actual profits in equation 8, savings from avoided production costs exceed expenditures for net-purchases.

5 Data

The main data source we employ consists of all supply and demand side bids in the Iberian day-ahead electricity market within the last three months of the year 2017. The data is available on the OMIE website. We chose this observation periods for two reasons. First, there were no substantial regulatory changes that could distort our analysis. Second, energy from fossil fuels had a large market share during this period, which renders our marginal cost curve estimations more accurate.

To ensure that our analysis is not affected by start-up and ramping cost of fossil fuel power plants, we restrict our sample to afternoon hours (17, 18, and 19). These hours

[9] For instance, if a firm's optimal supply function is flatter than its observed supply curve, firm i' optimal pricing is relatively more aggressive and thus yields a lower market clearing price p^{*cf}, and an increase in the market share of firm i.

exhibit rather low demand, but are nestled in high demand hours. Start-up cost thus not arise in our sample as power plants are already running.[10]

We match the bid information provided by OMIE (price, quantity, power plant identifier and a dummy stating whether the bid was called) with a list specifying the ownership structure of each power plant. This matching allows us to assign all bids to the respective parent company. We focus on the largest fossil power producers, i.e., EDP, Iberdrola, Endesa, Naturgy, Viesgo, Engie, REN, and Cepsa. All other plants are treated as belonging to a representative fringe firm. Given bidding information and ownership structure we construct the demand curve and individual supply curves for each company and hour in our sample.

We merge in data on the marginal cost of fossil power plants, which depend on the plant efficiency, i.e the heat-rate. Detailed information on individual efficiency rates were available for some, but not all coal and natural gas plants in our sample. When missing, we thus used the commissioning year of a plant as a proxy for its efficiency and linearly interpolated to assign all efficiency rates.[11]

Using power plant-specific heat rates and market prices for coal and natural gas, we then derive marginal cost for each fossil power plant in the sample. We account for respective fuel prices, the price of carbon emission certificates, variable operation and maintenance cost, as well as taxes and other levies in Portugal and Spain.[12] We provide a detailed overview of the input factors for our calculation in Table A.1 in the Appendix. Table A.2 in the Appendix, provides the magnitudes of cost components, levies, and taxes. Finally, Table 2 presents the summary statistics.

6 Results

This section presents our findings on the impact of firms' strategic ability on market efficiency and market externalities. Figure 2 and Figure 3 illustrate that there is clear evidence of heterogeneity in firms' strategic ability. In particular, Figure 2 plots the market outcomes for an exemplary hour for the four largest firms in our sample, and shows observed supply curves (red) and counterfactual optimal supply schedules (black). As can be seen, especially around the median clearing price of about 61 €/MWh, large firms' observed supply curves

[10] Reguant (2014) shows that for the chosen afternoon hours, start-up cost do not impede correct estimation of mark-ups.

[11] Willems et al. (2009) follow a similar approach to construct engineering estimates of marginal costs of power generation.

[12] Marginal cost of renewable non-hydro production are set to zero. For nuclear power production we calculate with marginal cost of 14€ / MWh, based on estimates by the WNA (2006), plus a fuel tax of 5€ / MWh. The 7% tax on electricity production is added accordingly.

Table 2: Summary statistics.

	Mean	Median	Std. dev.	Min	Max	Obs.
Observed bids [€/MWh]	61.9	57.1	50.4	0.0	180.3	176,631
Optimal bids [€/MWh]	43.5	52.2	25.9	0.0	179.2	176,631
Marginal cost [€/MWh]	43.4	50.8	18.1	0.0	67.4	176,631
Bid-size [MWh]	68.5	30.2	136.6	0.1	4,545.5	176,631
Res. demand slope [MW/€]	-549.2	-482.2	357.2	-2,472.2	0.0	176,631
Clearing price [€/MWh]	61.6	61.8	11.1	11.9	88.9	276
Load [MWh]	30,775	30,620	4,469.5	21,441	40,996	276
CO2 emissions [tons/hour]	9,043.4	9,949.4	3,498.0	54.6	15,838.1	276

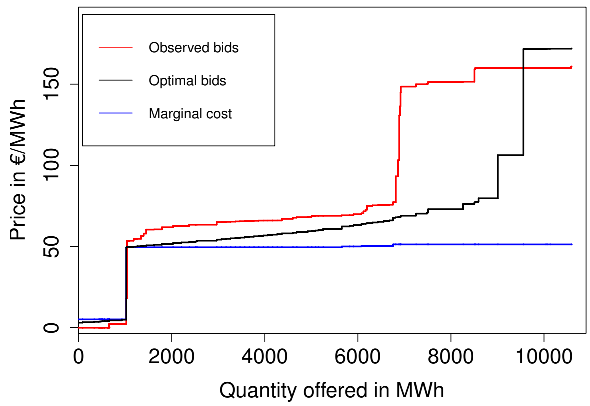
Notes: Sample from 01/10/2017 to 31/12/2017 for hours 17, 18, and 19. Observations are hourly and comprise data from the eight largest carbon emitting power producers (EDP, Iberdrola, Endesa, Naturgy, Viesgo, REN, Cepsa, and Engie).

match the optimal supply curves well. Where firms deviate, they mostly submit supply curves that are less aggressive when compared to optimal pricing. Significant deviations from the model only occur out of sample, i.e., at clearing prices above the maximum price in our sample of about 89 €/MWh, indicating that firms have a good prior on the likely range of equilibrium market prices.

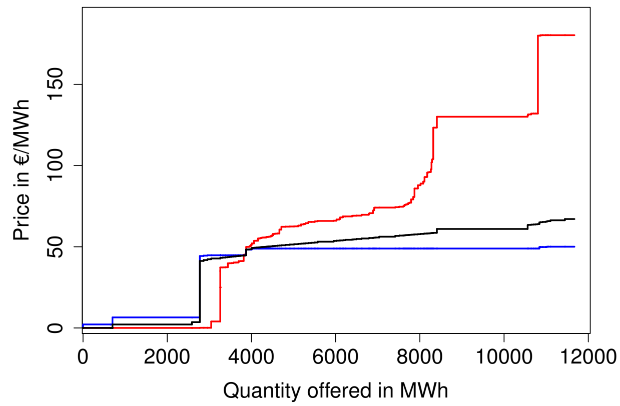
In contrast, Figure 3 plots the actual and counterfactual optimal supply curves for the four smallest firms in our sample. Clearly, the smaller firms follow optimal supply schedules to a significantly lesser extent. In particular, small firms submit excessively steep supply curves to the market, thereby diverging significantly from optimality and withholding too much capacity. As can be seen, the small firms in optimum should price very aggressively and close to marginal costs instead.

Our finding that larger firms show higher strategic ability and bid closer to optimality confirms similar results in Hortaçsu and Puller (2008) and Hortaçsu et al. (2019) for the Texas balancing market. Markedly, our results confirm this finding for the day-ahead market, where traded volumes are significantly larger and one would expect all companies to choose approximately optimal supply functions.

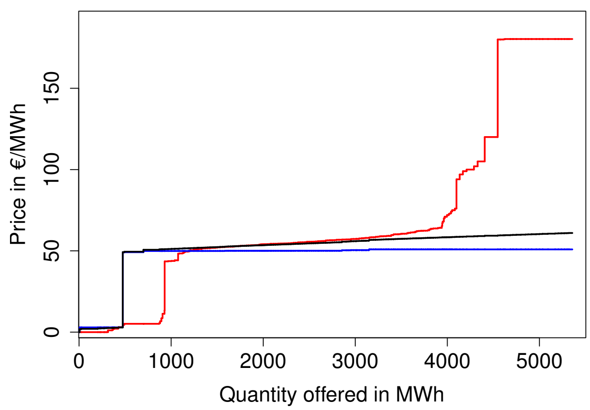
To assess the performance of companies over our entire sample, we aggregate market outcomes at a monthly scale. In line with Hortaçsu and Puller (2008), we measure the performance of firms as the percentage of potential profits that firms actually achieved. A higher percentage thus signals a higher degree of strategic ability, i.e., bids closer to optimal



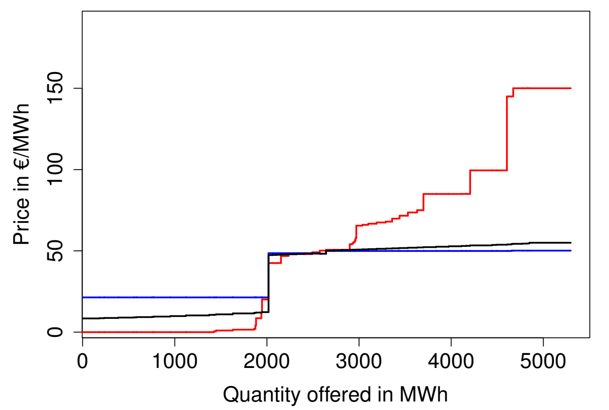
(a) *Iberdola*



(b) *EDP*



(c) *Naturgy*



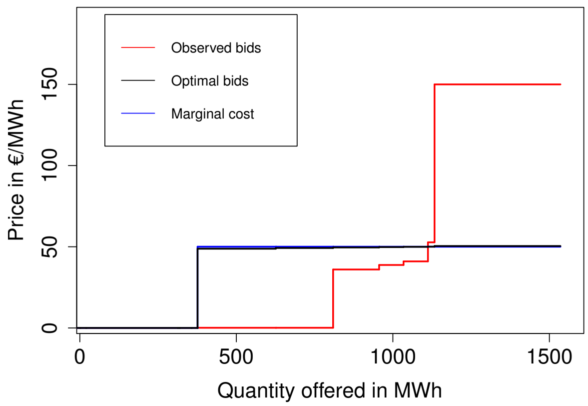
(d) *Endesa*

Figure 2: Large firms, hour 17 on 01/11/2017. Estimated marginal costs curves (blue), observed supply curves (red) and counterfactual optimal supply curves (black).

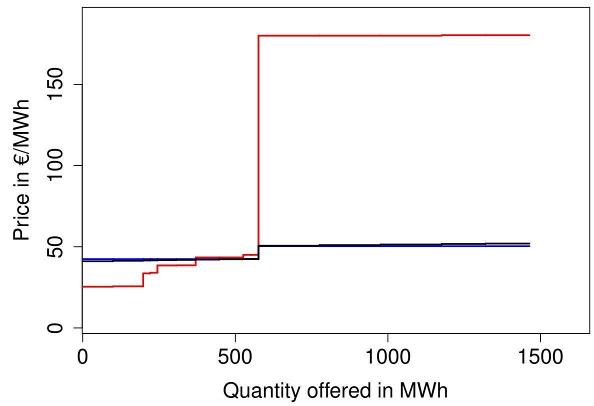
bidding schedules.

Panel (a) of Figure 4 displays our results and corroborates our findings. As shown, for larger firm size, the mean performance of the firms in our sample increases. Small firms, such as Cepsa, REN, and Engie leave substantial profits on the table, while the intermediate and large companies are performing substantially better. Especially Iberdrola, a traditionally large market player, displays close to optimal pricing behavior and shows high strategic ability.

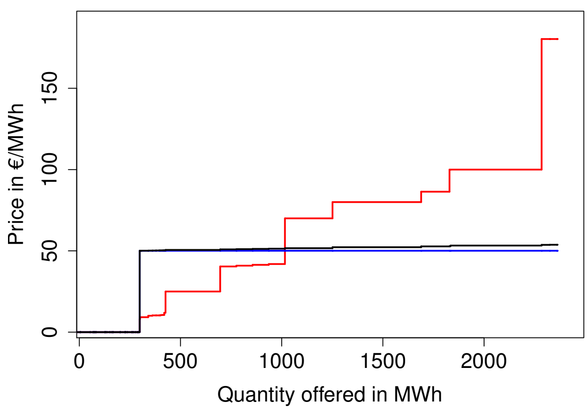
To illustrate the market impact of this heterogeneity in pricing strategies, Panel (b) of Figure 4 displays the impact on market prices when a company follows optimal bidding



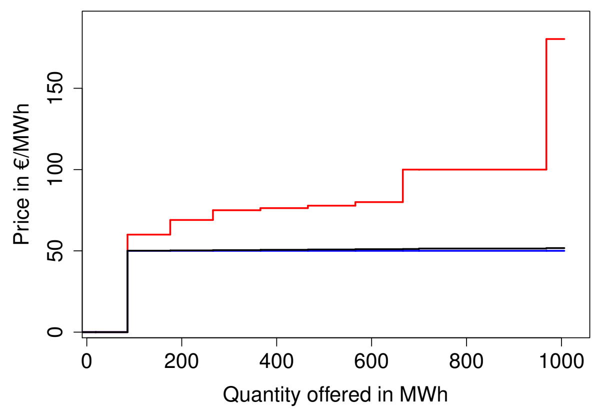
(a) *Cepsa*



(b) *REN*



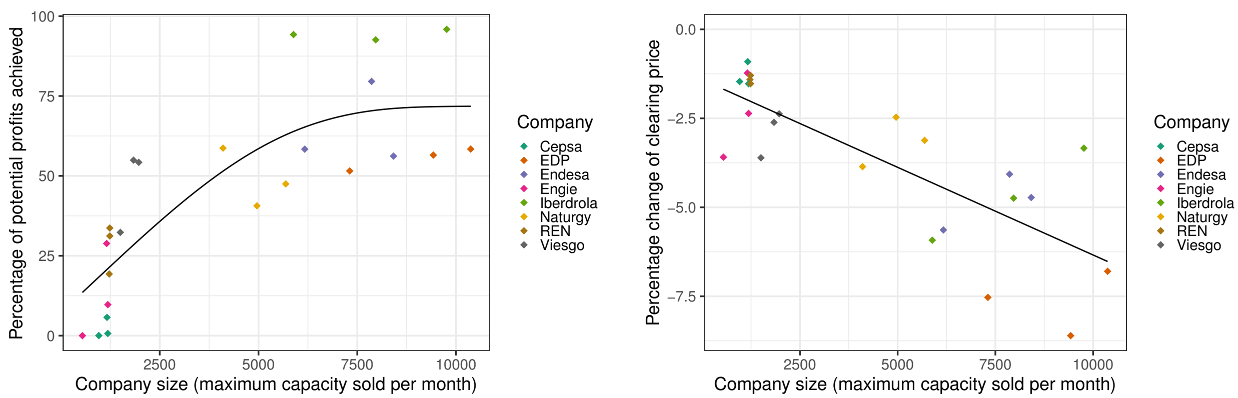
(c) *Viesgo*



(d) *Engie*

Figure 3: Small firms, hour 17 on 01/11/2017. Estimated marginal costs curves (blue), observed supply curves (red) and counterfactual optimal supply curves (black).

strategies. As shown, optimal pricing behavior would result in lower market prices for each firm. This is because optimal supply functions would imply more aggressive pricing. Furthermore, Panel (b) of Figure 4 shows that the price impact of optimal behavior by large firms is higher when compared to smaller firms. Hence, although larger firms tend to show more sophisticated pricing, their pricing strategies are pivotal for the market outcome so that even small improvements have large impact on market prices and rents. As such, we find that both, small deviations by large firms, and large deviations by smaller firms, can have large consequences on the market outcomes. Our findings therefore demonstrate that the observed and excessively steep supply curves of producers not only harm firms' own profits,



(a) **(b)**

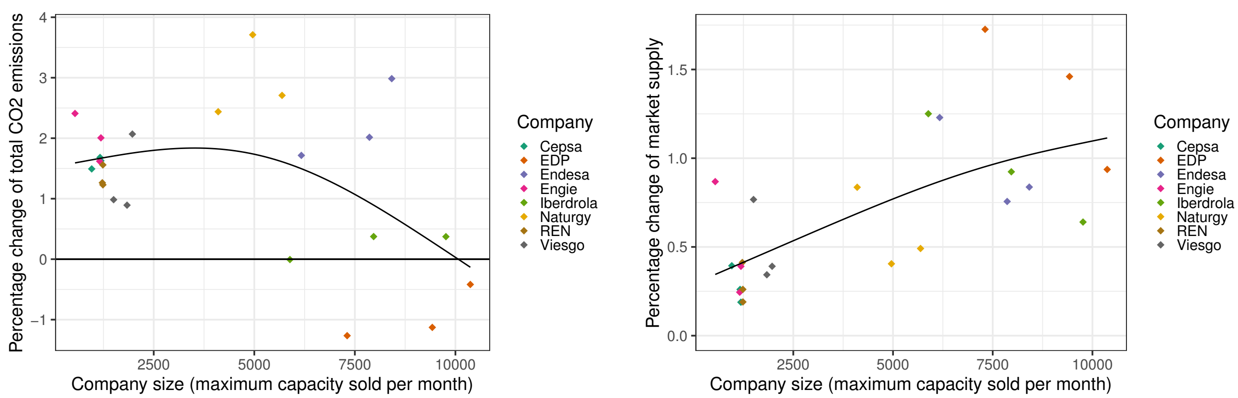
Figure 4: Panel (a) shows achieved profits in percent of counterfactual optimal profit, observations show monthly means. Panel (b) shows the effect of optimized bidding on clearing prices, observations show monthly means. Firm size is measured as maximum hourly output within a month.

but at the same time cause substantial cost for society due to inflated market prices.

6.1 Carbon emissions

Next, we investigate the effects of strategic ability on CO2 externalities. Panel (a) of Figure 5 shows counterfactual carbon emissions had firms been behaving optimally. We again plot these counterfactual emissions as percentage to actual emissions and against company size on the horizontal axis. As can be seen, carbon emissions within the market increase, except for optimized bidding of Iberdrola. The increasing market emissions are largely driven by the fact that firms optimal supply functions are more aggressive and firms' electricity production hence increases under optimal bidding. To confirm this, Panel (b) of Figure 5 shows that, irrespective of firm size, more electricity is traded in the market when firms submit optimal bidding schedules. This effect is more pronounced for large firms as their impact on market outcomes is larger. Hence, the increase in carbon emissions largely stems from an output effect.

Furthermore, Figure 5 shows significant differences in the impact on overall carbon emissions. To probe into the firm-specific differences, we investigate firms carbon intensity of generation. Table 3 displays the carbon intensity of production by each company and for observed and counterfactual optimal supply. Clearly, some firms rely on more carbon-intensive production than others. As can be seen, for most companies the CO2 intensity decreases upon expanding supply. This is because firms start using hydro and additional gas-fired supply at the margin, adding to their otherwise coal and renewable based supply.



(a) **(b)**

Figure 5: Panel (a) shows the effect of counterfactual optimal bidding on overall carbon emissions. Panel (b) shows the effect of counterfactual optimal bidding on overall quantity. Observations show monthly means. Firm size is measured as maximum hourly output within a month.

However, market-wide carbon emissions are also driven by a substitution effect: A firm that bids more aggressively crowds out its competitors. Hence companies with relatively high CO2 intensity, when bidding more aggressively, push cleaner and less carbon-intensive supply out of the market. Notably, and as shown in Panel (a) of Figure 5, when Endesa and Naturgy increase supply and bring more of their carbon intensive production to the market, overall emissions significantly increase. This explains the high magnitudes shown for these two firms in Figure 5. Conversely, Iberdrola and EDP bring relatively low carbon technologies into the market, decreasing the emission intensity of their production and of the overall market.

Table 3: CO2 intensity of production prior to and after optimization.

	EDP	Iberdrola	Endesa	Naturgy	Viesgo	Engie	REN	Cepsa
CO2-int. [g/MWh]	379	204	706	535	275	161	680	169
CO2-int. o. [g/MWh]	303	191	608	487	258	314	592	234

Notes: Sample from 01/10/2017 to 31/12/2017 for hours 17, 18, and 19. Carbon intensity of fossil production in our sample ranges between 337 g/MWh for the most efficient natural gas power plant and 1151 g/MWh for the least efficient coal power plant.

In sum, our analysis reveals that the welfare increasing effects of optimized bidding on quantity and prices come at the cost of potentially increasing carbon emissions, as shown in Figure 5. The magnitude of this effect is moderated by the firms' relative carbon intensities. If large and clean companies, e.g. Iberdrola, engage in optimal and more aggressive bidding, overall CO2 externalities can decline.

6.2 Robustness

Our previous analysis hinges on a set of implicit assumptions that we briefly address in this section. First, our analysis is based on the assumption that firms have accurate expectations regarding the slope of the residual demand curve they face. To show that our findings are not contingent on this assumption, we rerun our analysis with residual demand slopes from past demand realizations. Specifically, we assume that market patterns reoccur and allow firms to form reasonable expectations. We assume that patterns reoccur on a weekly basis, i.e., firms are able to learn from observations during the last week. To implement this robustness test, we use the residual demand realization on the same weekday and hour from the previous week instead of the actual realized demand slopes. We use these slopes for our optimality conditions and rerun our analysis. Our central findings remain unchanged, as shown in Figure A.1 in the Appendix. Though magnitudes differ slightly, the positive relationship between firm size and strategic ability prevails. Similar to achieved profits, also the results on carbon emissions are almost unchanged, as shown in Figure A.1 in the Appendix.

A further assumption in our analysis relates to our marginal cost estimates. For instance, the cost measures could be flawed as they are defined as incremental marginal cost that neglect start-up cost. We solve this problem by means of sampling and, in the empirical analysis, solely include afternoon hours (17, 18, and 19). These hours exhibit relatively low demand levels but are nestled in high demand hours. Thereby we ensure that start-up cost do not arise in our sample. In line with this approach, Reguant (2014) shows that for the chosen afternoon hours, start-up cost do not impede correct estimation of mark-ups. We hence view start-up costs to be negligible in our sample.

In addition, we employ a bottom-up approach to estimate marginal cost of thermal power plants, where we use engineering estimates for each plant and then fit a marginal cost curve. To that end we make use of an isotonic regression. To ensure that our results are not driven by the fitting of the marginal cost curves, we tested other fitting approaches, i.e. with a polynomial fit with various degrees of freedom and a monotonously increasing step function. Again, our results remain unchanged.

Last, electricity trading is organized in sequential markets. We study the day-ahead market. Yet, firms could exploit systematic price differences between the day-ahead and subsequent intraday markets as discussed in Ito and Reguant (2016). To rule out systematic arbitrage in our sample, Figure A.2 in the Appendix shows price differences between the day ahead and the intraday market. Differences are neither systematic, nor substantial. The mean price difference accrues to -0.55 €/MWh. On average, prices are thus slightly higher in the day-ahead market. This is in line with the findings of Ito and Reguant (2016) for their 2010 to 2012 sample. Following their rational, dominant suppliers hold back capacity in the day-ahead market, whereas fringe firms are overselling to profit from a price premium. However, we observe that especially smaller firms are holding back a relatively higher quantity (submitting excessively steep supply curves) as compared to large firms. Our findings can thus not be rationalized by the presence of subsequent trading opportunities, either.

6.3 Estimating the Effect of Mergers on Sophistication and Externalities

Lastly, we compute policy-relevant counterfactuals. In particular, we investigate the role of strategic ability and CO2 emissions in merger policy. The main idea is that when two companies merge, they will consolidate their strategy and trading departments. In turn, we consider counterfactuals where the merged company's strategic ability is determined by the more sophisticated firm participating in the merger. We are interested in the market outcomes ex-post of the merger and the effect on CO2 emissions.

In line with this approach, we merge a large, i.e. sophisticated, and a small, i.e. less sophisticated firm. To determine in how far firms follow the optimality condition in equation (6), we first estimate the first order condition for all companies in our sample. Our theoretical prediction is that firms set their mark-up such as to satisfy equation (6) for each submitted bid in period t. Observing all variables of equation (6), we calculate the mark-up on the left-hand side of equation (6) and the ratio of the market supply to the residual demand slope on the right-hand of equation.[13] We then, for each company i, estimate

$$p_{it} - C'_{it}(S_{it}(p)) = \beta \, \frac{S_{it}(p) - F_{it}}{-RD'_{it}(p)} + \epsilon, \tag{11}$$

where theory predicts $\beta = 1$. Where a company's β is above (below) 1, this company submits too steep (too flat) supply functions.

Table 4 summarizes the results of the linear regression, where we order firms according to their size. As expected, the coefficients of larger firms are closer to one than those of smaller firms, corroborating our earlier findings.

For our merger counterfactual, we then choose Iberdrola as a large firm that depicts relatively efficient bidding, and Engie, whose β coefficient in Table 4 indicates less sophisticated

[13] To make sure that we only include relevant bids with a positive probability to be price-setting, we only use bids within the 95% quantile of the observed clearing prices.

Table 4: Deviation from optimality.

	EDP	Iberdrola	Endesa	Naturgy	Viesgo	Engie	REN	Cepsa
β coefficient	2.56	1.37	0.94	1.80	9.18	30.54	4.70	190.23
Observations	8283	5397	6915	29144	134	1164	2090	112

Notes: Mark-up as dependent variable, coefficient is defined as inframarginal quantity over -RD'.

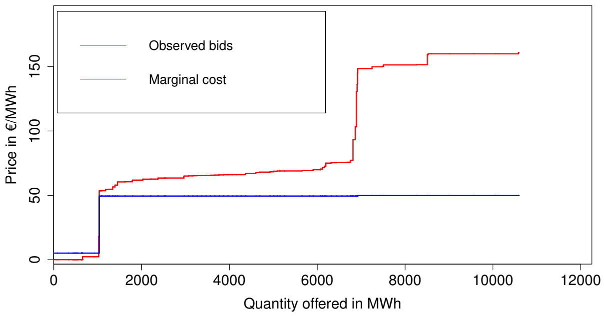
bidding behavior. Furthermore, recalling our discussion on the firm's production portfolios, Iberdrola owns a relatively diversified portfolio, whereas Engie operates renewable assets and gas-fired power plants. To compute the merger case under our assumption that the more sophisticated firm determines the "new" bidding strategy, we combine the production portfolios of Iberdrola and Engie and use Iberdrola's β coefficient of 1.37 in Table 4 to construct the joint supply curve ex-post the merger. This is, we use equation (11) and set $\beta = 1.37$ to obtain the counterfactual merged supply function, holding all other firms' strategies constant.

Table 5: Effect of merger on market outcomes and CO2 emissions

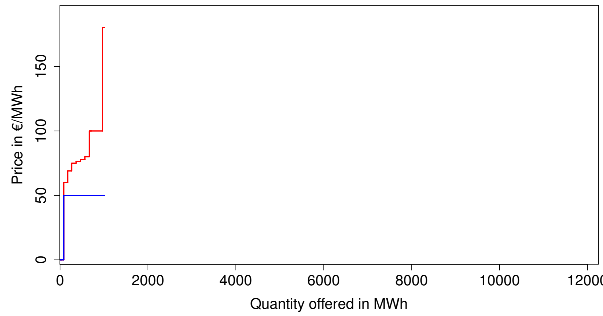
Week	Profits (firm)	CO2 (firm)	CO2 (all)	CO2 int. (all)	Quantity (all)	Price
1	164.27	124.69	99.40	97.45	102.09	94.82
2	84.55	108.04	99.47	98.61	100.89	93.31
3	98.80	128.68	100.03	99.27	100.69	93.36
4	102.42	127.61	100.35	99.10	101.35	93.79
5	122.87	125.56	101.77	100.72	101.05	94.99
6	136.57	105.46	99.48	98.56	100.86	96.06
7	99.47	108.59	100.46	99.57	100.85	95.42
8	99.52	110.10	100.15	99.05	100.95	93.98
9	94.43	108.97	100.63	99.29	101.20	94.79
10	100.54	103.88	100.17	98.74	101.43	95.44
11	92.84	107.22	100.24	99.94	100.25	95.73
12	109.01	111.14	100.64	99.62	100.93	93.81
Overall	100.81	112.20	100.28	99.21	101.00	94.82

Notes: All numbers are in percentage terms and reflect outcomes for the merger case as compared to original market outcomes with two distinct companies (Iberdrola & Engie)

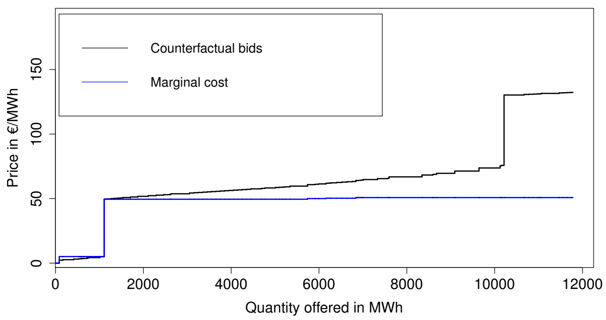
Figure 6 shows the original and counterfactual market supply for the two merged firms. In Panel (a) and (b) original supply curves are displayed in red and underlying marginal



(a) Iberdrola



(b) Engie



(c) Merged firm

Figure 6: Results for hour 17 on 01/11/2017. Panel (a) and (b) show observed bids and marginal cost for Iberdrola and Engie when both firms act individually. Panel (c) shows marginal cost and counterfactual bids of the newly merged company. For counterfactual bids we assume the merged firm features the mean strategic ability of Iberdrola ($\beta = 1.37$).

cost in blue. Panel (b) shows the submitted supply bids of Engie. Apart from neglectable renewable sales, Engie prices all its efficient, low-carbon gas-fired production out of the market by submitting an excessively steep supply function to the market. In Panel (c) we show the counterfactual supply function of the merged firm, displayed in black. The merged firm features the level of sophistication of Iberdrola and submits a nearly optimal supply function to the market. The efficient natural gas power plants of Engie are now integrated in the production portfolio of the merged firm and exhibit an increased probability to be called for production. This contributes to increased market efficiency and a lower carbon intensity of production.

Using the counterfactual supply curves for the merged company, we compare market outcomes with the merger to the observed market outcomes, i.e. the case where the two firms act independently. Table 5 summarizes our results. We aggregate market outcomes at a weekly level. Our counterfactual calculations show that the merger pays off and overall profits slightly increase upon merging, as shown in column one. Yet, also the CO2 emissions of the merged company increase as compared to the sum of both individual firms, as depicted in the second column of Table 5. The emission intensity of production decreases, thereby counteracting the effect of increased quantity sold in the market. Overall, our results suggest that the merger would increase market efficiency due to higher quantity sold at lower prices. As emissions are not significantly increased, our analysis shows that in this case a merger is beneficial for producers and consumers, while not significantly increasing overall CO2 emissions in the market.

7 Conclusion

Standard microeconomic theory suggests that all market participants are able to maximize profit, e.g. by choosing optimal prices. Recent findings in behavioral industrial organization however suggest that differences in firm characteristics can lead to heterogeneity in firms' strategic sophistication (Hortaçsu et al., 2019). As a result, the lack of strategic ability can be costly and further deteriorate market efficiency. The consequences of (a lack of) strategic ability on market externalities have received little attention in the extant literature.

In this paper, we have studied the impact of strategic ability on pricing and resulting market externalities. Our empirical setup exploits rich firm level data on the Spanish day-ahead electricity market. Using observed pricing strategies, we have found that especially small firms deviate substantially from optimal pricing rules and create market inefficiencies. We have also identified that deviations from optimality can substantially impact the market's CO2 emissions. In particular, emissions are inefficiently high when "clean" firms price low-carbon production out of the market due to a lack of strategic sophistication.

To propose policy counterfactuals, we investigate the effects of a potential merger between a sophisticated and a non-sophisticated company. Overall welfare impacts are substantial. Importantly, welfare gains come at no significant increase in overall CO2 emissions. Instead, the carbon intensity of the market declines. Our empirical method can serve as a first and easily applicable test of the effects of potential mergers on market externalities.

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Appendix

A Model and first-order condition

Rewriting expected profits in equation (2) as $\mathbb{E}[\pi_i] = \int_{\underline{p}}^{\overline{p}} \pi(S_i(p))H_p(p, S(p))dp$, we can integrate by parts and obtain

$$\mathbb{E}[\pi_i] = \pi(S_i(p))H(p) \mid_{\underline{p}}^{\overline{p}} - \int_{\underline{p}}^{\overline{p}} \left[\frac{d}{dp}\pi(S_i(p))\right] H(p)dp.$$

Using $H(\underline{p}) = 0$ and $H(\bar{p}) = 1$ yields

$$\mathbb{E}[\pi_i] = \pi(S_i(\overline{p})) - \int_{\underline{p}}^{\overline{p}} \left[\frac{d}{dp}\pi(S_i(p))\right] H(p)dp.$$

The first term is a constant, so maximizing the integrand of the second term suffices. The derivation then proceeds as in Hortaçsu and Puller (2008) and yields the optimality condition in equation (5).

To derive the cumulative price distribution $H_i(\cdot)$, let the index $-i$ denote aggregate market quantities net of firm i. Then, the probability that the clearing price p^* is below any price p can be written as the probability that supply is larger than demand at price p:

$$\begin{aligned} H_i(p, S_i) &= Pr\left(S_{-i}(p) + S_i > D(p) + \varepsilon \mid S_i\right) \\ &= Pr\left(-\varepsilon > D(p) - S_{-i}(p) - S_i \mid \hat{S}_i\right) \\ &= 1 - F_i\left(D(p) - S_{-i}(p) - S_i \mid S_i\right), \end{aligned} \tag{12}$$

where F_i is the cumulative distribution function of $-\varepsilon$. The derivatives are

$$H_S = \frac{\partial H_i}{\partial S_i} = -f_i(D(p) - S_{-i}(p) - S_i)\frac{\partial}{\partial S_i}\left(D(p) - S_{-i}(p) - S_i\right)$$

and

$$H_p = \frac{\partial H_i}{\partial p} = -f_i(D(p) - S_{-i}(p) - S_i)\frac{\partial}{\partial p}\left(D(p) - S_{-i}(p) - S_i\right).$$

Hence we can write

$$\frac{H_S(p, S^*(p))}{H_p(p, S^*(p))} = \frac{1}{RD_i'(p)},$$

with $RD_i'(p) = -\frac{\partial}{\partial p}\left(D(p) - S_{-i}(p)\right)$ being the slope of firm i's residual demand.

B Marginal cost

Table A.1: Overview of variable cost input data for coal and gas-fired generation.

Data type	Content	Scope	Source
Plant efficiencies	Plant-specific efficiency figures where possible; or else average efficiencies acc. to year of commissioning	All coal/ gas-fired plants bid into the day-ahead in 2017	Global Energy Observatory
Coal prices	Daily spot prices for imported coal	2017	Bloomberg MFE1 COMB
Natural gas prices	Daily spot prices for gas prices in the Iberian gas market	2017	MIBGAS Data 2017, product GDAES_D+1
EUA prices	Daily spot prices for EU-ETS allowances (EUAs)	2017	Bloomberg EEXX03EA
National environmental taxes	1) Taxes on use/ disposal of input resources 2) Energy generation tax (all technologies)	Power plants on Spanish territory; Rate levels of 2017	Ley 15/2012 Ttulo I, Ttulo III; Comisión Nacional de Energía (2013)
Clawback rate	Charge to compensate for unequal tax burdens	Power plants on Portuguese territory; Rate levels of 2017	Decreto-Lei n. 74/2013 Artigo 1.; EDP (2018)
Variable O&M costs	Median variable O&M costs per MWh	Coal and gas-fired plants, dataset of 2015	IEA (2015)

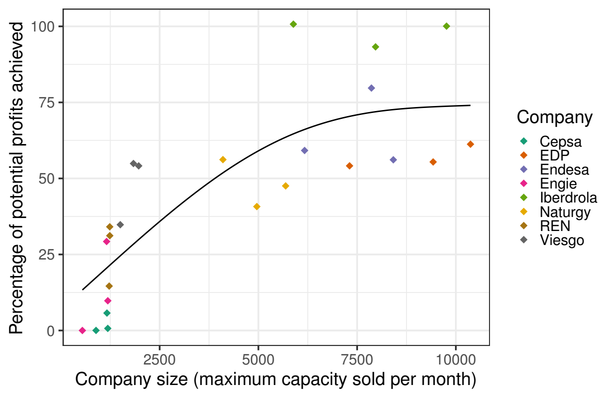
Notes: We abstract from additional variable cost factors that may be attributed to start-up or ramping cost.

Table A.2: Overview of magnitudes of parameters applied in the marginal cost estimation.

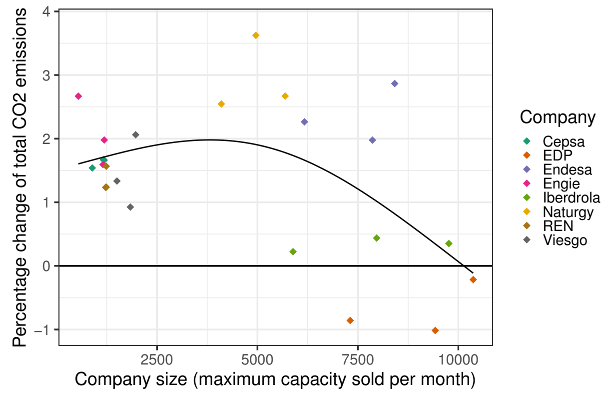
Data type	Value	Source
Clawback charge Portugal	6.50 € /MWh until 16.11.2017 4.75 € /MWh as of 17.11.2017	Decreto-Lei n. 74/2013 Artigo 1.; EDP (2018)
Energy generation tax Spain	7 % of revenue	Ley 15/2012 Ttulo I
Fossil fuel consumption tax Spain	0.65 € /GJ	Ley 15/2012 Ttulo III
Variable O&M cost coal	2.52 € /MWh	IEA (2015)
Variable O&M cost gas	3.18 € /MWh	IEA (2015)
Net calorific value hard coal (averaged for Spains main import origins Russia, Colombia, Indonesia)	7.333 MWh/ton	United Nations (2015)

Notes: The Portuguese clawback mechanism limited cost differences but failed to completely compensate taxation in Spain.

C Figures



(a)



(b)

Figure A.1: Panel (a) shows achieved profits applying past residual demand realizations, observations show monthly means. Firm size is measured as maximum hourly output within a month. Panel (b) shows the effect of optimized bidding on overall carbon emissions, applying past residual demand realizations, observations show monthly means. Firm size is measure as maximum hourly output within a month.

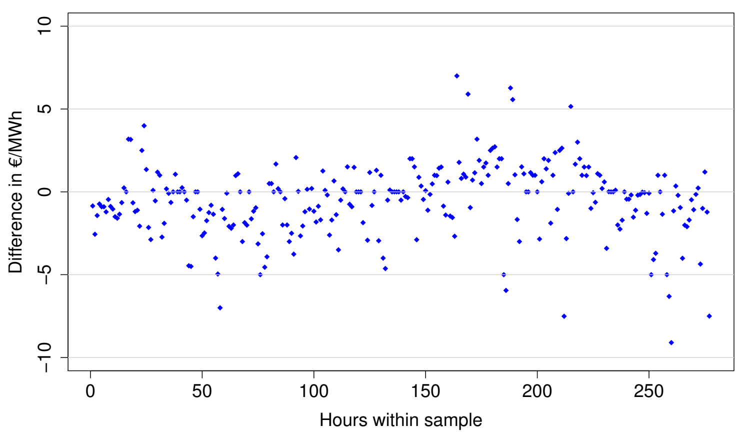


Figure A.2: Difference between clearing price in first intraday market and day-ahead market