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Competition Policy And Market Design In Low-Carbon Energy Markets

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Abstract

Recent decisions on more ambitious climate targets increase pressure on power markets to accelerate the decarbonization process. In this quickly changing and complex market environment, challenges for regulators are manifold. Besides guaranteeing security of supply and reasonable prices of electricity, regulators aim at incentivizing the transition to a low-carbon power market. In this thesis, I demonstrate that, to design optimal policies, regulators need to account for strategic behavior of power producing companies. In particular, I show how to design effective policies to foster both, decarbonization and market efficiency.

First, I demonstrate how firm behavior and market outcomes are shaped by different types of renewable support policies. I show how policy makers can reconcile effective support for renewable power production with increased market efficiency by considering implications on firms' incentives to abuse market power. Second, I investigate the relationship between firm behavior and carbon intensity of power production. I extend the link between a firm's size and its ability to behave optimally in complex market environments by implications on CO2 externalities. Thereby, I provide regulators with a tool to assess changes in market structure with regards to effects on firm-specific and market-wide CO2 emissions. Third, I show how to improve automated procedures to mitigate market power in power markets. In particular, I suggest new designs for the estimation of marginal production cost. Refined mitigation limits the redistribution of rents from consumers to producers and increases market efficiency.

My thesis provides policy makers with insights on the behavior and strategies of firms and presents ways to foster both market efficiency and decarbonization by appropriate competition policy, market design, and regulation.

Contents

List of Figures

List of Tables

1 Introduction

1.1 An Industry in Transition

In this introduction I motivate my research on the role of regulation and market design for the transition to a low-carbon power market. First, I present a short review on the development of liberalized power markets, associated challenges, as well es regulatory solutions in an European and US context. Then, I give an overview on current efforts to decarbonize power markets, emphasizing the crucial role of regulatory design for a swift and efficient transition. I proceed with a brief outlook on future developments in power markets before concluding the chapter with a summary of my main contributions and an outline of the distinctive research questions I address in this thesis.

1.1.1 Restructuring of Power Markets

Secure and affordable electricity provision is a crucial prerequisite for almost all forms of economic activity, from industrial purposes and services to transport and housing. Well functioning power markets are thus of utmost importance for ongoing economic development. In this first section, I line out how power markets developed over the last decades, discuss problems of the respective market designs and present regulatory solutions to misguided developments.

Within the last 30 years, power markets around the globe have been subject to radical change. Originally, power provision was organized by mostly state owned, vertically integrated companies that controlled the whole value chain from generation and transmission to retailing. These monopolistic utilities delivered electricity at mostly fixed, regulated prices. In the light of positive experiences from privatization of airlines and telecommunication, a period of privatization and liberalization in power markets was initiated in the late 80s and early 90s. Privatization and deregulation indeed proved to be effective in reducing cost and increasing productivity (see e.g. Newbery and Pollitt, 1997, Davis and Wolfram, 2012) but not necessarily in achieving lower prices for consumers (Newbery, 1997).

One of the first markets to be deregulated was the electricity market in England and Wales, where the government unleashed market forces in anticipation of increased efficiency and diminished prices for end consumers. In the course of the restructuring process, initiated in 1990, the government set up a wholesale spot market where the newly formed private companies were to sell their electricity. The market was organized as a multi-unit uniform-price auction and competition among producers was expected to ensure efficient market outcomes. In the first years after restructuring, market entry was substantial, but overall market concentration remained high. Even more importantly, the market clearing price was almost exclusively determined by the two dominant firms National Power and PowerGen, laying the foundation for market power exertion.

Scholars extensively debated both, advantages and disadvantages of the newly established market, mainly focusing on price formation and price levels, distribution of rents, and the occurrence of market power. Green and Newbery (1992) and Green (1996) build on the supply function equilibrium as described by Klemperer and Meyer (1989) and identify large potential for market power exertion that could, however, be mitigated by divestitures. In their characterization of the multi-unit auction, von der Fehr and Harbord (1993) highlight the discrete nature of supply bids, but likewise confirm the finding of substantial above marginal cost pricing. Lastly, Wolfram (1998) analyzes incentives for strategic behavior and finds empirical evidence of market power exertion.

In the late 90s, several US power markets nonetheless followed the British example of deregulation. The most prominent case is the restructuring of the Californian electricity market in 1998. Borenstein et al. (1999) quantify the degree of market power exertion by suppliers in the novel spot market. For their sample in 1998, they find substantial deviations of firms' offers from competitive, price-taking behavior, especially in high-demand hours. Triggered by increasing fuel prices and load as well as deficient market design, the Californian market experienced a period of very high electricity prices and frequent blackouts in the years of 2000 and 2001, also known as the California electricity crisis.

However, the performance of the restructuring process in the US differed substantially across markets. Bushnell et al. (2008) compare three liberalized US power markets, namely the Californian market (CAISO), the New England market (ISO-NE) and the Pennsylvania-New Jersey-Maryland Interconnection (PJM), and find that vertical integration of firms has a mitigating effect on market power exertion. When firms are active on both sides of the market, simultaneously acting as sellers and buyers, their incentives to inflate market prices artificially are reduced. This is similar to the mitigating effect of forward contracting on market power exertion (Allaz and Vila, 1993). In the Californian market, vertical integration was not permitted due to concerns of missing transparency. In hindsight, this lack of vertical integration turned out to be a major driver of the Californian electricity crisis.

The early experiences of electricity market restructuring hence have shown that appropriate market design and regulation of spot and forward markets are essential for efficient power markets. Apart from regulation of markets, recent developments in the Texas electricity market highlight the need for immediate regulation of electricity production units to ensure security of supply.

In February 2021, a winter storm coming with particularly low temperatures had induced high demand for heating in Texas. At the same time, substantial parts of the fossil fuel infrastructure (including power plants, refineries and pipelines) lacked appropriate weatherproofing. Power plants accordingly needed to shut down or reduce output, thereby aggravating the scarcity and letting prices surge to the price cap. The missing weatherproofing of power plants had already turned out to be problematic during a similar winter storm in 2011. However, protecting power infrastructure against these rare weather events seems not to be in the economic interest of the companies' stakeholders as cost are high and the forgone losses during potential outages moderate. In the aftermath of the 2011 incident, regulators failed to enforce appropriate weatherproofing, allowing history to repeat. This example shows that, to safeguard reliable power supply, additional regulations are required that demand resilience of production units to external shocks such as weather conditions, fuel shortages, or cyber threats.

As discussed above, research on the UK spot market has identified substantial scope for price manipulation by large suppliers, highlighting the need for mitigation of undue market power exertion. Potential mitigation strategies include the implementation of price caps (Wilson, 2000) and stringent application of antitrust policies, such as the enforcement of divestitures, splitting of large generating companies, or prevention of mergers (Green, 1996, Borenstein et al., 1999).

The example of the Californian electricity crisis has revealed the prominent role of vertical integration for the reduction of market power exertion (Bushnell et al., 2008). Regulators can employ this mitigating effect on market power by fostering vertical integration (Mansur, 2007, Bushnell et al., 2008) or implementing forward contracting obligations for electricity suppliers (Allaz and Vila, 1993, de Frutos and Fabra, 2012).

1.1.2 Decarbonization Efforts

Previous research on liberalized power markets, as well as regulation and market design, mainly focused on market efficiency and market power. For the coming years, however, the central issue for both, researchers and regulators, is the efficient decarbonization of power markets. In the following, I present the main challenges as well as regulatory solutions for a rapid decarbonization of power markets.

The first step to achieve a reduction of emissions is the internalization of externalities from fossil fuel consumption. This mainly refers to external cost from carbon emissions but also includes externalities from more local pollutants such as particulates, sulfur oxides, and heavy metals. To achieve efficiency and warrant a level playing field for competition among technologies, CO2 emissions should be priced at the social cost of carbon (SCC). The exact level of the SCC is heavily debated as the underlying derivation in Integrated Assessment Models (IAM) such as the DICE model (Nordhaus, 2017) is very sensitive to changes of the employed discount factors and risk parameters. Recent estimates locate the appropriate price level at about 100 $/ton of CO2 (Pindyck, 2019, Stern and Stiglitz, 2021). Current national pricing policies for carbon emissions in power markets, if existent, clearly fall below this value.

Appropriate pricing of carbon emissions is either achieved by introduction of a tax on emissions, or by implementation of a cap and trade mechanism where the price is determined by market forces. The European Union Emission Trading System (EU ETS) represents the largest emission trading system for greenhouse gas emissions. Up to the year 2017, the EU ETS failed to provide a reasonable price band for emissions due to excessive distribution of allowances and a consequential oversupply of certificates, leaving cheap mitigation opportunities on the table. Since the announcement of reforms and more ambitious European greenhouse gas reduction targets for the year 2030, prices increased significantly.

To counter inefficiently low certificate prices, policy makers can also set minimum price levels for emission allowances. Following the 2013 adoption of a Carbon Price Floor (CPF) as a supplement to the EU ETS in the UK, a fuel switch from coal to natural gas induced strong emission reductions (Wilson and Staffell, 2018). The CPF defined a minimum price for carbon emissions initially set at about 18 euros per ton. Even though relative fuel prices are likewise important for the occurrence of a fuel switch to less carbon intensive power production from natural gas, the current prices of the EU ETS should be sufficient to trigger a similar development in the EU. Meanwhile, cap-and-trade systems find wide adoption around the globe. In the US the Regional Greenhouse Gas Initiative (RGGI) on the eastern coast and the Californian Cap-and-Trade program are the first large scale systems, with several others currently under construction. Same applies to the largest carbon emitter China, where trading in a national cap-and-trade system covering the power market is expected to start within 2021 (World Bank, 2020).

Apart from strengthening the competitiveness of low-carbon technologies by appropriate pricing of high-carbon alternatives, many governments have large scale policies in place that support low-carbon power production immediately (Reguant, 2019). The bulk of support is targeted at wind and solar power, but there likewise exist subsidies for bio energy, geothermal energy or other renewable sources. Renewable support comes in various different forms, with the most widespread policies being direct payments per unit of produced electricity. These payments are either designed as a market-independent fixed remuneration in the form of feed-in-tariffs, or as payments which are granted on top of the market price in the form of feed-in-premiums. Other governmental policies include support for R&D expenditures directed at desired technologies, tax credits, portfolio standards, and green certificates.[1]

Especially fixed tariffs proved to be very effective in promoting investments into renewable production capacity. However, potential over-subsidization leads to excessive investments and high expenditures, which are ultimately borne by consumers. Within the last years, policy makers thus increasingly adopted renewable auctions to control the amount of capacity additions and expose potential investors to market forces. Given a sufficient level of competition, these tenders ensure cost-minimizing provision of renewable capacity. Even though renewable support is generally costly for consumers, there are substantial positive externalities from renewable investment that justify the introduction of subsidies. Increased demand for a subsidized

[1]For a detailed review of renewable support mechanisms, see Batlle et al. (2012).

technology entails returns to scale in manufacturing and incentivizes additional expenditures in R&D. Plummeting costs, in turn, increase the technologies' competitiveness and reduce the need for subsidization. This development was most sweeping for photovoltaics as e.g. shown by Nemet (2006) or Kavlak et al. (2018), but likewise applies to other renewable energies such as onshore and offshore wind power or bio-energy (Rubin et al., 2015). In fact, cost digressions within recent years were sufficiently pronounced to reach cost parity of photovoltaics and onshore wind power with fossil power production, enabling non-subsidized renewable investments in the foreseeable future.

Subsidization entails rising shares of renewable production in power markets and a replacement of conventional, mostly fossil, generation. The substitution of technologies leads to the desired decline in CO2 emissions. At the same time, these emission reductions cause inefficiencies when subsidization is combined with a cap-and-trade mechanism. In this case, subsidy-induced reductions exert downward pressure on carbon prices and in turn provoke relatively higher emissions in other industries. To achieve additional net reductions in CO2 emissions by means of subsidies for renewable energies, the amount of emission certificates would need to be corrected by a factor that equals the subsidy-induced reductions. For now, no such mechanism has been implemented, casting doubt on the efficiency of climate policy, particularly in Europe.

The two main properties that distinguish renewable technologies like solar and wind power from conventional power production are the next to zero marginal cost and the intermittent nature of production. Increasing market penetration of renewables shifts the supply of conventional power plants to the right, thereby exerting downward pressure on market clearing prices. This phenomenon is better known as the merit-order effect (MOE) (Sensfuß et al., 2008). Whereas consumers profit from lower market prices, conventional power producers lose revenues and face difficulties to recover their investments. At the same time, the flexibility of conventional power plants needs to increase in response to intermittent renewables, which further increases economic pressure on conventional production.

1.1.3 Outlook on Future Developments in Power Markets

Power markets face considerable challenges in the years to come. After transitioning from state controlled monopolies to liberalized markets, these markets are now in disturbance due to increasing penetration of intermittent renewable generation. Policy makers will need to decide whether they loosen the grip on power markets and realize their targets by clever market design and faith in market forces, or increase control and ensure security of supply and decarbonization by extended regulatory intervention.[2] There are two recent papers that elaborately discuss the current challenges for market design and regulation in power markets. Whereas Newbery et al. (2018) primarily focus on European power markets, Joskow (2019) adapts his analysis to the particularities of US power markets. In both cases, the authors identify considerable room for improvement in current policies and show ways how existing regulations and market design can be amended to better address peculiarities of low-carbon power markets.

[2]Bublitz et al. (2019) conduct an extensive review on current market designs around the globe, summarize existing literature and discuss current challenges.

1.2 Contribution

Appropriate market design and sensible regulation are crucial preconditions for efficiently working power markets. In my thesis I contribute to a better understanding of various aspects of regulation and market design and thus, ultimately, to well-informed policy making. I present research on the efficient design of renewable support policies and second order effects on firm behavior. If not considered by policy makers, regulatory intervention in the form of renewable support can foster market power exertion, entailing higher policy cost and efficiency losses. The crucial role of firm behavior and especially the deviations from optimal behavior receive increasing attention by scholars (see e.g. Hortaçsu and Puller, 2008, Hortaçsu et al., 2019). In my research, I make use of these differences in firms' behavior to affect the sector's carbon emissions. Establishing a link between firm size and firm behavior, I argue that policy makers can reduce carbon emissions by controlling the size of firms. Firm behavior is likewise central to understand how market power can best be addressed by regulators. My research contributes to pressing issues in power markets, offering advice on the efficient support of renewable power production, reduction of the sector's carbon emissions, as well as control of undue market power exertion.

A common aspect of the essays presented in this thesis is the underlying data that stems from the Iberian wholesale electricity market and has found wide application in the literature (see e.g. Fabra and Toro, 2005, Ciarreta and Espinosa, 2010, Reguant, 2014, Fabra and Reguant, 2014, Ito and Reguant, 2016, Ciarreta et al., 2017). Due to the exceptional data availability and quality I employ the detailed micro-level bidding data in all of the three essays. In the following, I give a short summary of the three chapters that present my research and address distinct aspects of regulation and market design.[3]

1.2.1 Renewable Support and Strategic Pricing in Electricity Markets

The first essay presented in this thesis investigates the effect of market design on firm behavior and, ultimately, market prices. Support for renewable energies comes in different forms and the choice of mechanism affects the behavior of market participants.

[3]For better readability, I use the first person singular when referring to chapter 2, 3, and 4, even though these chapters are based on joint work with co-authors.

I make use of a regulatory change in the Spanish power market in 2004. Until that year, renewable output was subsidized via a linear “tariff” per unit produced. Renewable production was thus rewarded independently of the market price, yielding revenues equal to its output times the per-unit subsidy. As from April 2004, power generating companies were permitted to chose between the tariff mechanism and a regulatory “premium” granted on top of the market clearing price. As the premium mechanism was designed such as to deliver higher expected payments for the generating company, firms gradually relocated their renewable capacity to the new mechanism and by the end of the year 2005 the bulk of renewable energy production was supported by the market-based premium mechanism.

I show both theoretically and empirically how this transition of renewable supply from fixed out-of-market remuneration to variable market-based remuneration affected the behavior of energy producers in wholesale auctions. A fixed payment in form of a tariff effectively constitutes a forward contract between the producer and the system operator and reduces the incentive for producers to artificially inflate the market price (Allaz and Vila, 1993, Wolak, 2007). Upon switching to the premium mechanism, renewable energy is traded within the market and mark-ups realized at the margin likewise apply to the renewable production.

I investigate how this additional inframarginal capacity shapes optimal pricing conditions for the firms. To that end, I follow the model of optimal bidding under uncertainty developed by Hortaçsu and Puller (2008) which, in turn, is based on the supply function approach of Klemperer and Meyer (1989). Using an adapted version of the model, I demonstrate how renewable remuneration schemes affect optimal pricing strategies under uncertainty.

In my empirical analysis I focus on the pricing behavior of firms at the margin. In line with the model predictions, I find that, upon shifting renewable capacities into the market, firms increase mark-ups. This relocates rents from consumers to suppliers and reduces welfare. I argue that, for an efficient design of renewable support, policy makers should take into account effects on firm behavior and pricing incentives.

1.2.2 Strategic Ability and CO2 Emissions in Electricity Markets

In the second essay, I focus on carbon emissions in the power sector. In comparison to renewable and nuclear power plants, carbon emitting power plants are typically situated in the steeper part of firms' supply functions. Consequently, these power plants predominantly determine the market clearing price and engage in competition.

However, not all firms follow the same strategies upon offering their capacity in the market. Hortaçsu and Puller (2008) and Hortaçsu et al. (2019) investigate bidding strategies in the Texas power market and detect substantial heterogeneity among firms. Whereas large firms submit rational, profit-maximizing supply schedules, small firms appear to be incapable of engaging in optimal bidding. I build on the model described by Hortaçsu and Puller (2008) and analyze the bidding behavior of fossil producers in the Iberian day-ahead market. As compared to the existing literature, I not only quantify effects on firms' profits and market efficiency, but likewise investigate how the sector's carbon emissions are shaped by this heterogeneity in strategic ability.

Theory-wise, I follow the growing literature on unilateral best-response bidding under uncertainty (Wolak, 2000, 2003b, 2007, Hortaçsu and Puller, 2008, Brown and Eckert, 2021). Building on this theoretical foundation, in the empirical analysis, I calculate counterfactual best-response bids for the eight largest carbon emitting power producers in Spain and Portugal. For a three months period in 2017, I subsequently compare the hypothetical best-response bids to actually observed bidding schedules and determine firms' ability to follow profit maximizing behavior.

Additionally, I calculate counterfactual market clearing prices, quantities and CO2 emissions to assess the impact of deviations from optimality. I show that, even though all firms divert from optimality, large firms perform significantly better and are able to realize a larger fraction of potentially attainable profits. As firms offer excessively steep supply functions, i.e. hold back more quantity than optimal, the inability of firms implies higher market prices and lower carbon emissions. Inability of small firms is thus desirable from an emission perspective.

Regulators cannot affect firm behavior directly, but they can control firm size via antitrust policies, i.e. prevent or promote mergers or even split up large producers. Therefore, I show for an exemplary case how regulators could test the implications of potential mergers on firm profits and CO2 emissions. My results thus guide more effective competition policy and contribute to the mitigation of CO2 emissions.

1.2.3 Designing Automated Market Power Mitigation in Electricity Markets

The third essay contributes to improved monitoring and mitigation of market power. Several US power markets make use of algorithms for automated oversight and mitigation of market power in wholesale markets. Within these algorithms, all supply bids submitted to the auctions are analyzed and tested upon potential market power exertion (Twomey et al., 2006, Shawhan et al., 2011). However, to detect undue market power exertion, information on the underlying marginal cost of submitted bids is crucial.

Whereas some variables for marginal cost estimation are publicly available, others like power plant efficiency, ramping cost, or variable operation and maintenance cost are private information. Yet, all information provided by the generators need to be treated with caution as they are better off overstating their costs. To receive genuine marginal cost estimates, system operators thus derive marginal cost from historical supply bids of the respective power plant.

I focus on the methodology applied by the New York Independent System Operator (NYISO), where marginal cost estimates are calculated based on supply bids of the previous 90 days (NYISO, 2020). To assess the accuracy of this approach, I apply it to data from Iberian day-ahead auctions in 2017. Here, I have available all required information on plant characteristics of fossil power plants for a precise, bottom-up calculation of the true underlying marginal cost. I then compare these true marginal cost to the estimated marginal cost from the NYISO approach. As the mean absolute deviation between the true and estimated marginal cost is substantial, I test three, more sophisticated approaches to estimate marginal cost from observed supply bids, all of which considerably outperform the approach currently applied by the NYISO.

My findings allow for considerably improved market monitoring and more targeted mitigation of market power. Additionally, precise marginal cost estimates facilitate research in power markets when a bottom-up calculation is infeasible due to unattainable information on cost components. Lastly, computerized market monitoring is also applicable to other markets, such as air and rail transport. For price monitoring in these markets a more sophisticated derivation of marginal cost estimates likewise improves the quality of surveillance.

1.3 Structure of the Thesis

The remainder is structured as follows. Chapter 2 presents findings on the impact of renewable support mechanisms on firms' pricing strategies and resulting costs for consumers. Chapter 3 sheds light on the interrelation between firm size, strategic ability and associated carbon emissions. In chapter 4, I show how to improve existing algorithms for automated market power mitigation by improving the estimation of marginal cost. Finally, chapter 5 concludes with policy implications of my research and propositions for market design in low-carbon power markets.

2 Renewable Support and Strategic Pricing in Electricity Markets

Moritz Bohland, Sebastian Schwenen[4]

We show how policies to support clean technologies change price competition and market structure. We present evidence from electricity markets, where regulators have implemented different policies to subsidize clean energy. Building on a multi-unit auction model, we show that currently applied subsidy designs either foster or attenuate competition. Contract-based output subsidies decrease firms' mark-ups. In contrast, market-based designs that subsidize clean output via a regulatory premium on the market price lead to higher mark-ups. We confirm this finding empirically using auction data from the Spanish power market. Our empirical results show that the design choice for renewable subsidies significantly impacts pricing behavior of firms and policy costs for consumers.

[4]Author contributions: This essay is based on a joint paper with Sebastian Schwenen. My contribution was, among others, the data gathering and processing, as well as the draft of major parts of the paper.

2.1 Introduction

Governments around the globe are adopting policies to limit climate change. The standard policy instruments include carbon prices, R&D grants, or subsidies for the deployment of "clean" technologies (e.g., Goulder et al., 1999, Acemoglu et al., 2012). While previous research has focused on the market impact of carbon prices and R&D support (e.g., Johnstone et al., 2010, Fabra and Reguant, 2014, Aghion et al., 2016, Calel and Dechezleprêtre, 2016), relatively less is known on how subsidies for clean technology change market outcomes and welfare. In this paper, we address this question by studying the impact of subsidies for clean energy on market outcomes in the power sector.

Support policies for clean technologies are omnipresent in power markets, where many governments have rolled out large-scale programs to subsidize renewable energy.[5] To better understand the impact of subsidies on market outcomes, we contribute by offering a model of pricing behavior under different policy designs. By exploiting detailed firm level data from the Spanish power market, we also investigate welfare effects empirically and find that the design of support mechanisms significantly affects market prices, rents, and as such overall policy costs.

Our model formalizes pricing decisions by firms that produce with "clean", i.e., low-carbon and "dirty" carbon-intensive inputs. The regulator implements a mechanism that establishes an output subsidy for the clean technology. Motivated by existing real-world mechanisms in electricity markets, we investigate two standard designs to reward this subsidy. First, subsidies may come as a linear tariff per unit produced from clean assets. Alternatively, subsidies are implemented via a regulatory premium that clean production earns on top of the market price. In the former mechanism, clean production is rewarded independently of the market price and yields profits equal to its output times the per-unit subsidy. In essence, this mechanism constitutes a forward contract for producing with clean technologies between producers and the regulator. We thus refer to this mechanism as contract-based "tariff".[6] In the alternative mechanism, profits from clean production depend on the equilibrium market price and are topped up by the regulatory premium. We thus refer to this mechanism as market-based "premium". In 2017, these two mechanisms were employed by more than 80 countries worldwide

[5] Next to the power sector, technology-specific subsidies are increasingly used to support low-emission vehicles in the automobile market (e.g., Huse and Lucinda, 2014, Adamou et al., 2014, Gulati et al., 2017).

[6] Also the *contracts for differences* currently applied in the UK represent schemes that rely on fixing output prices. For a more detailed taxonomy of subsidy mechanisms see Batlle et al. (2012).

(IRENA et al., 2018). Our model investigates pricing behavior under these two regimes and allows for both perfect and imperfect competition.

We find that under perfect competition, the design of the support mechanism is irrelevant. However, when firms are able to charge mark-ups, the design of the support mechanism affects market prices and rents. In particular, our results highlight the critical role of market size effects on pricing incentives. Contract-based tariffs decrease market size, as only conventional, carbon-intensive capacity is sold on the market. Consequently, firms that own conventional capacity merely face demand left unsatisfied from clean production. When firms charge strategic mark-ups, they hence face a smaller market, resulting in lower equilibrium market prices. In contrast, when the support mechanism rewards clean production by a premium on top of the market price, the market size remains large. In this case, profits for both clean and conventional technologies are a function of the equilibrium market price, and firms have ample incentives to charge higher mark-ups.

We empirically test this prediction on pricing strategies under different support designs. Next to detailed bidding data from Spanish electricity wholesale auctions, we exploit an institutional change in the support design. In Spain, both the tariff mechanism and the premium mechanism have been applied, where the latter successively replaced the former during the years 2004 and 2005 (Batlle et al., 2012). We conjecture that, following the transition to the premium mechanism, we observe higher equilibrium mark-ups and thus market prices.

We investigate this effect using hourly observations on price-quantity decisions by Spanish power producers. Our empirical findings show that the mark-up significantly increases under the premium mechanism as compared to the tariff mechanism. The magnitude of this effect is economically significant. Counterfactual calculations show that during our period of observation the market-based premium design increased firms' mark-ups on average by about 5%. The policy hence was costly to consumers who had to pay for the regulatory premium and in addition lost rents due to higher mark-ups on the electricity wholesale market.

We also document this effect when focusing on the two largest firms in the market, as especially larger firms with high shares of clean production increased their mark-ups. In addition, we illustrate how the policy change impacts market concentration. Specifically, we show that mark-ups increase parallel to a decrease in market concentration and rapid entry of new firms. As such, measuring the competitive benefits of different support designs by market concentration or firm entry can be misleading.[7]

Our paper contributes to the vast literature on policy designs to mitigate climate change. One strand within this literature has focused on carbon pricing and its effect on electricity prices (e.g., Fabra and Reguant, 2014), as well as its effects on investment in clean energy (e.g., Calel and Dechezleprêtre, 2016). A second strand, to which we more closely relate, examines subsidies for clean energy provision. Reguant (2019) investigates the interaction between carbon taxes, feed-in tariffs, and renewable portfolio standards in California, and shows trade-offs between efficiency and distributional concerns. Dressler (2016), Acemoglu et al. (2017), and von der Fehr and Ropenus (2017) analyze the market impact of renewable support mechanisms and their costs to consumers theoretically. They propose oligopoly models to analyze pricing decisions when firms hold a portfolio of conventional and subsidized wind and solar capacity. Ritz (2016) also provides a theoretical study on the impact of renewable subsidies, but examines the equilibrium interaction between renewables competition and forward contracting. Focusing on the Texas power market, Cullen (2013) evaluates both costs and benefits of renewable support empirically and estimates that the value of emission offsets from wind power outweighed its subsidies. Furthermore, Gowrisankaran et al. (2016) develop a method to quantify the economic value of subsidized solar energy and highlight the social costs of intermittent renewable production. Indeed, while the existing empirical literature has thus far mostly evaluated the costs and benefits of clean energy subsidies, their optimal design and consequences for firms' pricing decisions have not been empirically documented yet. One exception is a recent study by Fabra and Imelda (2020) who focus on the role of renewable regulation, and illustrate the effects on pricing and arbitrage across sequential markets using a dominant firm model.

Our paper also adds to the literature on strategic pricing in multi-unit auctions for electricity (e.g., Green and Newbery, 1992, von der Fehr and Harbord, 1993, Wolfram, 1998, Fabra et al., 2006, Reguant, 2014). More specifically, our model draws from the share auction framework in Wilson (1979) and multi-unit auction models that explore bidding strategies in power markets (e.g., Hortaçsu and Puller, 2008). We rely on the modeling approach in Hortaçsu and Puller (2008) as it aids us in tailoring our model to renewable energy provision in power markets. We amend the model by adding different support mechanisms for clean generation. The mechanism through which our model demonstrates the effect of subsidies on equilibrium market prices is

[7] The finding of misleading concentration measures in power markets goes back to Borenstein et al. (1999).

similar to the one outlined in the literature on forward markets (e.g., Allaz and Vila, 1993, Wolak, 2003b, Bushnell et al., 2008, van Koten and Ortmann, 2013, van Eijkel et al., 2016, Ito and Reguant, 2016). Equivalent to forward contracts, clean generation that is rewarded by a contract-based tariff reduces spot demand and thus prices. With a premium, this effect vanishes and prices increase.

The remainder of this article is organized as follows. Section 2.2 presents the regulatory environment and data. Section 2.3 outlines a model of bidding behavior in multi-unit auctions in electricity markets. The model incorporates the two standard mechanisms of renewable support and closely guides our empirical investigation. In the second part of section 2.3, we illustrate our empirical strategy and discuss different econometric specifications. Section 2.4 presents our empirical findings. Section 2.5 concludes.

2.2 Regulatory Environment, Market Places, and Data

We investigate the impact of subsidies for clean energy by studying the Spanish electricity market. We focus on the Spanish market to exploit a regulatory change in the support mechanism introduced in 2004. Furthermore, this market allows us to utilize detailed firm level data from wholesale electricity auctions. During our period of observation, from January 2004 to December 2005, clean energy in the Spanish power market mainly came from wind power, but also included production from small-scale hydro resources, bio-energy, and small combined heat and power plants.[8] In contrast, conventional non-subsidized technologies comprise thermal power plants that use natural gas, coal, or fuel oil as input, as well as nuclear power plants and large-scale hydro plants.

2.2.1 Market and Regulatory Environment

During the years 2004 and 2005, the Spanish power market exhibited an oligopolistic market structure. The market was dominated by four large power producers: Endesa, Iberdrola, Union Fenosa, and Hidrocantábrico, who jointly covered about 80% of the market. Endesa and Iberdrola alone supplied about 50 % of electricity to the market.

[8] Small scale hydro refers to units with capacity less than 50 MW. Waste incineration and small cogeneration plants are also subsidized. Our results are robust to excluding CHP plants and waste incineration, hence are largely driven by wind power.

The electricity mix was largely dominated by thermal power plants. Coal power plants contributed most (more than 25 percent), followed by nuclear power stations and combined cycle gas turbines.[9] Spain, however, was an early adopter of renewable power, especially with regard to onshore wind. The installed base of onshore wind power amounted to about 10 gigawatt (GW) at the end of our observation period. For comparison, daily peak demand during our observation period varied around 26 GW.

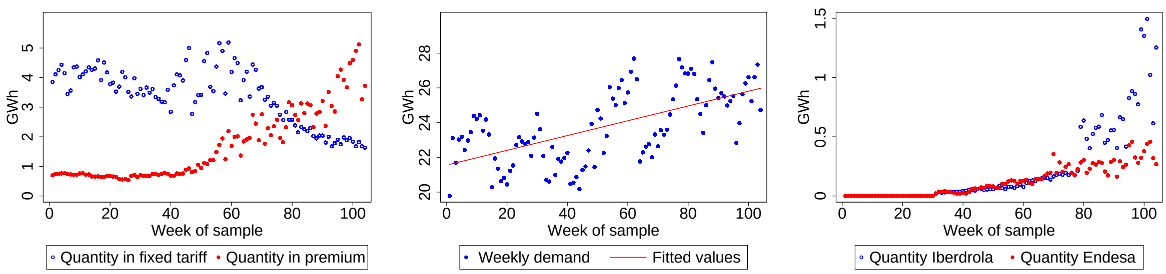
In March 2004, new regulations introduced by the Royal Decree 436 entered into force. After the regulation became binding, substantial quantities of electricity from renewable plants successively entered the spot market. The regulation permitted power producers to choose between a fixed, contract-based tariff and a market-based remuneration, where the latter included a regulatory premium on top of the market price for production from renewable sources. The tariff in effect constituted a contract between the government and renewable producers. In contrast, under the premium design, renewable output was sold in the electricity spot market. This is, renewable power had to be marketed as any other type of power generation, but received a top-up on the equilibrium market price. In terms of magnitude, the tariff was set at about 65 €/MWh, while the premium plus average market prices yielded about 71 €/MWh.[10] In fact, the premium mechanism was constructed to yield higher revenue as compared to the tariff mechanism (del Río, 2008).

Although the expected revenue of selling electricity in the market and receiving the additional premium exceeded the expected revenue of the tariff, not all producers changed to the premium scheme immediately. The transition took place continuously rather than instantaneously, as can be seen in the left panel of Figure 2.1, that plots the evolution of clean output sold in the tariff and in the premium design. Upon choosing to switch to the market-based premium, producers were set to stay within this mechanism for at least one year. This commitment and potential risk aversion may in parts explain the continuous transition.

The center panel of Figure 2.1 depicts the volumes sold in the wholesale market. As can be seen, the cleared volumes in the wholesale market grew significantly. Over the entire time period, the growth in cleared volumes roughly corresponds to the amount of renewable energy that firms have migrated from the tariff into the market, and for which they hence receive the

[9] Information are from the Spanish market operator OMIE (Operador del Mercado Ibérico de Energía).

[10] Numbers refer to subsidy levels for onshore wind power in 2004 following del Río and Gual (2007) and del Río (2008).



(a) (b) (c)

FIGURE 2.1: Panel (a) plots the weekly average renewable generation in the tariff mechanism and in the premium mechanism. Panel (b) plots the weekly average sales on the day-ahead market, along with conditional means for each week of the sample. Panel (c) plots the weekly average of quantities sold in the market-based premium design for the two firms Iberdrola and Endesa.

market-based premium. The right panel of Figure 2.1 shows the evolution of renewable energy marketed under the premium scheme for the two largest companies, Iberdrola and Endesa.

2.2.2 The Day-ahead Market

Our empirical analysis investigates pricing and mark-up strategies on the day-ahead electricity market. The day-ahead market represents the by far most liquid electricity market in Spain and covered about 70 percent of produced electricity in 2004 and 2005.[11] The day-ahead electricity market clears as a multi-unit uniform price auction, where producers and retailers participate. Subsequent to the day-ahead market, participants may balance their positions on an intraday market, which during our period of observation however constituted a much smaller market in terms of volume. Also the market for forward contracts was negligible during our observation period (Vázquez et al., 2006).[12] Producers mostly hedged via vertically integrating their retail business. Indeed, Crampes and Fabra (2005) report that the large producing companies also held significant stakes in the retail sector. Below, we therefore address vertical integration in our empirical specification by controlling for a firm's subsidiary retail demand in the day-ahead market.

The day-ahead market is organized by the Spanish market operator OMIE. Generators and retailers are placing bids for each hour of the consecutive day. In contrast to many other EU markets and in line with most US markets, supply bids have to be submitted at the plant level,

[11] About 84 percent of electricity was traded in centralized spot markets (day-ahead and intraday). The remaining sales mainly include generation subject to the tariff, and to a lesser extent bilateral trades.

[12] The EU DG Competition energy sector inquiry (SEC(2006)1724, 10 January 2007, Part II) likewise finds that forward markets were insignificant.

instead of covering a firm's portfolio of production units. For each power plant, generators can place up to 25 distinct supply bids, specifying different prices and quantities. The market operator gathers and sorts supply (demand) bids in increasing (decreasing) order and clears the market. Hourly prices and quantities are determined in uniform price auctions, i.e., all production units with bids below the clearing price receive the latter.

All units are obligated to place bids for their entire available capacity. Power producers can place both simple and complex bids. Whereas simple bids signal the willingness to sell a certain amount of power at or above this bid, complex bids add constraints on the minimum daily revenue required by a plant. Firms make use of complex bids, for instance, whenever plants face additional costs to start-up.[13] If operating margins throughout a day do not cover a plant's revenue requirement, all bids by this plant are excluded from the auction. Complex bids thus change the probability of winning and being dispatched for the respective plants (Reguant, 2014). Lastly, there exists a price cap of 180.30 € /MWh, which was never binding during our observation period. Clearing prices ranged from 10 € /MWh to 127 € /MWh.

2.2.3 Data

To study the effects of subsidies on pricing behavior, we require data on firms' mark-ups, that is, their supply bids and marginal costs, as well as data on demand and actual sales. We therefore collect all market participants' supply and demand bids on the day-ahead market, the type of technology for which a supply bid was submitted, the equilibrium clearing price and resulting sales for each firm. The data come, as market clearing does, in hourly granularity. In detail, our main dataset consists of all hourly supply bids for each plant and each company for the years 2004 and 2005. As we are interested in the pricing decisions by the dominant producers, we restrict our sample to bids submitted by the four largest companies, which cover about 80% of the market. For all fringe firms, we keep the data on their joint output. The fringe consists mostly of small renewable producers. Last, we use fuel price data and EU ETS carbon prices from Bloomberg and Thomson Reuters to estimate plant-specific marginal cost of power production. We use engineering estimates to attach the efficiency to each thermal power plant in the sample. Appendix A.1.1 illustrates our data in more detail. In sum, the data allow us

[13] Doraszelski et al. (2018) study related mechanisms that remunerate wear and tear costs for ramping up and down power plants in the UK electricity market.

to study firm-specific sales for clean and conventional generation, as well as the firms' pricing strategies and mark-ups in the wholesale market.

2.3 Model and Empirical Strategy

To formalize firms' pricing decisions, we model bidding behavior in multi-unit uniform price auctions, which constitute the standard clearing mechanism in electricity markets. The literature on multi-unit auctions considers continuous bid functions (e.g., Wilson, 1979, Klemperer and Meyer, 1989, Hortaçsu and Puller, 2008, Holmberg and Newbery, 2010) and discrete bids (e.g., Fabra et al., 2006, Kastl, 2011, 2012). Both modeling approaches have been applied to electricity markets. Wolfram (1998), Fabra et al. (2006), Reguant (2014), and Schwenen (2015) study discrete bids, while Green and Newbery (1992), Wolak (2000), and Hortaçsu and Puller (2008) study continuous supply functions. Our model follows the framework in Hortaçsu and Puller (2008) as it aids us in formally incorporating stochastic wind and solar output into our analysis.[14]

2.3.1 A Model for Strategic Pricing with Technology Support

We model strategic firms who decide on their supply to the market at any possible market price p. Each firm i therefore chooses its supply function $S_i(p)$, where supply may stem from "clean" renewable production (wind and solar) or from conventional production. We denote firm i's clean production as x_i^c and model its output as random variable, whose realization is private information to firm i. Firm i's conventional and emitting output is denoted as x_i^e. The total supply function hence can be written as $S_i(p) = x_i^c(p, \varepsilon_i) + x_i^e(p)$, where ε_i captures the uncertainty in firm i's renewable output. At the time of submitting bids, firm i knows its own renewable output, but not the one of its rivals. Last, we assume that firms are capacity constrained in their clean output so that $S_i(p^*) > x_i^c(p)$ always holds, where p^* denotes the

[14] In models with discrete bids, a large domain of supply or demand shocks can lead to mixed strategies if bids are long-lived and used for several rounds of market clearing (Fabra et al., 2006). Kastl (2012), Holmberg et al. (2013), and Anderson and Holmberg (2018) show conditions under which the difference in discrete and continuous models is qualitatively negligible. Fabra and Llobet (2019) provide a model with discrete bids and uncertain renewable output.

equilibrium market price. This assumption guarantees that conventional plants are always price-setting.[15]

The regulator implements a set of support mechanisms for firm i's clean production. Specifically, the regulator offers two types of support mechanisms: In the first mechanism, the firm receives a fixed tariff t for every unit produced from clean assets. In the alternative mechanism, the firm opts for a premium on top of the market price for its clean supply. This premium is denoted by s.

To incorporate both mechanisms into our model, we allow firms to have a share α_i of their clean production subsidized by the premium, while they receive the tariff for the remaining share, $1 - \alpha_i$. This modeling approach matches our empirical application and many real-world mechanisms, where firms can decide on their preferred form of subsidy over a specified period of time. Firms decide on their share α_i in advance of participating in the market, so that the choice on the support mechanism is sunk when firms submit their supply function.

We model demand to be deterministic and denote demand as a function of price by $D(p)$.[16] When N firms participate in the market, the clearing price p^* must satisfy

$$\sum_{i}^{N} S_i(p^*, x_i^c) = D(p^*). \tag{2.1}$$

Ex-post of market clearing, each firm's profits yield

$$\pi_i = S_i(p^*)p^* - C_i(S_i(p^*)) + s\alpha_i x_i^c + (t - p^*)(1 - \alpha_i)x_i^c, \tag{2.2}$$

where C_i is the firm's cost function. The first two terms capture standard revenue and cost considerations. The third term represents the premium on top of the market price that firm i receives for its share α_i of clean energy sold at the respective market price. The last term adds firm i's profits for its remaining share of renewable output for which the firm receives the contract-based tariff.

Note that firm i faces uncertainty on the clearing price, because the clean production of its competitors is unknown prior to market clearing. Put differently, the market price depends on

[15] Otherwise, there would be little need for subsidies. Also in our empirical setting, firms always produce output larger than their renewable capacity.

[16] Demand may be stochastic. Our results are independent of this modeling choice and we therefore stick to deterministic demand.

the realization of the aggregate clean output of firm i's rivals, and how this output changes their supply function. To capture this uncertainty in firm i's pricing, we follow Wilson (1979) and Hortaçsu and Puller (2008) and map randomness in rival supply to randomness in price. Denoting the cumulative distribution function of the market clearing price, given firm i's supply at this price, as $H_i(p, S_i) \equiv Pr(p^* < p \mid S_i)$, the maximization problem can be written as

$$\max_{S_i(p)} \mathbb{E}[\pi_i] = \int_{\underline{p}}^{\overline{p}} [S_i(p)p - C_i(S_i(p)) + s\alpha_i x_i^c + (t-p)(1-\alpha_i)x_i^c] \, dH_i(p \mid S_i). \tag{2.3}$$

Using calculus of variations, the Euler-Lagrange first-order condition yields

$$p - C_i'(S_i^*(p)) = (S_i^*(p) - (1-\alpha_i)x_i^c) \, \frac{H_S(p, S^*(p))}{H_p(p, S^*(p))} \tag{2.4}$$

where $S_i^*(p)$ is firm i's optimal supply function, C_i' marginal costs, and H_S and H_p are derivatives 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 and the amount of clean production supported by the tariff or premium. Appendix A.1.2 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.[17]

In addition, the optimality condition shows that all clean output rewarded by the tariff, $(1-\alpha_i)x_i^c$, decreases the mark-up. Note that this effect is conditional on a firm indeed having the ability to impact the market price distribution. As this probability approaches zero, also the effect of a firm's inframarginal capacity on its mark-up vanishes.

The effect of the tariff mechanism on price is similar to the price-reducing effect of forward contracts as first suggested by Allaz and Vila (1993) and as documented in Wolak (2003b), Bushnell et al. (2008), and Hortaçsu and Puller (2008). The two cases are similar because both,

[17] As discussed in Wolak (2003a) and Hortaçsu and Puller (2008), the strategies that follow equation (2.4) are also ex-post optimal, as long as shocks to supply or demand are additive.

capacity sold at forward prices and clean production sold via the tariff, reduce a firm's residual demand. As a result, the equilibrium mark-up must decrease accordingly.

To compute equation (2.4), 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 strategies to be additively separable. In our context, this assumption translates into renewable shocks that shift supply curves for conventional generation in a parallel fashion. We therefore consider strategies where renewable shocks translate into parallel shifts of the conventional supply curve. This is, different renewable shocks ε_i in $S_i(p) = x_i^c(p, \varepsilon_i) + x_i^e(p)$, cause parallel shifts of the conventional part of the supply curve $x_i^e(p)$.[18]

As shown in Appendix A.1.2, restricting strategies to be additive allows to derive $\frac{H_S}{H_p}$ analytically with $\frac{H_S}{H_p} = \frac{1}{m_i(p)}$, where $m_i(p)$ denotes, in absolute terms, the slope of firm i's residual demand at price p. Hence, for higher $m_i(p)$, i.e., for a more price-elastic residual demand, mark-ups must decline.[19] Furthermore, recalling that we study a setting where firms are capacity constrained and sell all of their subsidized output, we can write $S_i^*(p) = x_i^e(p) + x_i^c$. The optimal strategy in equation (2.4) hence simplifies to

$$p - C'(S_i^*(p)) = (\alpha_i x_i^c + x_i^e(p)) \frac{1}{m_i(p)}. \tag{2.5}$$

Given that price, marginal costs, demand, as well as clean and conventional production are observable, the optimality condition is also estimable. Equation (2.5) states that clean supply under the premium mechanism contributes positively to a firm's mark-up. This is because, under the premium mechanism, the equilibrium market price applies to both clean and conventional output.[20] Therefore, while the premium itself is not relevant for optimal pricing, the remuneration of clean supply under the premium regime nonetheless depends on the market price and as such impacts a firm's pricing decision. We summarize this finding, that we test in our empirical application, in the following proposition.

[18] Note that this supply function still allows for mark-ups on renewable supply up to the capacity constraint in renewable output. In Hortaçsu and Puller (2008), parallel shifts are instead introduced by forward contracts with volume unknown to firm i's competitors. In our setting, the additive separability assumption captures that renewable shocks in electricity markets typically shift the entire supply curve.

[19] Formally, the slope of residual demand is $m_i(p) = -\frac{\partial}{\partial p}(D(p) - S_{-i}(p))$, where $S_{-i}(p)$ denotes the aggregate supply function of firm i's competitors.

[20] The result that mark-ups increase in offered quantity is in line with a range of specifications for standard oligopoly and multi-unit auction models (e.g., Klemperer and Meyer, 1989). Note that firms can sell this additional output because demand in the spot market increases by the same amount by which renewable sales in the tariff mechanism are reduced.

Proposition 2.1. *The optimal mark-up of firm i depends positively on firm i's share of clean output sold under the premium mechanism, i.e., the mark-up increases in $\alpha_i x_i^c$.*

2.3.2 Empirical Strategy

Our empirical strategy closely follows Proposition 2.1 and the optimality condition in equation (2.5). Hence, we are interested in evaluating the mark-up effects of the market-based premium design. To estimate mark-ups as a function of marketed renewable production $\alpha_i x_i^c$, we test the optimality condition at the margin, this is, for all mark-ups at the clearing price p^* and submitted quantities $S_i(p^*)$.

We use three econometric approaches. First, we test a log-linearized version of the optimality condition. Second, we estimate a specification where we test Proposition 1 in level effects. Lastly, we use an IV approach as specified further below. For the first approach, note that log-linearizing the optimality condition in equation (2.5) at $p = p^*$ yields

$$ln\,(p^* - C_i'(S_i(p^*))) = ln\,(\alpha_i x_i^c + x_i^e(p^*)) - ln\ m_i(p^*), \tag{2.6}$$

To capture price effects of subsidized renewable sales over time, we estimate a version of equation (2.6) by pooling data across auctions, controlling for observed and unobserved factors that may vary from one auction to the next. In detail, we add hourly time indeces to equation (2.6) and estimate the following specification:

$$ln\,(p_{it}^* - C_{it}'(S_{it}(p^*))) = \beta_0 + \beta_1\ ln\ \alpha_i x_{it}^c + \beta_2\ ln\ x_{it}^e(p^*) + \beta_3\ ln\ m_{it}(p^*) + \gamma W + \epsilon_{it}, \tag{2.7}$$

which differs from the model in (2.6) in that we estimate separate effects for conventional and renewable output. The matrix W comprises different time fixed effects and, depending on the specification, plant and company fixed effects. Note that time fixed effects capture regularly reoccurring patterns in power markets, such as demand or temperature. We include hour, day-of-week, week, and month fixed effects that capture hourly, daily, and seasonal demand patterns as well as other time-specific heterogeneity. To the extent that unobserved production costs re-occur on hourly or daily patterns, fixed effects also capture higher mark-ups due to regularly emerging ramping or start-up costs.

Second, to interpret level effects, we also estimate:

$$p^*_{it} - C'_{it}(S_{it}(p^*)) = \beta_0 + \beta_1\ \alpha_i x^c_{it} + \beta_2 x^e_{it}(p^*) + \beta_3\ m_{it}(p^*) + \gamma W + \epsilon_{it}, \tag{2.8}$$

where W comprises the same fixed effects and control variables as for the log-log specification.

The log-log specification and the level specification each put our model to a different test: We use the regression in log-terms in equation (2.7) to investigate relative magnitudes. For instance, where a company has high amounts of renewable generation, we expect a one-percentage change in renewable output to have a larger effect on the mark-up as compared to a one-percentage change of a firm with little renewable output. Conversely, we use the level regression in equation (2.8) to estimate the effect of one additional MWh of renewable generation. We expect this latter estimate to be similar across smaller and larger firms.

Third, we use an IV approach. Our econometric specifications above rely on our model of equilibrium bidding, where mark-ups increase because firms account for inframarginal renewable sales in their pricing strategy. Although this finding is in line with standard oligopoly models where mark-ups increase in output, in our application high mark-ups could, in turn, lead to more companies switching to the market-based premium mechanism. This is, we cannot exclude that the share of renewable energy sold in the market is endogenous. For instance, firms may be risk-averse, avoid price volatility, and require sufficiently high mark-ups for selling their renewables in the market. If this is the case, higher mark-ups can drive additional renewable output sold under the premium design and introduce reverse causality. To address potential endogeneity concerns, we in addition run specifications where we instrument firm i's renewable output sold under the market-based premium design.[21] We test our model using two different instruments. First, we use the aggregate renewable output of firm i's competitors as instrument for $\alpha_i x^c_{it}$. Second, we use wind speed as instrument for $\alpha_i x^c_{it}$. Both instruments are out of control of firm i but correlate with its renewable sales under the market-based premium.

Taken together, all three specifications above (log-log, level, IV) estimate the mark-up effect of renewable energy sold in the market, controlling for conventional output, demand slope, and a range of fixed effects. Put differently, we test whether firms increase their mark-ups when selling additional renewable output in the market, all else equal.

[21] We thank the reviewers and the editor for this suggestion.

Our data allow to compute all required variables. First, we can compute the hourly mark-up on marginal costs, defined as the price-bid submitted at the quantity $S_i(p^*)$ by firm i in auction t minus marginal costs of the respective plant. Second, the renewable output marketed under the premium design, $\alpha_{it}x^c_{it}$, as well as the amount of conventional production $x^e_{it}(p^*)$ are directly observable in the data. Last, we use the data on demand bids to compute the slope of the residual demand around the clearing price.[22] Table 2.1 presents the summary statistics.

Table 2.1: Summary statistics.

	Mean	Median	Std. dev.	Min.	Max.	Obs.
Clearing prices [€/MWh]	40.3	38.0	18.5	10.1	127.0	13,868
Marginal costs at $S_i(p^*)$ [€/MWh]	26.0	27.2	11.1	8.9	87.9	29,035
Mark-up [€/MWh]	10.1	7.8	9.5	0.0	82.9	29,035
Renewable output in premium [MW]	104.1	5.9	226.1	0.0	2108.5	29,035
Conventional generation [MW]	4707.5	3771.4	3040.2	745.6	13,064.5	29,035

Notes: Sample from January 2004 to December 2005. Observations are hourly and comprise the largest four firms in the market. Hours where pumped storage, hydro power plants, imports, or nuclear power produce at the margin are excluded, as their marginal production costs are prone to measurement bias. Whenever other technologies set the clearing price, inframarginal capacity however includes generation from these sources.

Note that firms submit discrete bid functions. Therefore, the mark-up $p^*_{it} - C'_{it}(S_{it}(p^*))$ may not be defined, if a firm's residual demand intersects its supply function in between steps. Indeed, in most hours there is only one of the four dominant firms that submits a bid that is identical to the clearing price. To compute the mark-up for all four firms, we therefore use each firms price-bid at its equilibrium quantity $S_i(p^*)$, which may be equal to or lower than p^*. Our results are robust to computing the mark-up using the unique clearing price for all firms instead of their marginal bid.[23]

Finally, we do not model forward contracts. This is because during our period of observation, forward contracts have been negligible (Vázquez et al., 2006). If, however, hedging incentives and forward volumes were to increase, e.g., in response to additional price exposure for renewable output, our model estimates are likely to be downward biased, because a simultaneous increase in forward sales would negatively effect spot market prices (see e.g., Wolak, 2000, Bushnell et al., 2008).

[22] We present our approach to construct the slope of residual demand in Appendix A.1.1.

[23] To investigate the distance between the clearing price and a firm's price-bid at $S_i(p^*)$, we calculated a distance ratio defined as $\frac{p^* - bid}{p^*}$. The median difference between the clearing price and a firm's bid is below 3%. We therefore conjecture that modeling smooth supply functions, at least at the margin, depicts the firms' pricing strategies reasonably well.

2.4 Results

Table 2.2 shows the results for our log-log and level specifications in equations (2.7) and (2.8), based on the pooled sample with the four largest firms as summarized in Table 2.1. The first three columns report estimates for the log-log specification. In column one, the estimates for the coefficients of renewable output and conventional output are positive, and, as conjectured, the estimated percentage effects are larger for the conventional output. This is because firms' conventional output by far outweighs their renewable production, so that the effect of a one-percentage increase in conventional output on the mark-up is larger as compared to a one-percentage change in the renewable counterpart. Also the estimates for the slope of residual demand are negative, as expected.

In column two, we in addition control for a company's degree of vertical integration. Similar to the well-studied effect of forward contracts, a high share of subsidiary retail firms that act on the demand side may attenuate incentives to submit high bids.[24] To construct this control, we first sum up the aggregate quantity of satisfied demand from retailers that are owned by each respective generating company. As control variable, we then use the sum of a firm's "own" retail demand relative to total demand satisfied. As shown in column two, the estimates suggest that indeed firms submit lower bids if a larger portion of the market demand stems from their own retail firms. Importantly, our main coefficients of interest however remain robust.

Last, specification three disregards plant level fixed effects and instead controls for technology-specific fixed effects for gas, coal, or lignite technologies. As can be seen, when not accounting for unobserved heterogeneity between the individual production units, the estimates slightly change in magnitude but remain comparable. Also, the explanatory power of the model reduces. That estimates change may result from unobserved production costs at the plant level, which we study further below in our robustness checks.

In specifications four to six, we then use the absolute amount of subsidized renewable generation and present estimates for equation (2.8). The estimates again show signs as expected. In terms of magnitude, the estimates for a unit change in renewable output and conventional output are comparable. All effects are significant and robust also when controlling for the demand

[24] During our period of observation, incumbent generators received subsidies to recover stranded assets. Subsidies were granted based on the share of incumbent retailers in the retail market (Ciarreta and Espinosa, 2010). Crampes and Fabra (2005) show that firms with higher retail market shares have less incentives to submit high bids to the wholesale market.

TABLE 2.2: Mark-up regressions.

	Log-log regressions			Level regressions		
	Mark-up	Mark-up	Mark-up	Mark-up	Mark-up	Mark-up
Renewable output	0.0221***	0.0221***	0.0355***	0.00157***	0.00181***	0.00374***
$\alpha_i x_i^c$	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Conventional output	0.173***	0.165***	0.0614**	0.00077***	0.00081***	0.00057***
$x_i^e(p^*)$	(0.000)	(0.000)	(0.008)	(0.000)	(0.000)	(0.000)
Demand slope	-0.522***	-0.520***	-0.531***	-0.0330***	-0.0328***	-0.0315***
$m_i(p^*)$	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Firm i's retail demand		-0.426***	-0.305***		-11.87***	-11.52***
Retail demand share		(0.000)	(0.000)		(0.000)	(0.000)
Plant fixed effects	Y	Y	N	Y	Y	N
Technology fixed effects	N	N	Y	N	N	Y
Company fixed effects	Y	Y	Y	Y	Y	Y
Observations	29,035	29,031	29,031	29,035	29,035	29,035
R^2	0.58	0.58	0.48	0.51	0.52	0.43

Notes: Dependant variable is the mark-up by firm i in auction t. Columns (1) to (3) show results of a log-log specification. Columns (3) to (6) display level effects. Columns (2) and (3) lack four observations where a firm's retail demand is zero and the logarithm undefined. The Sample runs from January 2004 to December 2005. All regressions include hour, weekday, week, and month fixed effects. p-values are in parentheses, * p<0.05, ** p<0.01, *** p<0.001. Standard errors are clustered at the auction level.

of subsidiary retailers in specification four. The last specification in Table 2.2 again shows estimates when not controlling for plant level fixed effects and instead using technology-specific fixed effects.

To probe into the magnitudes, we take our estimates in Table 2.2 to the data. We use specification (5) as it includes controls that yield the highest R^2. Specifically, we apply our estimated coefficient of 0.00181 to the mark-ups in our sample and subtract the effect of renewable sales. This is, we use the observed mark-up and subtract *0.00181*{renewable output sold in the premium design}*, assuming all other variables are unchanged. We find that the average mark-up –over our entire sample– was about 5% lower, had all renewable energy been sold in the contract-based tariff design. Furthermore, we also calculate a counterfactual mark-up for the last month of our sample, where the bulk of clean energy has been migrated to the market-based premium. In this last month of our sample, the average renewable sales in the market equal about 4300 MWh (as compared to average power demand of 25.000 MWh). Here, we find the counterfactual mark-up to be about 11% lower, had all renewable output been sold in the tariff instead. To conclude, the estimates in Table 2.2 show that the change in the renewable support mechanism led to a statistically and economically significant increase in producer rents.

2.4.1 Robustness: Start-up Costs and Congestion

Our findings above rely on engineering estimates for marginal production costs at the plant level. To obtain cost estimates, we follow the large body of literature that models firm behavior and measures marginal costs and mark-ups in electricity markets (e.g., Wolfram, 1999, Borenstein et al., 2002, Mansur, 2007, Hortaçsu and Puller, 2008). In particular, we construct marginal costs by accounting for each plant's fuel type, fuel efficiency, and regulatory permit costs. As common, we assume that each plant has constant marginal cost up to its hourly operating capacity.

Wolak (2007) and Reguant (2014) show that this standard approach abstracts from ramping or start-up costs of power plants. These costs mainly arise from depreciation of the equipment when plants quickly increase or decrease generation, and would lead us to understate the costs and to overstate the mark-up. When this measurement bias is correlated to a firm's inframarginal renewable or conventional generation, our estimates in turn are biased.

To rule out such engineering-based explanations, we perform two robustness checks. First, we exploit the Spanish market design that allows firms to submit complex bids to announce start-up and ramping costs. We therefore investigate a sub-sample that only includes plants for which firms did not submit complex bids and for which we presume the absence of start-ups costs.[25] When re-running our regressions with this sample, the estimates for renewable and conventional capacity remain significant and robust in magnitude. Also the effect of the slope of residual demand remains robust. The estimation results are shown in Table A.1 in the Appendix.

Second, we restrict our analysis to plants that have submitted bids of zero (for their first of 25 possible bid steps per plant) in hour t and t-1. In doing so, we restrict our sample to plants that have already been operating in the previous hour, and in addition seek to operate with certainty in hour t. Consequently, these plants should not face significant start-up or ramping costs from hour t-1 to hour t. We again confirm our main findings, as shown in Table A.1 in the Appendix.

[25] To focus on sub-samples is a standard approach. For instance, to rule out engineering-based explanations for mark-ups, Hortaçsu and Puller (2008) consider early morning hours where flexible plants without ramping costs operate.

Our last robustness check addresses transmission congestion. Recent literature shows that transmission congestion can be closely related to renewable production (e.g. Fell et al., 2019). To rule out potential confounding effects from transmission congestion, we run a robustness check focusing on non-congested hours only, i.e., morning hours from 5 am to 7 am. Column three of Table A.1 shows that, albeit the estimates slightly reduce, the overall effects remain robust. In sum, our robustness checks support our findings.[26]

2.4.2 Effects for Large Producers

Next, we explore the pricing behavior of the main renewable producers in the market. Our empirical results above rely on pooling all big generating companies in one sample. However, Hortaçsu et al. (2019) show that pricing strategies and mark-ups can differ among firms. In the following, we therefore investigate bidding behavior for the two largest generators, Endesa and Iberdrola, as they control the main share of renewable production. Both companies also own substantial conventional capacities. Endesa at times supplied more than 14,000 MWh per hour of thermal generation and Iberdrola up to 12,000 MWh. The picture reverses for renewable generation. Endesa sold up to 700 MWh, while Iberdrola's sales reached more than 2,100 MWh.[27]

With only two firms owning the main shares of renewable capacity, our results are subject to the concern that their choice on the preferred subsidy scheme is endogenous. As argued, we cannot rule out that the decision to migrate renewable production out of the tariff and into the market-based premium design was driven by high mark-ups. If so, especially Endesa and Iberdrola, with their large renewable capacities, could have successively added renewable production to the market, because higher mark-ups made the premium design more and more attractive.

We therefore re-examine bidding strategies at the firm level and instrument for a firm's renewable output. Table 2.3 below presents our results. Columns one to three estimate the mark-up of Endesa. Columns four to six estimate the mark-up of Iberdrola. For each company, we estimate one OLS and two IV regressions. For the first IV regression, we instrument the firm's renewable

[26] To test the theory model behind our empirical specifications, we also investigated whether renewable output is additive and only shifts, but does not pivot, the slope of a firms bid function. We could not identify any underlying patterns that would violate the assumption on additive renewable supply. More specifically, we do not find evidence that renewable generation structurally pivots bid functions in any direction.

[27] The firm with the third-highest renewable output in our sample is Hidroelectrica del Cantabrico. Its maximum hourly renewable sales in the market however only amount to about 240 MWh, indicating the relevance of Iberdrola and Endesa for our study.

Table 2.3: Mark-up regressions for Endesa and Iberdrola, in levels.

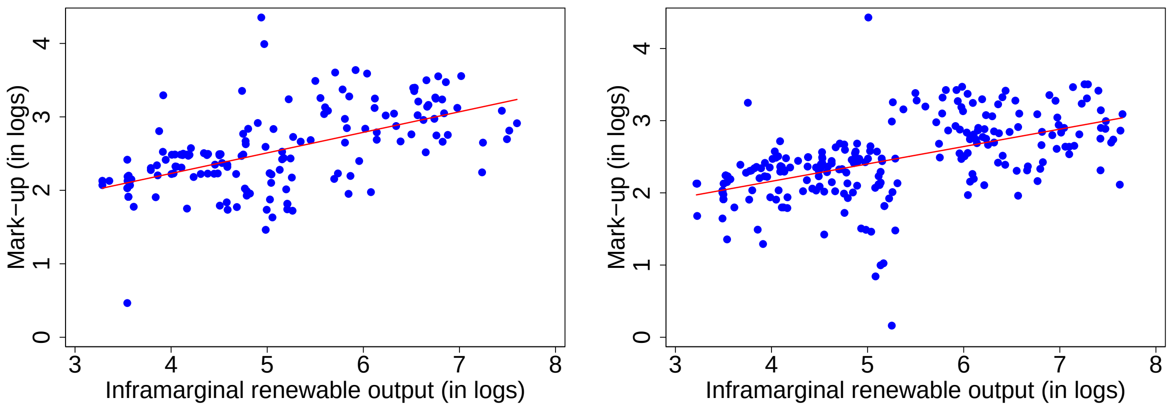
	Mark-up Endesa			Mark-up Iberdola		
	OLS	IV: Rival renewables	IV: Wind speed	OLS	IV: Rival renewables	IV: Wind speed
Renewable output $\alpha_i x_i^c$	0.00245*** (0.000)	0.00170* (0.017)	0.00510*** (0.000)	0.00154*** (0.000)	0.00331*** (0.000)	0.00314*** (0.000)
Conventional output $x_i^e(p^*)$	0.00160*** (0.000)	0.00124*** (0.000)	0.00136*** (0.000)	0.00177*** (0.000)	0.00083*** (0.000)	0.00097*** (0.000)
Demand slope $m_i(p^*)$	-0.0377*** (0.000)	-0.0341*** (0.000)	-0.0333*** (0.000)	-0.0263*** (0.000)	-0.0200*** (0.000)	-0.0207*** (0.000)
Retail demand	Y	Y	Y	Y	Y	Y
Plant fixed effects	Y	Y	Y	Y	Y	Y
Company fixed effects	Y	Y	Y	Y	Y	Y
Observations	7617	7616	7617	7281	7281	7281
R^2	0.47	0.41	0.42	0.63	0.60	0.60

Notes: Dependent variable is the mark-up of Endesa in columns (1), (2), and (3) and of Iberdrola in columns (4), (5), and (6). Columns (1) and (4) show OLS estimates. In columns (2) and (5), we instrument firm i's renewable output sold in the market with aggregate renewable output of all firms. In columns (3) and (6), we use wind speed as instrument. The sample runs from January 2004 to December 2005. All regressions include hour, weekday, week, and month fixed effects. p-values are in parentheses, * p<0.05, ** p<0.01, *** p<0.001. Standard errors are clustered at the auction level.

output with the aggregated renewable output of all its competitors. For the second IV regression, we instrument a firm's renewable output using hourly wind speed. As can be seen, for both firms the effect of renewable output on the mark-up is somewhat larger than the estimates for the aggregate sample with all main firms, indicating that the main effects in our market sample are indeed driven by the two firms that dominate the renewable production, i.e., Endesa and Iberdrola.

To put our model to a further test, we also estimate the log-log specifications for Endesa and Iberdrola. Iberdrola has larger renewable output than Endesa. Hence, we expect a one-percentage change in Iberdrola's renewable output to have a relatively larger effect on the mark-up. Indeed, the estimated log-log coefficients for renewable sales are larger for Iberdrola than for Endesa. Conversely, the log-log estimates for conventional output are higher for Endesa, in line with Endesa owning more conventional capacity than Iberdrola. The results of these regressions are shown in Table A.2 in the Appendix.[28]

[28] Finally, we also investigated whether Iberdrola and Endesa charge higher mark-ups and withhold relatively more capacity because they expect to sell more quantity on the intraday market. Yet, we could not identify structurally positive or negative positions for Iberdrola and Endesa in the intra-day market.

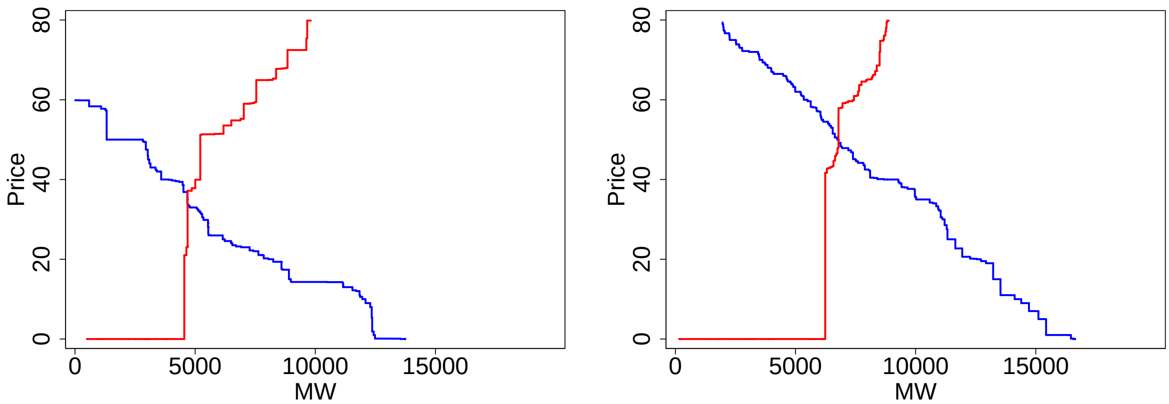


(a) Iberdrola, 12 noon

(b) Iberdrola, 4 pm

FIGURE 2.2: Mark-up (in logs) over inframarginal renewable output (in logs) for selected hours for Iberdrola. The graph comprises all hours over the full sample from January 2004 to December 2005 with positive renewable output.

We conclude this section by providing graphical illustrations of the mark-up effect. Figure 2.2 graphs Iberdrola's hourly mark-up over its marketed renewable output in that hour. We plot selected hours, i.e., 12 noon (to 1 pm) and 4 pm (to 5 pm). The graphs are clearly indicating the positive relationship of mark-up and renewable output.

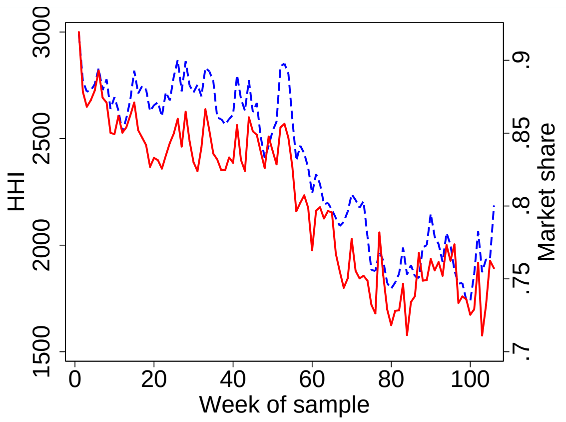


(a) Iberdrola on 12/28/2004 4 pm

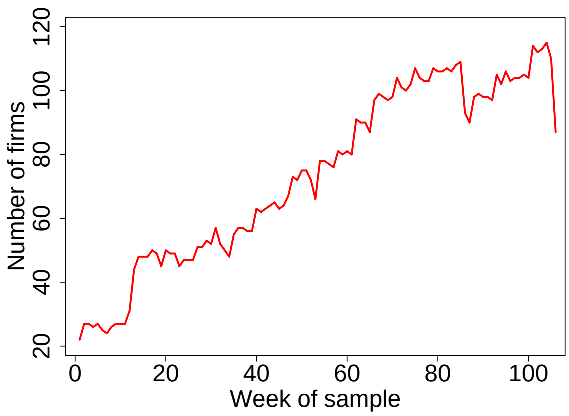
(b) Iberdrola on 11/10/2005 4 pm

FIGURE 2.3: Bid curves for Iberdrola with few marketed renewable output (left) and a high amount of renewable capacity (right). Both plots are showing bids and residual demand for 4 pm and on a weekday. In the left graph, Iberdrola sells conventional output of 4,600 MW and renewable output of 100 MW. In the right graph, Iberdrola sells conventional output of 5,100 MW and renewable output of about 1,700 MW.

Finally, Figure 2.3 plots the supply function for Iberdrola in two selected and exemplary hours. We plot two hours, where Iberdrola dispatched the identical power plant at the margin, and where Iberdrola produced similar amounts of conventional production. The left panel then



(a) HHI and market shares



(b) Number of firms

FIGURE 2.4: Panel (a) plots the HHI (blue dashed line) and aggregate market share of the four largest firms (red solid line). The HHI is computed on a weekly base. For each hour in a respective week, we compute the HHI as $(100 * s_i)^2$ for all $i = 1, ..., n$ firms where $s_i \in [0, 1]$ is firm i's market share and n is the number of active firms in hour n. The weekly HHI then represents the average HHI in each week. Panel (b) plots the number of firms active in each week of the sample. Specifically, panel (b) shows the maximum number of firms active in any hour of a given week in the sample.

shows a selected hour at the end of 2004, where Iberdrola only sold about 100 MW of renewable output via the premium design, and received the tariff for the bulk of its clean output. In contrast, the right panel depicts the bid curve at a later point in our sample, where Iberdrola had migrated nearly all of its renewable output to the premium design and, in that hour, sold about 1,700 MW of renewable generation in the market. The right panel clearly indicates higher residual demand, allowing for higher strategic mark-ups.

2.4.3 Market Structure and Entry

In closing, we illustrate changes in the market structure in the aftermath of the policy change. In particular, we show that the market concentration declined and that market entry rapidly increased, especially by small renewable producers. Panel (a) of Figure 2.4 plots the evolution of the HHI and the market share of the four largest firms. As can be seen, the four largest firms have lost significant market shares during our observation period. The HHI shows a corresponding downward trend.[29] Panel (b) of Figure 2.4 shows that also the number of firms has increased considerably. These new market entrants mainly are small renewable producers that began marketing their output on the wholesale market.

[29] Note that the declining HHI could in parts result from the fact that the dominant firms increased mark-ups and withheld quantity, hence leading to lower market shares (Borenstein et al., 1999).

The trends in Figure 2.4 underscore the impact of the subsidy mechanism. First, we rule out that higher mark-ups have been the result of a more concentrated market. Instead, we observe a falling trend in market concentration and a rapid increase in firm entry. Our findings thus suggest that while policies to support renewable energy can potentially lead to positive effects from market entry in the longer run, dominant firms still face ample incentives to increase mark-ups and equilibrium prices to their favor.

2.5 Conclusion

In this paper, we have studied how policies to support clean production influences competition and market structure in power markets. We have tailored our analysis to multi-unit auctions, the dominant clearing mechanism in power markets around the globe. The model draws from canonical multi-unit auction frameworks and adds the effects of different mechanisms to support clean energy. We have applied our model to detailed bid data from the Spanish power market, to a period of time when regulators re-organized the subsidy mechanism. The support mechanism changed from a contract-based tariff to a market-based premium for renewable generation.

We have shown that tariff mechanisms work equivalently to forward contracts and, in line with standard forward market models such as in Allaz and Vila (1993), decrease the mark-ups set by strategic firms. When regulators change the support design to a market-based premium, this pro-competitive effect vanishes and mark-ups ceteris paribus increase, as do policy costs. We also find that this effect is conditional on firms indeed having the ability to exercise market power. That is, our findings are conditional on imperfect spot market competition and illiquid forward markets that otherwise could attenuate observed effects.

In line with these model findings, our empirical estimates show that firms that sell large shares of subsidized clean energy to the market account for these in their pricing decisions and significantly increase their mark-up. At the same time, we have documented that the market concentration has fallen in parallel, as indicated by a decline in the HHI and rapid firm entry. Consequently, market concentration measures can be misleading when evaluating policies to promote clean energy in power markets.

Our findings highlight the role of the subsidy design for supporting renewable generation in power markets. Our findings also pertain to other forms of support schemes, e.g., for procurement auctions for clean energy, where the choice of the auction design and the payment schemes should be considered in view of our findings.

3 Strategic Ability and CO2 Emissions in Electricity Markets

Moritz Bohland, Sebastian Schwenen[30]

We measure the ability of electricity generating firms to play oligopoly games, and the consequences for market efficiency and CO2 emissions if firms deviate from Nash-equilibrium prices. Making use of rich micro-level data from the Iberian electricity market, we show that large incumbent firms approximately charge optimal prices, while smaller firms lack strategic ability and tend to "price their generation out of the market". From a policy perspective, we find that large and strategically able firms with high shares of low-carbon generation are pivotal for decreasing the sector's overall carbon intensity. We also compute counterfactual merger cases that can increase market efficiency and decrease overall carbon intensity in the market.

[30] Author contributions: This essay is based on a joint paper with Sebastian Schwenen. My contribution was the development of the research idea, the design of the empirical strategy, the data gathering and processing, as well as the draft of major parts of the paper.

3.1 Introduction

The emerging literature on behavioral industrial organization suggests that differences in firm characteristics can lead to heterogeneity in firms' strategic sophistication, e.g., in their ability to charge optimal oligopoly prices (Hortaçsu et al., 2019). Paramount examples for oligopolistic behavior can be found in electricity markets, where scholars have provided a wealth of evidence for strategic pricing (e.g. Green and Newbery, 1992, Wolfram, 1999, Wolak, 2003b, Reguant, 2014). The consequences of –more or less sophisticated– strategic pricing on externalities have however received little emphasis so far, although especially electricity markets are prone to significant CO2 externalities.

Amid efforts to decarbonize power generation, large incumbent firms often kept a portfolio of CO2-intensive conventional power stations, but increasingly started to produce wind and solar energy. Other large firms remain operating conventional plants only, whereas small entrant firms often rely exclusively on low-carbon production. In addition, power generating companies typically 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).

In this paper, we study 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 optimal pricing decisions and firms' CO2 emissions. Specifically, we characterize firms' deviations from optimal pricing rules and quantify the effect on market outcomes, on the use of clean and carbon-intensive technologies, and on resulting CO2 emissions. We also calculate policy counterfactuals to increase sophistication, i.e., we examine the impact of mergers on firms' strategic ability, market efficiency, and CO2 externalities.

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 (2003b), 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 likely 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, 2003b, 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 3.2, we provide an overview of the market environment and introduce our empirical setup. In section 3.3, we present our model framework. Section 3.4 outlines how we proceed empirically, while section 3.5 illustrates our data. In 3.6, we present our results and robustness checks, and compute policy counterfactuals. Section 3.7 concludes.

3.2 Market Environment and Empirical Setup

Our empirical setup exploits rich firm level data from the Iberian electricity market. The Iberian electricity market, Mercado Ibérico de la Electricidad (MIBEL), is the main market place for electricity in Spain and Portugal.[31] 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

[31] 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.

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.

3.2.1 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.

3.2.2 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 essentially price setting most of the time. In the Portuguese market region, EDP controls nearly 80% of the market. During our period of observation, i.e. the year 2017, mean 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.

3.2.3 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 3.1: 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 3.1 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 3.1 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.

3.3 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.[32] 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

$$\sum_i S_i(p^*) = \tilde{D}(p^*). \tag{3.1}$$

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

$$E[\pi_i] = \int_{\underline{p}}^{\bar{p}} \pi_i(S_i(p))dH_i(p\ |S_i), \tag{3.2}$$

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

$$\pi_i(S_i(p)) = S_i(p, F_i)p - C_i(S_i(p)) - (p - p^F)F_i, \tag{3.3}$$

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

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 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 (3.3) to

$$\pi_i(S_i(p)) = (S_i(p, F_i) - F_i)p - C_i(S_i(p)) + p^F F_i. \tag{3.4}$$

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 (3.4) into the expected profits in equation (3.2) and derive the first-order condition with respect to $S_i(p)$. The resulting Euler-Lagrange optimality condition for the optimal supply function yields

$$p - C_i'(S_i^*(p)) = (S_i^*(p) - F_i)\,\frac{H_S(p, S^*(p))}{H_p(p, S^*(p))}, \tag{3.5}$$

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.2.1 presents more details on the derivation of the optimality condition.[33]

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

[33] Note that the derivation of the equilibrium strategy is similar to the one presented in chapter 2.

and determines a non-zero mark-up, unless the supply effect of firm i on the price distribution is infinitely small.[34]

To compute equation (3.5), 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 continue with the assumption below:

Assumption 3.1. *Uncertainty ε causes parallel shifts in the demand function but does not rotate the demand curve.*

Using this assumption, as shown in Appendix A.2.1, the optimal pricing rule greatly simplifies and yields the standard inverse elasticity mark-up rule:

$$p^* - C_i'(S_i^*(p^*)) = \frac{S_i^*(p^*) - F_i}{-RD_i'(p^*)}. \tag{3.6}$$

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 $RD_i'(p^*)$.[35] 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 (3.6) 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.

[34] As discussed in Wolak (2003b) and Hortaçsu and Puller (2008), the strategies that follow equation (3.5) are also ex-post optimal, as long as shocks to supply or demand are additive.
[35] We refer to a setting with quantity on the y-axis and price on the x-axis.

3.4 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.

3.4.1 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 (3.6). Starting from equation (3.6), 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.[36] 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.

[36]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.

We then use an isotonic regression to fit an upward sloping step function and assign marginal cost to each unit within the merit order.[37]

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 (3.6): 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.

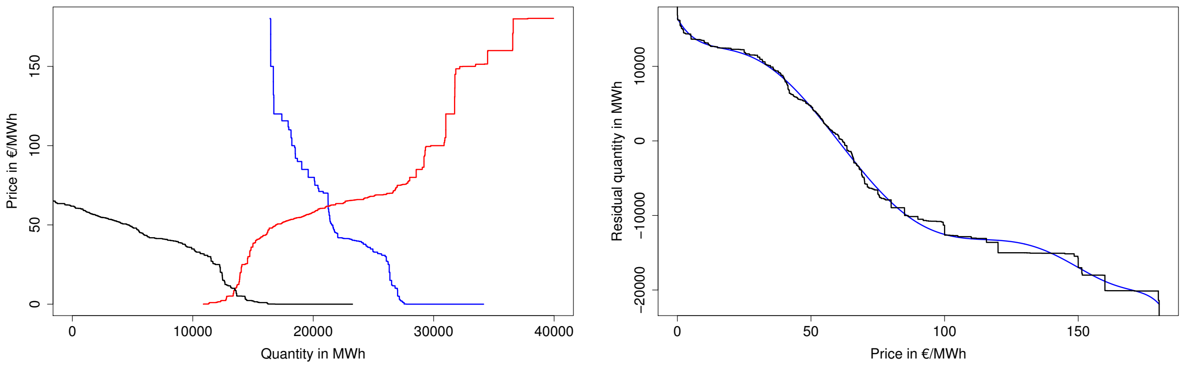
Following Hortaçsu and Puller (2008) and Reguant (2014), we exploit this condition to infer a firm's forward position. This is, we combine observed bidding schedules and the estimated marginal cost curves, and determine their intersection to infer a firm's hedging position F_i in each hour t. Technically, 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 3.1 illustrates this approach. Note that residual demand becomes negative as soon as the sum of competing offers suffices to cover all demand.

Finally, to obtain the slope of residual demand, $RD_i^{'}$ in equation (3.6), we estimate the slope by fitting a polynomial with nine degrees of freedom and enforce it to be monotonically decreasing.[38] In essence, the slope is a measure for the market power of firm i. We illustrate this approach in Panel (b) of Figure 3.1.

[37] 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.

[38] 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.



(a) (b)

FIGURE 3.1: 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 (3.6), we plot residual demand on the y-axis over price on the x-axis.

Given all variables computed as above, we are able to derive optimal supply functions for all suppliers using the optimality condition in equation (3.6). 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 3.6. This minimization delivers an optimized bidding schedule for each firm that we can use to quantify firms' strategic ability.

3.4.2 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

$$\pi_i^a = (S_i(p^*) - F_i)\, p^* - \sum_{j=1}^{m} C_i^{'}(j) s_i(j). \tag{3.7}$$

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

$$\pi_i^a = (S_i(p^*) - F_i)\, p^* + \sum_{j=1}^{m} C_i^{'}(j) s_i(j), \tag{3.8}$$

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.[39] We calculate counterfactual optimal firm profits as

$$\pi_i^{cf} = \left(S_i(p^{*cf}) - F_i\right) p^{*cf} - \sum_{j=1}^{m^*} C_i^{'}(j) s_i(j), \tag{3.9}$$

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

[39] 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.

$$\pi_i^{cf} = \Big(S_i(p^{*cf}) - F_i\Big)\, p^{*cf} + \sum_{j=1}^{m^*} C_i'(j) s_i(j). \tag{3.10}$$

In line with the calculation of actual profits in equation 3.8, savings from avoided production costs exceed expenditures for net-purchases.

3.5 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 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.[40]

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

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

the commissioning year of a plant as a proxy for its efficiency and linearly interpolated to assign all efficiency rates.[41]

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.[42] We provide a detailed overview of the input factors for our calculation in Table A.3 in the Appendix. Table A.4 in the Appendix, provides the magnitudes of cost components, levies, and taxes. Finally, Table 3.2 presents the summary statistics.

Table 3.2: 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).

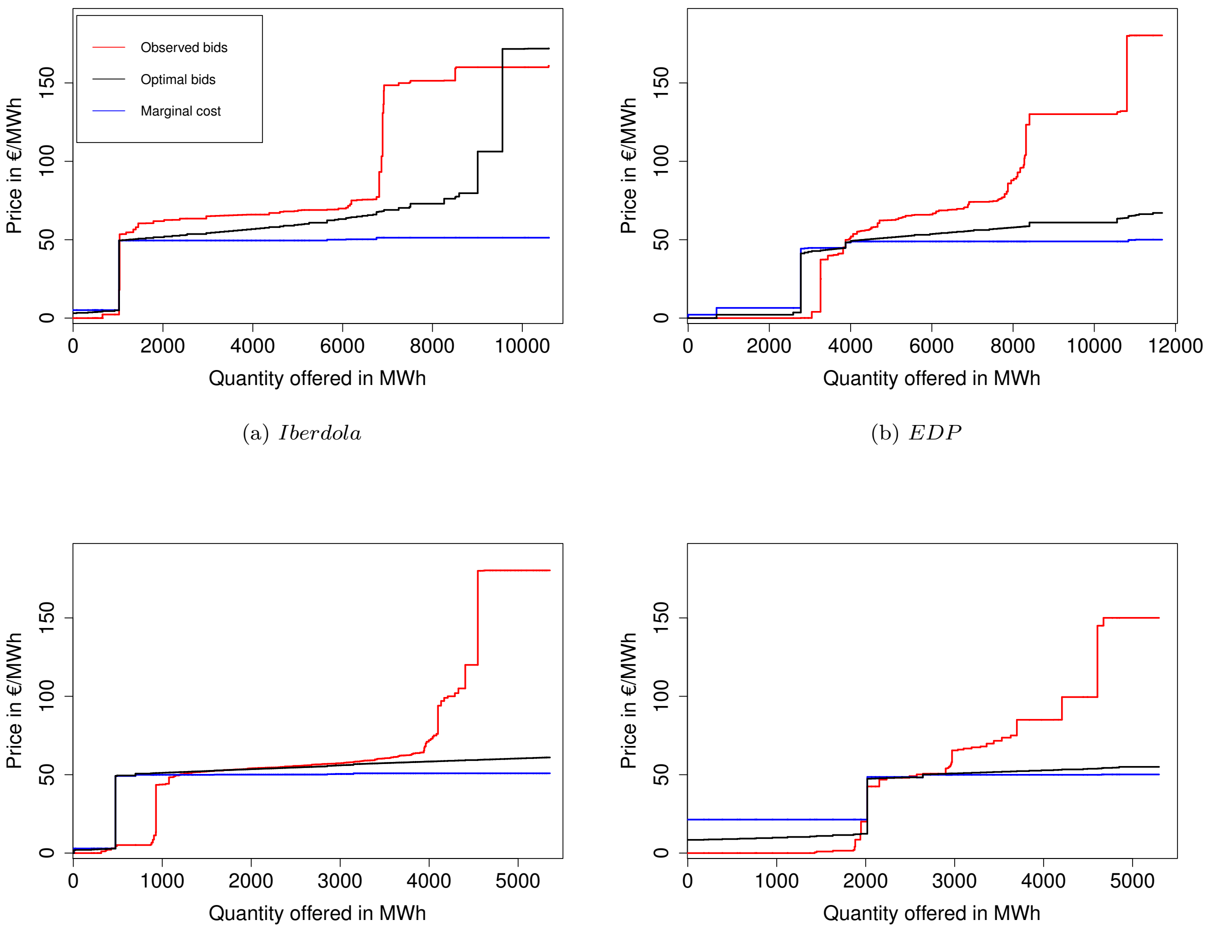
3.6 Results

This section presents our findings on the impact of firms' strategic ability on market efficiency and market externalities. Figure 3.2 and Figure 3.3 illustrate that there is clear evidence of heterogeneity in firms' strategic ability. In particular, Figure 3.2 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 match the

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

[42] 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.

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.



(a) *Iberdola*

(b) *EDP*

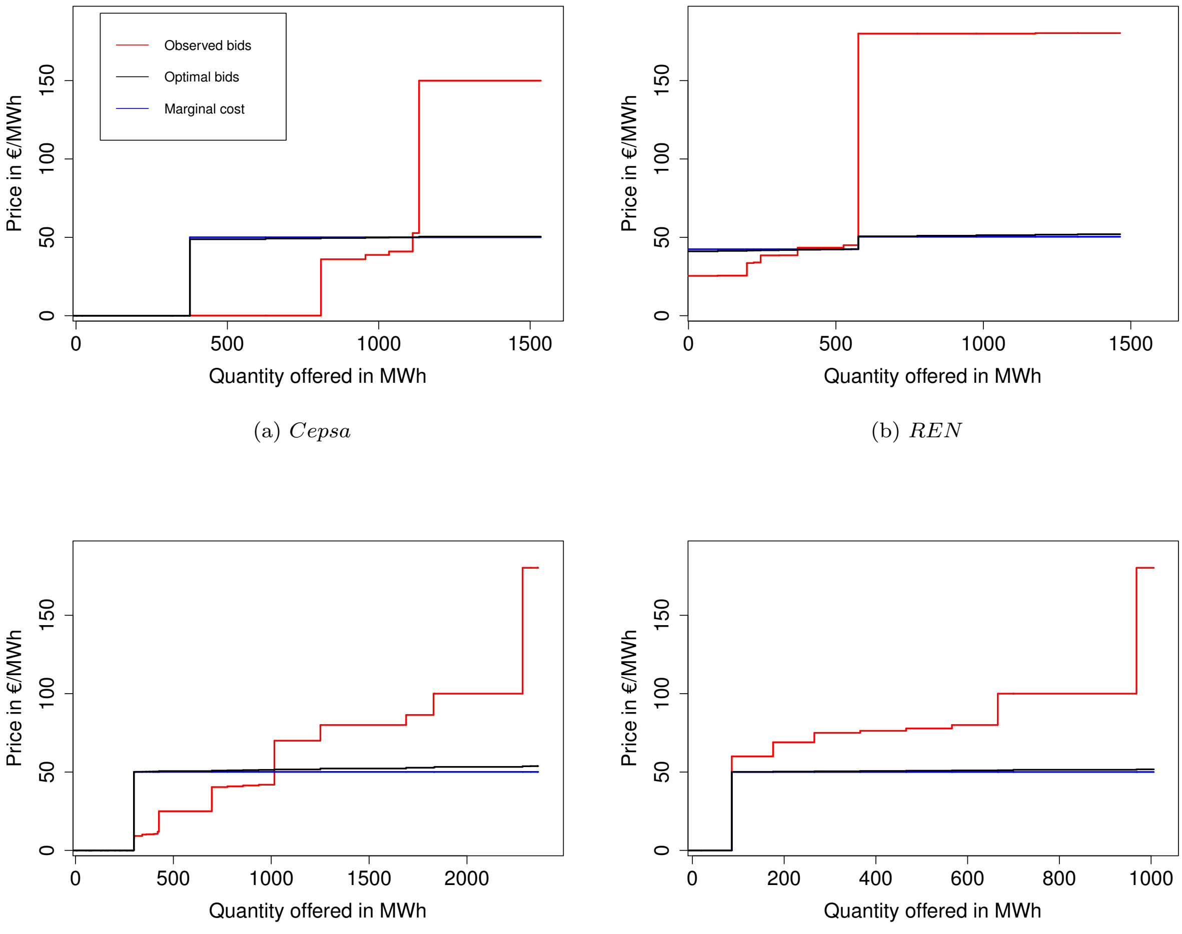
(c) *Naturgy*

(d) *Endesa*

FIGURE 3.2: Large firms, hour 17 on 01/11/2017. Estimated marginal costs curves (blue), observed supply curves (red) and counterfactual optimal supply curves (black).

In contrast, Figure 3.3 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.



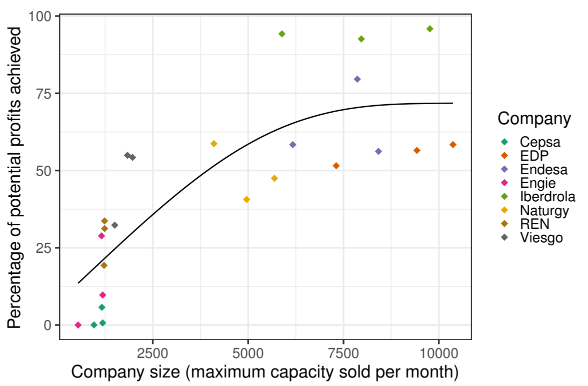
(a) *Cepsa* (b) *REN* (c) *Viesgo* (d) *Engie*

FIGURE 3.3: Small firms, hour 17 on 01/11/2017. Estimated marginal costs curves (blue), observed supply curves (red) and counterfactual optimal supply curves (black).

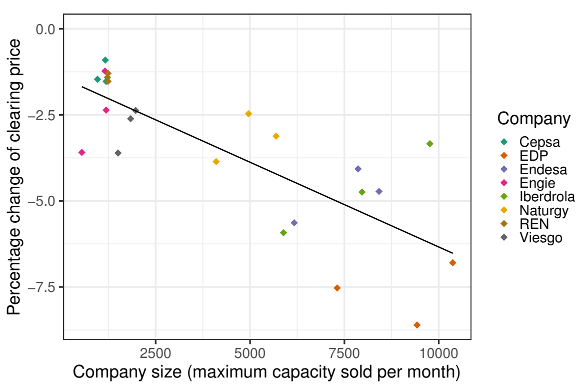
Our finding that larger firms show higher strategic ability and bid closer to optimality confirms similar results in Hortaçsu and Puller (2008) and Hortaçsu et al. (2019) for the Texas balancing market. Markedly, our results confirm this finding for the day-ahead market, where traded volumes are significantly 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 bidding schedules.

Panel (a) of Figure 3.4 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.



(a)



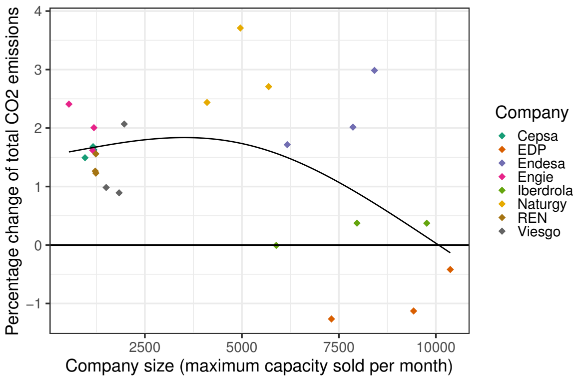
(b)

FIGURE 3.4: 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.

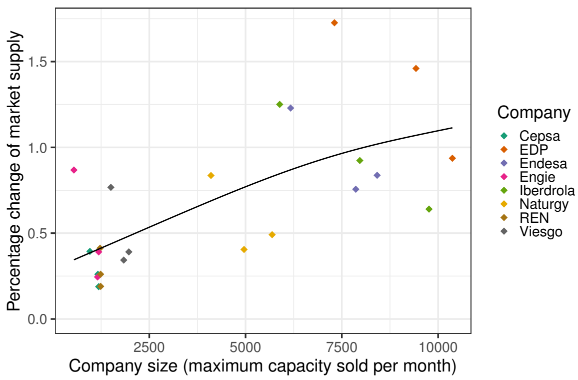
To illustrate the market impact of this heterogeneity in pricing strategies, Panel (b) of Figure 3.4 displays the impact on market prices when a company follows optimal bidding strategies. As shown, optimal pricing behavior would result in lower market prices for each firm. This is because optimal supply functions would imply more aggressive pricing. Furthermore, Panel (b) of Figure 3.4 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, but at the same time cause substantial cost for society due to inflated market prices.

3.6.1 Carbon Emissions

Next, we investigate the effects of strategic ability on CO2 externalities. Panel (a) of Figure 3.5 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 3.5 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.



(a)



(b)

FIGURE 3.5: 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.

Furthermore, Figure 3.5 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 3.3 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.

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 3.5, 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 3.5. 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 3.3: 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 3.5. 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.

3.6.2 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.

3.6.3 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 (3.6), 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 (3.6) for each submitted bid in period t. Observing all variables of equation (3.6), we calculate the mark-up on the left-hand side of equation (3.6) and the ratio of the market supply to the residual demand slope on the right-hand of equation.[43] We then, for each company i, estimate

$$p_{it} - C'_{it}(S_{it}(p)) = \beta \, \frac{S_{it}(p) - F_{it}}{-RD'_{it}(p)} + \epsilon, \tag{3.11}$$

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

Table 3.4: Deviation from optimality.

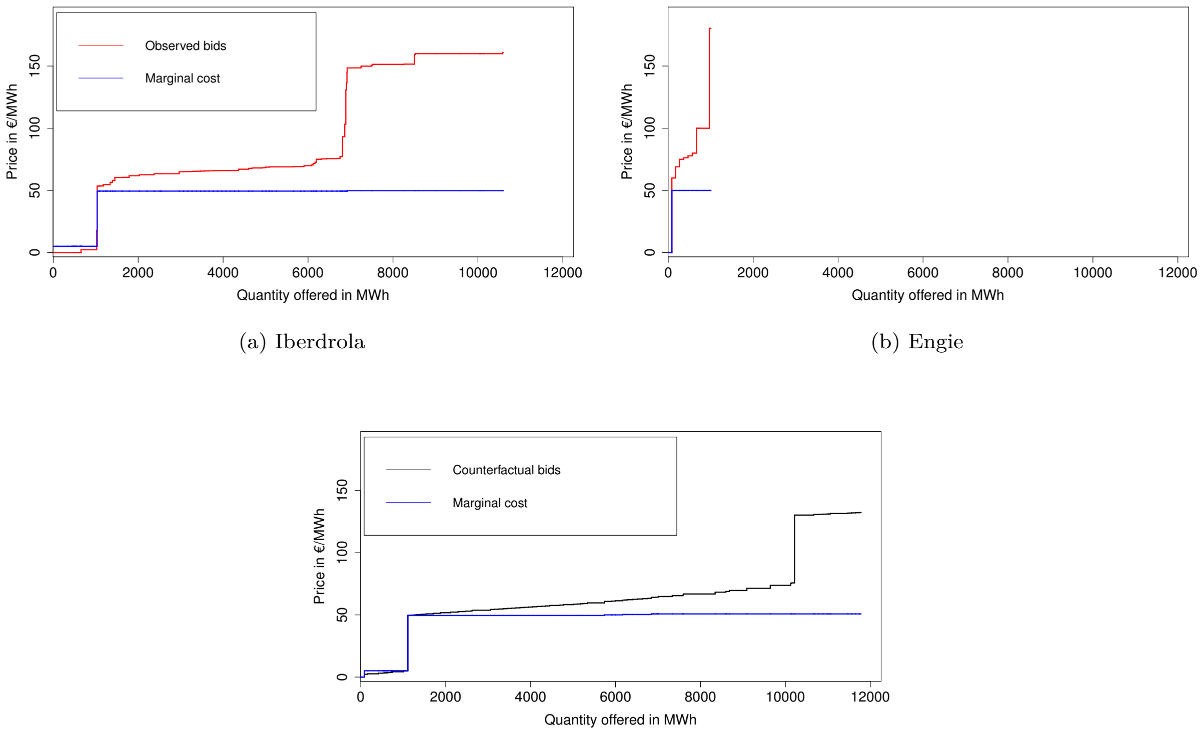
	EDP	Iberdrola	Endesa	Naturgy	Viesgo	Engie	REN	Cepsa
β coefficient	2.56	1.37	0.94	1.80	9.18	30.54	4.70	190.23
Observations	8283	5397	6915	29144	134	1164	2090	112

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

Table 3.4 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.

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

For our merger counterfactual, we then choose Iberdrola as a large firm that depicts relatively efficient bidding, and Engie, whose β coefficient in Table 3.4 indicates less sophisticated 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 3.4 to construct the joint supply curve ex-post the merger. This is, we use equation (3.11) and set $\beta = 1.37$ to obtain the counterfactual merged supply function, holding all other firms' strategies constant.



(a) Iberdrola

(b) Engie

(c) Merged firm

FIGURE 3.6: 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 ($\beta = 1.37$).

Figure 3.6 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 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

Table 3.5: Effect of the 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).

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 3.5 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 3.5. 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.

3.7 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.

4 | Designing Automated Market Power Mitigation in Electricity Markets

Jacqueline Adelowo, Moritz Bohland[44]

Electricity markets are prone to the abuse of market power. Several US markets employ algorithms to monitor and mitigate market power in real time. The performance of automated mitigation procedures (AMPs) is contingent on precise estimates of firms' marginal production costs. Currently, marginal cost are inferred from past offers of a plant. We present new estimation approaches and compare them to the currently applied benchmark method. To that end, we test the performance of all approaches on auction data from the Iberian power market. The results show that our novel approaches outperform the benchmark approach significantly, reducing the mean absolute estimation error from 11.53 €/MWh to 2.78 €/MWh for our most precise alternative approach. Our research contributes to accurate monitoring of market power and improved automated mitigation. Although we focus on power markets, our findings are likewise applicable to the monitoring of renewable energy tenders or market power surveillance in rail and air traffic.

[44] Author contributions: This essay is based on a joint paper with Jacqueline Adelowo. My contribution was the development of the research idea, the design of the empirical strategy, as well as the draft of large parts of the paper.

4.1 Introduction

The liberalization of power markets entailed efficiency gains and cost reductions for electricity producers (see e.g. Newbery and Pollitt, 1997, Davis and Wolfram, 2012), but these gains not necessarily translated into lower market prices (Newbery, 1997). The missing link between cost reductions for producers and reductions in power prices is at least partially attributed to market power exertion by power producing companies. Market power exertion in liberalized electricity markets is documented for a wide range of markets and periods (see e.g. Green and Newbery, 1992, Borenstein et al., 1999, Ciarreta and Espinosa, 2010). Limited storage capacities, inelastic short-run demand, and high market concentration render power markets especially prone to market power exertion. As market power exertion is both, inefficient and undesired by policy makers, regulators aim at mitigating undue market power.

Existing mitigation strategies include the implementation of price caps (Wilson, 2000), stringent application of antitrust policies (Green, 1996, Borenstein et al., 1999), fostering of vertical integration (Mansur, 2007, Bushnell et al., 2008), and the implementation of forward contracting obligations for suppliers (Allaz and Vila, 1993, de Frutos and Fabra, 2012). In several US markets, system operators go one step further and monitor and mitigate market power in real time. To that end, system operators implemented automated mitigation procedures (AMP), i.e. algorithms to screen all supply offers, detect undue market power, and mitigate affected offers (Twomey et al., 2006, Helman, 2006, Shawhan et al., 2011).

In this paper we contribute to improved algorithms for automated mitigation of market power. In electricity markets, market power is typically measured as the difference between observed offers and underlying marginal cost of power production. Therefore, marginal cost estimates need to be as accurate as possible to ensure unbiased measurement as well as decent mitigation of market power. When all cost components of power production are known, engineering based bottom-up calculations deliver precise estimates of marginal cost. However, cost components and power plant characteristics are private information and firms have an incentive to overstate costs. Instead, system operators thus infer marginal cost of power plants from past offers of the respective plant. We employ this approach as benchmark for further analysis. We present alternative methods that deliver more accurate estimates of marginal cost. In turn, our results allow for improved automated mitigation of market power compared to benchmark methods.

To test the accuracy of the benchmark approach and alternative methods, we employ micro-level bidding data from the Iberian day-ahead electricity market. First, we calculate marginal cost of power production bottom-up to obtain the "true" marginal cost. To that end, we employ detailed information on power plant characteristics and all relevant cost components. In a second step, we test the benchmark approach based on past offers and compare the outcomes to the true marginal cost we derived in the first step. We then proceed by testing the accuracy of alternative estimation methods and assess their performance as compared to the benchmark approach currently employed by system operators.

First, we test a theory-driven approach, which is based on Wolak (2003b, 2007). We assume power producing companies to submit offers which maximize a company's expected profits. Under this assumption, we infer marginal cost of power production that justify observed offers. To achieve accurate estimates, we follow Wolak (2007) and account for the price reducing effect of a firm's forward obligations. As the submitted offer curves represent a best-response to the offers of competing firms, we designate this approach as "best-response" approach.

Additionally, we present two approaches which methodologically build on the benchmark approach used by system operators but address major flaws of the existing method. In the first of these two approaches, we likewise infer marginal cost estimates from past offers of a plant but control for distortions caused by potential start-up and ramping costs. Therefore, we refer to this approach as the "start-up" approach. The last estimation method we propose represents an extension to the start-up approach and also controls for complementary cost components. However, instead of estimating marginal cost on the unit level, we now define clusters of similar power plants and estimate marginal costs for the whole cluster of plants. We refer to this method as the "clustering" approach.

The results of our empirical analysis reveal a poor estimation accuracy of the currently applied benchmark approach. For the sample we analyze, we find a mean absolute deviation of 11.53 € /MWh between marginal cost estimates following the benchmark approach and true marginal costs. All suggested alternative approaches deliver more precise estimates. Mean absolute deviations accrue to 8.92 € /MWh for the best-response approach, 7.27 € /MWh for the start-up approach, and merely 2.78 € /MWh for the clustering approach. The clustering approach not only delivers the most precise estimates, but likewise limits the scope for strategic manipulation of estimates by firms. This is because estimates are based on past bids of a group of plants instead of just one plant. Strategic manipulation of estimates and thus mitigation would hence require a significant extent of coordination among firms.

Our findings provide system operators with improved estimation techniques of power plants' marginal cost and with more accurate methods for monitoring and real time mitigation of market power. Equipped with precise marginal cost estimates, system operators can apply automated mitigation more stringently, and achieve increased market efficiency and reduced costs for consumers. At the same time, improved accuracy benefits producers as the scope for unjust mitigation of offers based on flawed marginal cost estimates reduces. The main use cases for our suggested approaches are automated procedures for market power mitigation in spot, balancing, and reserve electricity markets. Yet, the approaches can likewise find application in other markets, e.g. for monitoring in renewable energy tenders or price and market power surveillance in rail and air traffic. Additionally, marginal cost estimation approaches which are not contingent on private information facilitate power market research for scholars. Our suggested approaches are especially valuable when a bottom-up calculation is infeasible due to limited accessibility of private information on cost components.

Considering the widespread application of AMPs in US power markets and the immediate effect of mitigation procedures on market prices, producer and consumer rents, as well as investment decisions, literature on AMPs is rather scarce. Twomey et al. (2006) and García and Reitzes (2007) address AMPs in their reviews of market power monitoring and mitigation measures. Helman (2006) assesses and compares market power monitoring and mitigation procedures in several US markets. Kiesling and Wilson (2007) follow an experimental approach to investigate effects of AMPs on market prices and investments. Shawhan et al. (2011) likewise make use of an experimental setting to test the impacts of AMPs, but account for the fact that firms influence marginal cost estimates, and thus mitigation measures, strategically. For the suggested best-response approach, we additionally draw from the literature on strategic bidding in multi-unit auctions (see e.g. Wolfram, 1999, Wolak, 2003b,a, 2007, Hortaçsu and Puller, 2008) and the literature on the impacts of forward contracts and vertical integration on optimal pricing strategies (see e.g. Allaz and Vila, 1993, Wolak, 2007, Bushnell et al., 2008)

The remainder is organized as follows. Section 4.2 gives an overview on AMPs in US power markets. In section 4.3, we proceed with a description of the suggested estimation approaches and their empirical implementation. In section 4.4, we present the market environment in the

Iberian electricity market. Section 4.5 proceeds with a description of the employed data. In section 4.6, we show our results and section 4.7 concludes.

4.2 Automated Market Power Mitigation in US Markets

4.2.1 Overview and Procedure

Multiple Independent System Operators (ISO) have implemented automated mechanisms for the mitigation of market power exertion in wholesale auction markets. These ISOs are the California Independent System Operator (CAISO), the Independent System Operator New England (ISO-NE), the New York Independent System Operator (NYISO), the Pennsylvania-New Jersey-Maryland Interconnection (PJM), serving various Eastern states, and the Midcontinent Independent System Operator (MISO), whose network also covers parts of Canada. The CAISO, ISO-NE, NYISO, and MISO use market observations such as historical bids and prices to construct so called reference levels. Reference levels serve as unit-specific proxies for marginal costs and simulate a competitive bid. The precise derivation of reference levels is further described below. We exclude the PJM from our further review, where reference levels are derived by a cost-based method. The ISOs are regulated by the US Federal Energy Regulatory Commission (FERC) and publish their full tariffs online, which serve as business practices manuals and operating rules. These FERC-approved tariffs allow an extensive understanding of the procedures applied for automated mitigation, whose generalized concept can be summarized as follows.

The basic condition for mitigation is a market situation that implies potential for market power. This is defined by the ISOs as the occurrence of local transmission constraints or as the occurrence of pivotal supply; or both cumulatively. For the latter, a pivotal supplier test is carried out after bid submission that either tests individual suppliers or the group of n-largest suppliers for pivotal supply conditions (MISO, 2019, ISO-NE, 2020, NYISO, 2020). In the case of the CAISO, this screening is further specified by an Residual Supply Index (RSI) analysis (CAISO, 2019).

If this structural test identifies a situation in which there is potential for market power, then respective suppliers' bids are tested against a conduct threshold in order to identify actual exercise of market power. In the case of the CAISO the conduct threshold is met when bids exceed the competitive locational marginal price (LMP) (CAISO, 2019). The other ISOs specify a certain percentage (e.g. 200% or 300%) or absolute amount (e.g. 100$/MWh) by which the submitted bid has to exceed the unit's reference level. If the conduct threshold is exceeded, the bid is deemed non-competitive (MISO, 2019, ISO-NE, 2020, NYISO, 2020).

However, to avoid excess intervention, the bids are then tried against an impact test, which describes the consequential price impact. One possibility is to define the impact as significant as soon as the bid sets the LMP or if the bid effectively removes the unit from the economic merit order (CAISO, 2019). Another possibility is to set an impact threshold as a percentage (e.g. 200%, less for constrained areas) or absolute amount (e.g. 100$/ MWh, less for constrained areas) by which the clearing price would be decreased in a collectively mitigated scenario. This may also be measured by comparing the unit's node's LMP against the node's hub LMP (MISO, 2019, ISO-NE, 2020, NYISO, 2020).

Provided the impact threshold is exceeded, the automated mitigation takes place by overriding the respective bid by a unit-specific reference level. For all analyzed ISOs this practice is applied in day-ahead markets and other spot markets (CAISO, 2019, MISO, 2019, ISO-NE, 2020, NYISO, 2020). Yet, ISOs are heterogeneous when it comes to the possibilities for the calculation of reference levels. The applicability ranking of the available methods is either at the supplier's choice or set by the ISO. The cumulated variety of methods found in the operating procedures of the analyzed ISOs consists of accepted offer-based, LMP-based, and cost-based calculations as well as a negotiation-based method.

The first calculation method is based on previously accepted offer bids of the respective unit and is applied by ISO-NE, MISO and NYISO. In general, the reference level is calculated as the mean or median of accepted offers over the last 90 days during competitive periods, adjusted for changes in fuel prices (MISO, 2019, ISO-NE, 2020, NYISO, 2020).

The second calculation method is based on previous LMPs at the unit's node and is used by all four ISOs. The reference level is calculated as the mean or median of the lowest 25% (50% for NYISO) of LMPs during hours, in which the respective unit was scheduled within the past 90 days. The calculation again includes an adjustment for changes in fuel prices. CAISO additionally distinguishes peak and off-peak hours in the calculation (CAISO, 2019, MISO, 2019, ISO-NE, 2020, NYISO, 2020).

The third calculation method is based on cost-estimates and is also applied by all ISOs. This approach considers unit-specific heat rates and fuel costs, unit-specific emissions with respective permit prices, opportunity costs and variable operation and maintenance (O&M) costs. The calculation is done in a consultative approach together with the supplier, who has to provide required information and documentation of all cost components that cannot be gathered by the ISO (CAISO, 2019, MISO, 2019, ISO-NE, 2020, NYISO, 2020). The approach delivers good estimates of firms' marginal cost, yet requires detailed plant level information on cost structures. It is not clear to regulators whether the cost data disclosed by generators is accurate or not. Generators naturally have an incentive to overstate their costs, e.g. by overstating the heat rate or the operation and maintenance cost of the power plant.

TABLE 4.1: Overview of automated market power mitigation across US markets.

Procedures	CAISO	ISO-NE	MISO	NYISO
Application tied to transmission constraint	Yes	No	Yes	No
Test for pivotal supply	Yes + RSI	Yes	Partly	Partly
Conduct threshold	Bids exceeding the competitive LMP	% / $ amount per MWh	% / $ amount per MWh	% / $ amount per MWh
Impact threshold	Bid sets LMP/ moves unit out of economic MO	% / $ amount per MWh	% / $ amount per MWh	% / $ amount per MWh
Basis for reference level	a) Prev. LMP b) Negotiated c) Cost	a) Accepted bids b) Prev. LMP c) Cost	a) Accepted bids b) Prev. LMP c) Cost	a) Accepted bids b) Prev. LMP c) Cost
Types of reference levels	Incremental + dynamic cost components	Incremental + dynamic cost components	Incremental + dynamic cost components	Incremental + dynamic cost components
Relevance for day-ahead	Yes	Yes	Yes	Yes

Notes: Summary of the application procedures of automated market power mitigation by different US ISOs. Compiled from CAISO (2019), MISO (2019), ISO-NE (2020), NYISO (2020).

The last method is based on negotiations and exclusively applied by the CAISO. In this approach suppliers propose an appropriate reference level, which, if not immediately accepted by CAISO, will be further negotiated (CAISO, 2019). In Table 4.1, we summarize the procedures followed in US power markets, providing insights on when mitigation is executed and how reference levels are determined.

4.2.2 Calculation of Reference Levels

Our analysis focuses on the estimation of reference levels, which are crucial for efficient mitigation. As the accepted offer-based method is the default method applied by ISO-NE, MISO and NYISO, we use this method as our benchmark. The accepted offer-based method uses previously accepted bids from competitive periods over the recent 90 days as a basis for a mean or median calculation. The definition of competitive periods is, however, not consistent across analyzed ISOs. For the ISO-NE "competitive" refers to the mere economic scheduling of a unit (ISO-NE, 2020), whereas for the MISO the term is tied to the absence of transmission constraints (MISO, 2019). The NYISO tariff, despite stating the term, does not provide an explicit definition at all (NYISO, 2020).

Some ISOs impose additional conditions that narrow down the scope of relevant offers to certain periods or hours within the competitive periods (see Table 4.2). The NYISO takes only hours into account that start from 6am to 9pm and categorically excludes weekend and holiday hours from the calculation (NYISO, 2020). The MISO does not restrict the calculation to certain hours of the day but instead distinguishes between peak and off-peak hours (MISO, 2019). Last, the ISO-NE does not further narrow down the scope of considered accepted bids apart from its definition of competitive periods (ISO-NE, 2020).

Table 4.2: Conditions for acceptance of bids for reference level calculations.

Criterion	**ISO-NE**	**MISO**	**NYISO**
Retrospective time frame	90 days	90 days	90 days
Definition of competitive period	Scheduling of the unit in economic merit order	Absence of transmission constraints	None given
Distinction/ exclusion conditions	None given	Distinction of peak and off-peak hours	Only hours starting 6am-9pm, Exclusion of weekends + holidays, Exclusion of bids below 15$/MWh

Notes: Compiled from MISO (2019), ISO-NE (2020), NYISO (2020).

The detailed calculation approaches for the default accepted offer-based method reveal a lacking consistency in the definition of which categories of hourly bids are most appropriate as a basis for reference level calculation. From the calculation practices no consensus can be found particularly on the handling of peak and off-peak periods in terms of their distinctive use, inclusion or exclusion. In case of the ISO-NE no attempt of distinguishing peak and off-peak hours is even made, which leads to a rudimentary mean or median calculation. The different approaches to accepted offer-based calculation among the ISOs imply differing calculation results. It is however unclear, which ISO's approach yields reference levels that best approximate competitive bids. Moreover, under certain conditions the ISOs may switch to a cost-based calculation for individual bids. The cost-based methodologies are more uniform among all ISOs as compared to the accepted offer-based methodologies. As a consequence, the cost-based calculation can be expected to yield more similar reference level results across the ISOs, when compared to results from accepted offer-based calculations. This inevitably raises the question of how comparable reference levels of the same ISO really are, if, within the same territory, some bids are regulated using cost-based reference levels, whereas others are regulated using accepted offer-based reference levels.

Both the accepted offer-based calculation as well as the cost-based calculation bear risks of Principal-Agent problems arising from hidden information. As the ISOs rely severely on the accepted offer-based method, this has evoked discussions on possible strategic bidding behavior that aims at increasing reference levels. Shawhan et al. (2011) find evidence in an experimental study that, in case of sufficiently high market power, bidders have an incentive to strategically raise their bids during competitive periods and thus manipulate the calculation basis for reference levels – so called reference creep. Competitive periods were defined as periods without transmission constraints in the study. Currently, this issue is addressed in none of the analyzed ISO tariffs; consequently, there are no measures in place to detect or account for reference creep.

The second problem of hidden information arises in the cost-based reference method, where the ISOs depend on suppliers to truthfully disclose information on cost components, which cannot be obtained otherwise by the ISO. This information includes e.g. unit-specific opportunity costs. Depending on the agent to disclose such private, unobservable information provides opportunity for strategic behavior. Even at the PJM, an ISO that is particularly experienced in working with cost-based reference levels, these information asymmetries are hitherto unaddressed. The PJM's independent market monitor describes the occurrence of resulting strategic behavior of market participants in the submission of cost components and criticizes that true competitive proxies cannot be obtained if suppliers' submissions are not truthful and uniform (Monitoring Analytics, 2019). The complexity of bottom-up cost calculation as well as the information asymmetries of this approach may be a reason why all analyzed ISOs, except for the CAISO, explicitly present the cost-based method as least applicable option to calculate reference levels.

4.3 Method and Empirical Strategy

In this section, we illustrate different empirical approaches to calculate reference levels of power plants' marginal costs based on observed supply bids. To ensure comparability, all approaches make use of the same data from the Iberian day-ahead market, as described below in section 4.5. First, we present the benchmark procedure as conducted by the NYISO, where we use observations of the preceding 90 days to calculate reference levels. We then proceed by describing the best-response approach, which builds on Wolak (2003b, 2007) and Hortaçsu and Puller (2008). We present two more approaches which are bid pattern-driven and represent extensions to the NYISO benchmark method. Here, we address problems which arise due to start-up cost and reference creep and increase the precision of estimation.

4.3.1 The NYISO Benchmark Approach

To assess the relative performance of our proposed calculation approaches we first define a benchmark. To that end we chose the NYISO method of calculating reference levels of plants' marginal cost. As compared to other ISOs, the NYISO provides relatively more information on the composition of the calculation basis, i.e. the set of historical bids which is employed for the estimation of reference levels. All US system operators we analyzed follow similar procedures, yet approaches differ in details such as the exclusion of bids from the calculation basis (see Table 4.2 for an overview).

We calculate reference levels of plants' marginal cost for an exemplary week in December 2017 (December 4 to December 10). For each fossil power plant and day within this week, we determine a reference level, which should optimally reflect the bottom-up calculated marginal cost for the respective plant and day.[45] As calculation basis, we use historical bids of the plant within the last 90 days. In line with the NYISO procedure, we define the reference level as the mean or median (whichever is lower) of bids in the calculation basis. Note that we only use bids

[45]We present a detailed description of our bottom-up calculation of "true" marginal cost is section 4.5.

within the range of 20 €/MWh to 125 €/MWh, firstly to comply with the NYISO procedure, and secondly to limit the leverage of complementary cost considerations of the firms.[46]

Within the 90 days period that serves as calculation basis, variation in underlying fuel cost and cost for carbon emissions is substantial (see Table 4.3). The precision of reference levels on the one hand benefits from the large calculation basis, but should, on the other hand, not be affected by changes of input prices. System operators account for fuel price changes NYISO (2020), yet do not specify how they proceed exactly.[47] We present our strategy to empirically control for changes in input prices in the Appendix. Reference levels are then defined as the mean or median of all adjusted bids in competitive hours within the last 90 days.

4.3.2 Best-response Bidding

The second approach is based on Wolak (2003b, 2007), who derives underlying marginal cost directly from observed bids. We use his model of best-response pricing, which assumes that a profit maximizing firm will submit a set of bids that is ex-post optimal given its residual demand. Assuming profit-maximizing behavior, it is possible to derive a firm's marginal cost C' for observed residual demand RD, observed market clearing prices p and its forward contracted quantity QC. The resulting firm profit function for a single scheduling hour is further dependent on the price received on forward sales PC as well as the uncertain demand shock η and can be expressed as follows:

$$\pi(p) = RD(p,\eta)p - C(RD(p,\eta)) - (p - PC)QC, \tag{4.1}$$

We take the first order derivative with respect to the price and solve for the marginal cost component to receive the following condition

$$C'(RD(p^*,\eta)) = p^* - \frac{QC - RD(p^*,\eta)}{RD'(p^*,\eta)}. \tag{4.2}$$

[46]Companies alienate simple bids to signal that a plant is already running (by bidding at very low prices), or that it would need to start-up (by bidding close to the price cap) (Reguant, 2014).

[47]Adjustments are contingent on detailed price information over time. As fuel prices and emission allowance prices are publicly available, we assume that regulators possess the required information.

All bids are submitted in the expectation that the respective bid could determine the market clearing price, therefore each bid can be regarded as an optimal price p^*. Marginal cost C' are thus derived from observed bid levels p^*, the amount of inframarginal quantity offered by the firm RD, the slope of the residual demand function faced by the firm RD', and its contracted quantity QC. As we possess information on all supply and demand bids as well as the owning structure of the firms, we can derive the inframarginal quantity and the residual demand curves. However, residual demand functions are stepwise bid functions in electricity markets and not continuously differentiable. We follow Wolak (2003b) and solve this by applying smoothing parameters for the residual demand curve.[48]

The contracted quantity QC is a crucial element for the bidding strategy of the firm. This element of contracted quantity incorporates both, forward sales (Wolak, 2007, Holmberg, 2011) as well as sales to vertically integrated retailers (Kühn and Machado, 2004, Mansur, 2007, Bushnell et al., 2008), as the underlying incentives are identical. If the contracted quantity exceeds sales in the market, the firm acts as a net-buyer and aims at lowering the market clearing price by bidding below marginal cost. If market sales exceed the contracted quantity, the firm acts as a net-seller and bids above marginal cost to increase its profits. In case the regulator possesses information on vertical sales and forward contracts, it can directly derive QC and thus the underlying marginal cost C'. Unfortunately, we lack information on firms' forward sales and need an alternative approach for the estimation of QC. We make use of the nature of firm strategies and identify the contracted quantity as the position where the marginal cost curve of a firm intersects its supply function (Hortaçsu and Puller, 2008). The rationale is that, if the uncertain residual demand materializes at the exact contract position of the firm, the firm has no incentive to influence the market clearing price and bids equal to marginal cost.[49]

We derive all parameters of equation 4.2 and calculate marginal cost as a function of the observed bid-level, the firm's hourly net-position, and the slope of the residual demand curve at the chosen bid-level. We determine reference levels for all fossil plants and days within the analyzed week in December 2017 (December 4 to December 10). To ensure comparability across methods, we again restrict input bids to the range from 20 €/MWh to 125 €/MWh in competitive hours

[48]We use the *monpol* function in R, which is part of the *MonoPoly* package and ensures a monotonic fit. We allow for nine degrees of freedom. Note that our findings are not contingent on the exact specification of smoothing parameters.

[49]To retrieve the intersection between the supply curve and the marginal cost curve, we first need to fit a marginal cost curve. We use an isotonic regression that delivers monotonically increasing step-functions and is best-suited to mimic the nature of marginal cost curves.

(from 7am to 11pm). Last, we define daily reference levels for each plant as the mean of all calculated marginal cost estimates for the respective plant and day.

4.3.3 Accounting for Start-up Cost

In this section we present an extension of the benchmark NYISO method. By following the NYISO approach as presented in section 4.3.1, we do not structurally incorporate additional cost components such as start-up cost. Yet, the bids in our calculation basis may partly be driven by the presence of start-up cost. Reguant (2014) shows that the neglect of start-up costs leads to biased estimates of marginal cost and eventually to flawed mark-ups and measures of market power. Nevertheless, for the sake of simplicity and clarity, we abstain from including start-up cost in the bottom-up calculated marginal cost estimates.[50] We assess the performance of the presented approaches by the deviation between the related reference levels and the bottom-up estimates of marginal cost. To achieve coherence, we thus need a calculation basis that excludes bids driven by start-up costs.[51]

Empirically, we address this problem by further limiting our calculation basis to those plants which are clearly not affected by start-up cost. Firms submit very low first step bids for plants that are already running to ensure that these plants will be called with certainty (Reguant, 2014). Note that firms are permitted to submit up to 25 discrete steps per power plant. Using the first step to determine whether the plant should be running or not therefore comes at negligible opportunity costs. We make use of this signaling behavior and limit the calculation basis to bids of power plants for which at least one low-priced bid has been submitted within a certain hour.[52] Apart from this constraint, we use the same calculation basis as in our benchmark approach (see section 4.3.1) and likewise account for changes in input prices.

[50] A distinct assessment of start-up cost is difficult as firms use both complex bids and simple bids to express start-up cost.

[51] The alternative would be to include start-up cost in the bottom-up estimates of marginal cost and in the reference levels. However, we see no feasible option to determine the extent to which a reference level is driven by start-up cost.

[52] We set the boundary at 30 € /MWh and thus significantly below the minimum clearing price within our sample period which equals 41.1 € /MWh.

4.3.4 Clustering

In our final approach, we address several additional shortcomings of the NYISO method, namely the large dispersion of results across power plants, the missing calculation basis for a set of plants, and the potential occurrence of reference creep. We solve these problems by departing from the calculation of unit-specific reference levels. Instead, we cluster the power plants in our sample with respect to their main characteristics, i.e. efficiency and size. Figure 4.1 depicts the results of the clustering process, showing four clearly distinguishable clusters. Clusters one and two incorporate large (cluster 1) and small (cluster 2) coal power plants, whereas clusters three and four show large (cluster 3) and small (cluster 4) combined-cycle gas turbines (CCGT).

We use these clusters and calculate reference levels analogously to our procedure in section 4.3.3, yet not for each power plant individually, but on the cluster-level. Thereby we solve the problem of the large dispersion of precision across plants and receive a more concentrated distribution of results. At the same time we limit the influence of outliers, which are usually attributed to a small calculation basis. Furthermore we solve the problem of missing calculation basis. As the calculation basis is now identical for all power plants within a cluster, we obtain reference levels for a larger set of power plants.

For the purpose of AMPs, the main advantage of clustering the plants is the prevention, or at least complication, of reference creep. As long as reference levels for mitigation are merely based on the historical bids of a single power plant, strategically inflating these bids may prove to be beneficial for the firm. The incentives to strategically alter the calculation basis decrease when the regulator shifts to a clustered approach. Firstly, strategic bidding would become more apparent as the clusters comprise plants of similar size and efficiency. Strong deviations from the mean bidding behavior of the plants within the cluster would be conspicuous and could hardly be justified. Secondly, plants within a cluster belong to a set of different firms as long as clusters are sufficiently large. Conducting reference creep would thus require significant coordination among firms. The clustering approach thus solves several elementary problems of accepted offer-based calculations of reference levels.

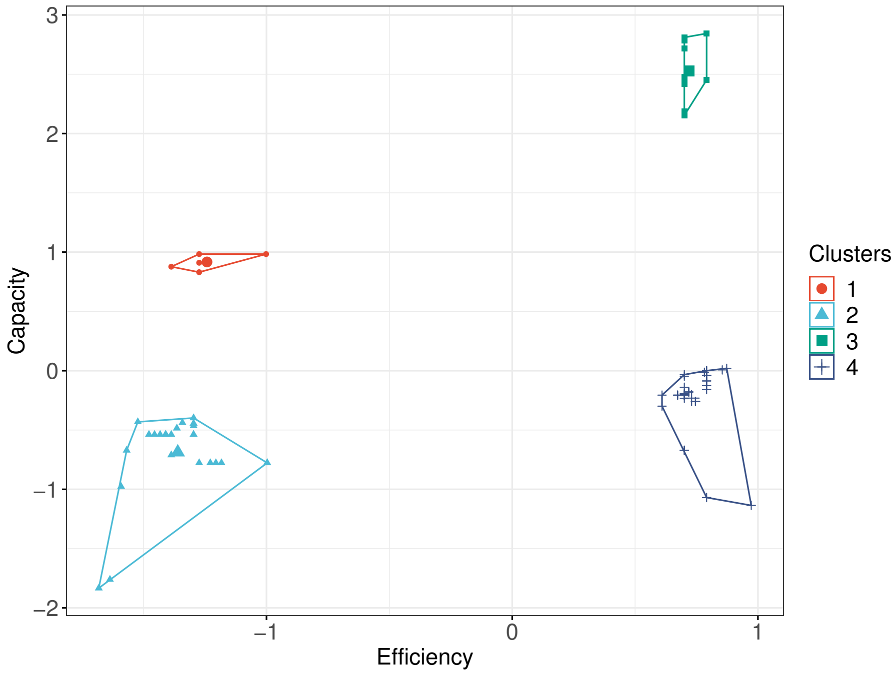
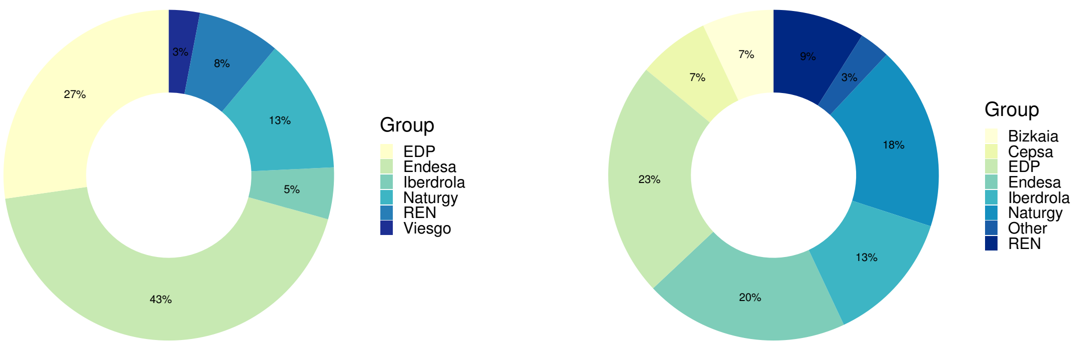


FIGURE 4.1: Clustering of plants with respect to efficiency and size. Clusters 1 and 2 represent inefficient coal power plants, where cluster 1 comprises large coal power plants and cluster 2 small coal power plants. Clusters 3 and 4 represent efficient CCGT plants with cluster 3 comprising large CCGT plants and cluster 4 smaller CCGT plants.

4.4 Market Environment

The Iberian electricity market consists of the geographical regions of Spain and Portugal. In 2007 the two countries integrated their electricity markets into one administrative market called Mercado Ibérico de la Electricidad (MIBEL). The peninsular electricity spot market of MIBEL is managed by the nominated electricity market operator called Operador del Mercado Ibérico de Energía – Polo Español (OMIE), which is based in Spain. The organized forward market is managed by the Portuguese equivalent OMIP.

OMIE is responsible for the MIBEL day-ahead and intraday (auction and continuous) energy markets within the spot market management. The OMIE market represents the most important place of electricity exchange within MIBEL, as its markets traded 85% of the total MIBEL electricity demand in 2017, which is our year of study. Whenever interconnections between Spain and Portugal are not at capacity limits, OMIE consists of only one pricing zone. This was the case in 94.4% of the time in 2017. The OMIE market can therefore be regarded as one coupled market consisting of the geographic zones of peninsular Spain and Portugal.



(a) Coal-fired

(b) Gas-fired

FIGURE 4.2: Distribution of fossil power generation across firms (05/09/2017 to 10/12/2017).

This study concentrates on OMIE's day-ahead market, as it represents the most important trading market accounting for more than 86% of the total OMIE trading in 2017. In 2017, a total of 247 TWh was traded in the day-ahead market, of which Spanish generation accounted for the large majority of 72%, whereas Portuguese day-ahead generation accounted for 22%. On the day-ahead market, agents submit sale and purchase bids on electricity transactions for the following day. Buying agents can be direct consumers, retailers, resellers and representative agents; selling agents can be owners of production units, retailers, resellers and representative agents (OMIE, 2015).

The daily scheduling horizon consists of 24 hourly periods, which are all auctioned in a single session. Each bid is comprised of up to 25 blocks for each hourly scheduling period, with decreasing prices for purchase bids and increasing prices for sale bids. The maximum possible bid price is regulated to 180.30 €/MWh. Purchase bids are always simple bids, meaning that they consist only of a price and an amount of power for each block of a scheduling period. Sale bids are tied to a production unit and can be either simple (only price and amount) or complex. Complex bids contain additional conditions that the agent can submit to the market operator and typically cover complementary cost factors such as start-up or ramping cost. OMIE verifies the bids and matches sale to purchase bids with the Euphemia matching algorithm that is commonly used in multiple European electricity markets. The algorithm creates two aggregate stepwise curves for purchase and sale bids, considering any complex conditions, and finds the corresponding system marginal price as a uniform clearing price (OMIE, 2015).

The day-ahead market is characterized by the presence of few large players dominating the market. Roughly two thirds of generation can be accounted to five company groups owning the respective generation units, namely Endesa, Iberdrola, EDP, Naturgy, and Viesgo (Comisión Nacional de los Mercados y la Competencia, 2019). At the same time, these companies are vertically integrated, and likewise act as electricity resellers and retailers. With small renewable producers entering the market, the overall market share of the dominant producers shrank after liberalization. Yet, the fossil fuel production, which is at the center of our research, is still in the hands of a few large companies. Only six companies accounted for all production from coal-fired units within our sample period, namely Endesa, Iberdrola, EDP, Naturgy, Viesgo and REN. Production from CCGTs stemmed from the same companies along with Engie, Cepsa, and Bizkaia. These seven companies were responsible for 97 % of CCGT production within our sample period. Figure 4.2 visualizes the highly concentrated market environment of fossil power production in Spain and Portugal.

4.5 Data

The centerpiece of our dataset stems from the Iberian market operator OMIE and comprises all supply and demand side bids in the Iberian day-ahead market.[53] Our analysis focuses on fossil power generation, i.e. power production from coal and natural gas. Therefore, we chose a sample period with a high market share of fossil production. The week we analyze in detail is week 49 in 2017, starting on December 4 and ending on December 10. As we need input data that stretches back 90 days, our sample includes all bids from September 5 to December 10 and extends over a period of slightly more than three months.

We focus on fossil production as we compare the derived reference levels to bottom-up calculated marginal cost. For fossil generation this calculation is straight forward and delivers precise estimates of the true underlying marginal cost. Our bottom-up estimation of short-run marginal cost includes fuel cost, cost for carbon emissions, variable O&M cost as well as all relevant additional taxes and levies. Figure 4.3 displays the estimated marginal cost across both technologies in Spain and Portugal. For a detailed overview of the determinants of our calculation, as well as sources of fuel prices and plants' efficiency rates, please see Table A.3 in

[53]Monthly files including all supply and demand curves are provided on the website of OMIE.

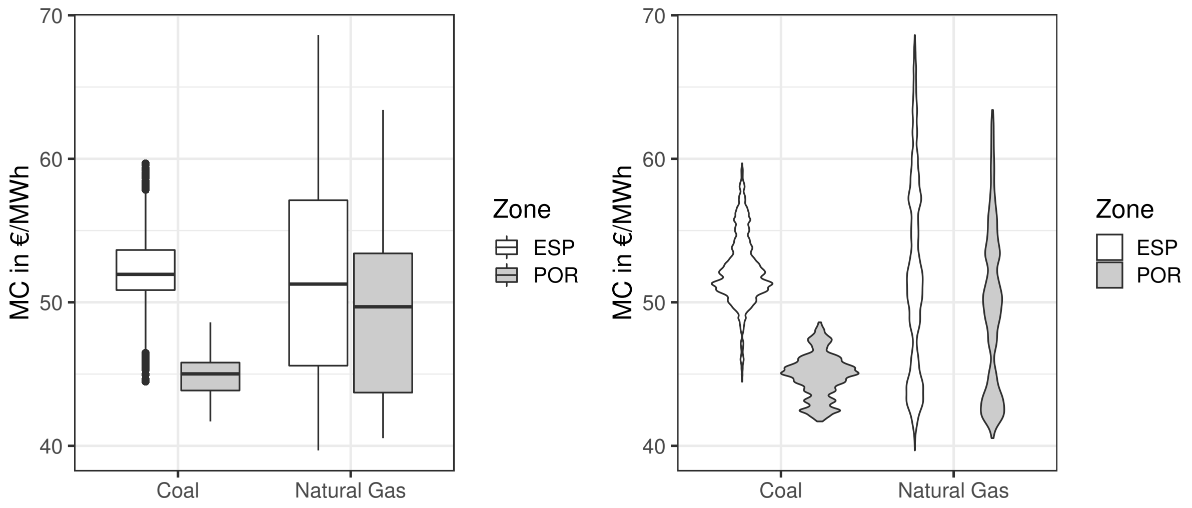


FIGURE 4.3: Distribution of button-up estimated marginal costs across fossil power plants within the sample period (05/09/2017 to 10/12/2017).

the Appendix. Table A.4, likewise displayed in the Appendix, provides the detailed magnitudes of parameters we use for our calculation.

Figure 4.3 gives an overview of the bottom-up estimated marginal cost in our final sample. The difference of marginal cost levels between Spain and Portugal stems from the additional taxation prevalent in Spain. Even though Portugal implemented a clawback mechanism to mitigate the difference in marginal cost via an additional charge, this mechanism lacks the ability to fully compensate the cost gap. At the same time it is apparent that marginal cost of coal power plants are subject to less volatility than marginal cost of CCGT plants, which is attributed to the higher volatility of natural gas prices as compared to hard coal prices.

As part of our analysis is based on firm behavior, we additionally assign the parent companies to each power plant, or more precisely, to each bid, to account for ownership structures. This provides us with a dataset that comprises all demand and supply bids within the sample period, enriched by bottom-up estimated marginal cost, information on fuel types, and an indicator variable specifying the owning parent company of the respective plant.

For the benchmark method to calculate reference levels of underlying marginal cost, we mimic the procedure of the NYISO and bring it to the Iberian data. Analogous to the NYISO procedure, we thus restrict our calculation basis to a certain range of bids, which we deem to be competitive. In the NYISO calculation, all bids lower than 15 \$/MWh are excluded. We slightly

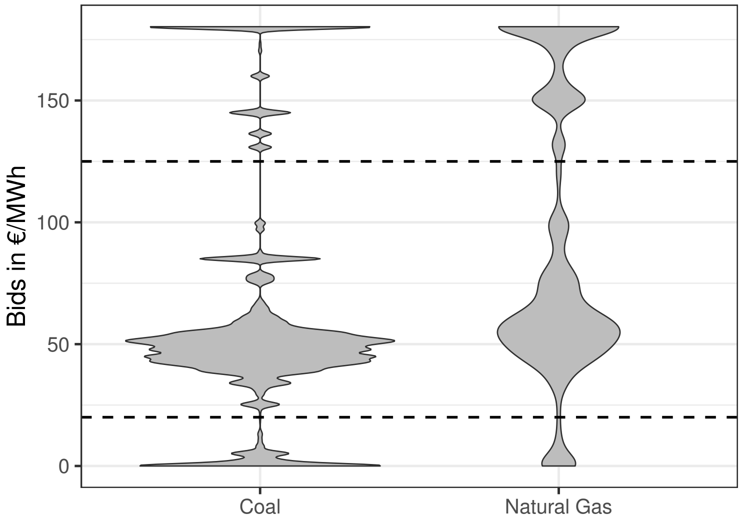


FIGURE 4.4: Distribution of bids submitted by fossil power plants within the sample period (05/09/2017 to 10/12/2017).

increase this boundary to 20 € /MWh and furthermore set an upper boundary of 125 € /MWh. This means we exclude all those bids, which we are sure not to reflect short-run marginal cost. Figure 4.4 displays the observed bid levels of both technology types within our sample period, as well as the boundaries at 20 € /MWh and 125 € . Even though firms can make use of complex bids to cover cost complementaries such as start-up or ramping cost, they simultaneously use simple bids to either ensure that the respective power plant is running (and bid close to zero), or to signal that they not intend to start-up a plant (and bid close to the price cap). This explains the high density of bid levels at 0 € /MWh and 180.30 € /MWh as displayed in Figure 4.4. Additionally, we limit the sample to competitive hours (from 7am to 11pm) on weekdays to be consistent with the NYISO procedure.

In Table 4.3, we present the summary statistics of our final sample. Note that the dispersion of natural gas prices by far exceeds the dispersion of hard coal prices, further shedding light on the distribution of marginal cost in Figure 4.3.

Table 4.3: Summary statistics.

	Mean	Median	Std. dev.	Min.	Max.	Obs.
Coal bid level [€/MWh]	50.3	48.7	12.7	22.4	100.0	122,655
Gas bid level [€/MWh]	59.1	55.5	17.1	20.1	123.8	135,239
Coal marginal cost [€/MWh]	50.5	51.2	3.9	41.7	59.7	122,655
Gas marginal cost [€/MWh]	51.9	51.7	6.6	41.0	68.6	135,239
Coal mark-up [€/MWh]	-0.1	-2.2	11.1	-31.2	50.1	122,655
Gas mark-up [€/MWh]	7.1	3.2	17.3	-42.3	78.0	135,239
Coal bid size [MWh]	45.5	36.5	48.1	0.3	555.0	122,655
Gas bid size [MWh]	65.1	30.0	94.1	0.2	805.0	135,239
Clearing price [€/MWh]	61.7	61.5	9.4	41.1	170.0	4160
Hard coal price [€/MWh]	10.7	10.7	0.3	10.1	11.1	69
Natural gas price [€/MWh]	21.9	21.9	3.4	17.1	30.2	69
EUA price [€/ton of CO2]	7.3	7.4	0.3	6.5	7.9	69

Notes: Sample from 05/09/2017 to 10/12/2017 for hours 8 to 23, excluding Saturdays and Sundays. Sample is further restricted to bids higher than 20 € /MWh and lower than 125 € /MWh. Observations are hourly and comprise bids from nine large carbon emitting power producers (EDP, Iberdrola, Endesa, Naturgy, Viesgo, REN, Cepsa, Engie, and Bizkaia).

4.6 Results

In this section we present the results of our empirical analysis. As described in detail in section 4.3, we tested the benchmark approach as well as three alternative approaches to calculate reference levels of marginal costs. We assess the performance of the approaches based on two quality criteria. First, we compare the mean absolute error between the derived reference levels and the true marginal costs. The second criterion for the performance of each estimation method is the number of covered plants. The more we restrict the calculation basis within our empirical setting, the lower is the number of plants for which we receive reference levels. To ensure stable operation of an AMP, reference levels should at best be available for all power plants in the market.

In Table 4.4, we present our main findings.[54] The benchmark NYISO approach clearly performs worst and exhibits a mean absolute error across plants of 11.52 € /MWh. The best-response approach delivers smaller mean error terms as well as less dispersed outcomes across plants. Moreover, the maximum error term falls short of what we observe for the benchmark approach.

[54]In the Appendix, we present a similar table on mean errors in relative terms.

Table 4.4: Deviations from true marginal costs in absolute terms.

Approach	Mean	Median	Std. dev.	Min.	Max.	Plants
NYISO [€/MWh]	11.52	6.95	14.27	0.19	67.76	82
Best response [€/MWh]	8.92	5.10	7.60	1.26	36.76	85
Start-up [€/MWh]	7.27	4.32	9.55	0.24	61.57	72
Clustering [€/MWh]	2.78	1.92	1.87	0.19	9.61	89

Notes: Deviation is defined as the difference between derived reference levels and the true marginal cost we calculated bottom-up. In total, there are 89 power plants in our sample.

For the start-up approach, where we exclude bids from the calculation basis that could be driven by complementary cost factors, we receive a low mean error of 7.27 €/MWh, which clearly constitutes an improvement over the benchmark method. Yet, the lower error comes at the price of a reduced set of plants due to the restricted calculation basis.

Our last approach overcomes this downside and delivers reference levels for all 89 fossil power plants in our sample. The clustering approach thus covers the broadest set of power plants, which is a crucial aspect for the potential application in AMPs. At the same time it delivers reference levels that lead to the lowest mean error terms of just 2.78 €/MWh.

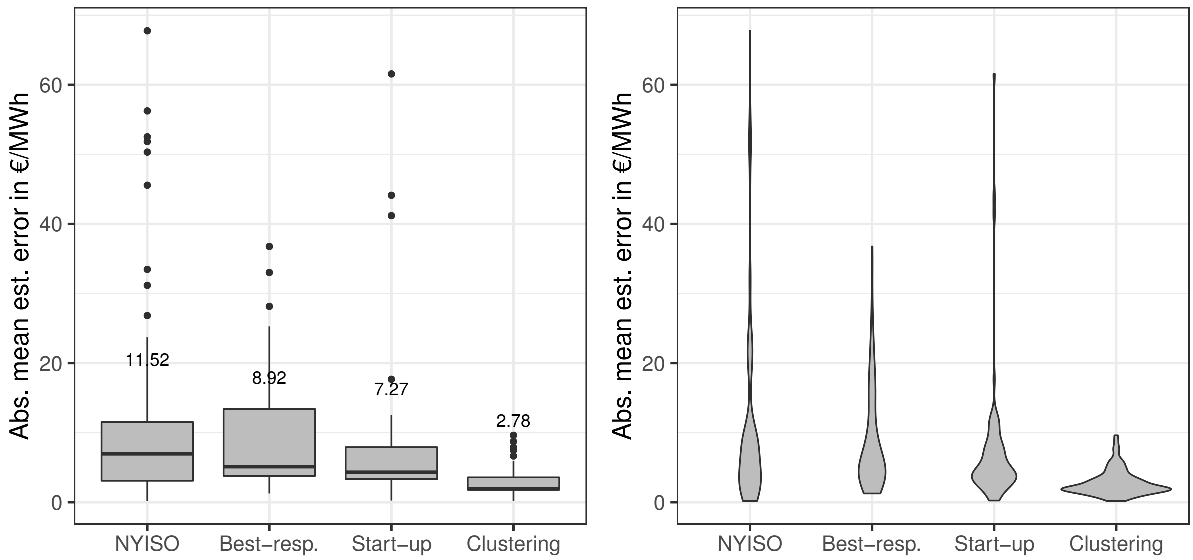


Figure 4.5: Accuracy of marginal cost estimation across approaches in absolute terms.

The box-plots and violin-plots in Figure 4.5 and Figure 4.6 illustrate graphically that all proposed alternatives outperform the method which is currently applied by the NYISO. We deem absolute values of deviations from the underlying marginal cost to be better suited to assess the performance of an approach than relative deviations. Ultimately, a regulator applying automated mitigation or a researcher who seeks to receive appropriate estimates of marginal cost, is mainly interested in achieving precise estimation.

Nevertheless, it is crucial whether a method leads to systematic positive or negative bias. To that end, Figure 4.6 shows our results in relative terms.[55] It is apparent that overestimation of marginal cost is more prevalent than underestimation. The preponderance of overestimation is especially pronounced in the NYISO approach and the start-up approach. In an AMP environment, overestimation may turn out to be costly for consumers as incidents of market power exertion could stay unnoticed due to erroneous high reference levels.

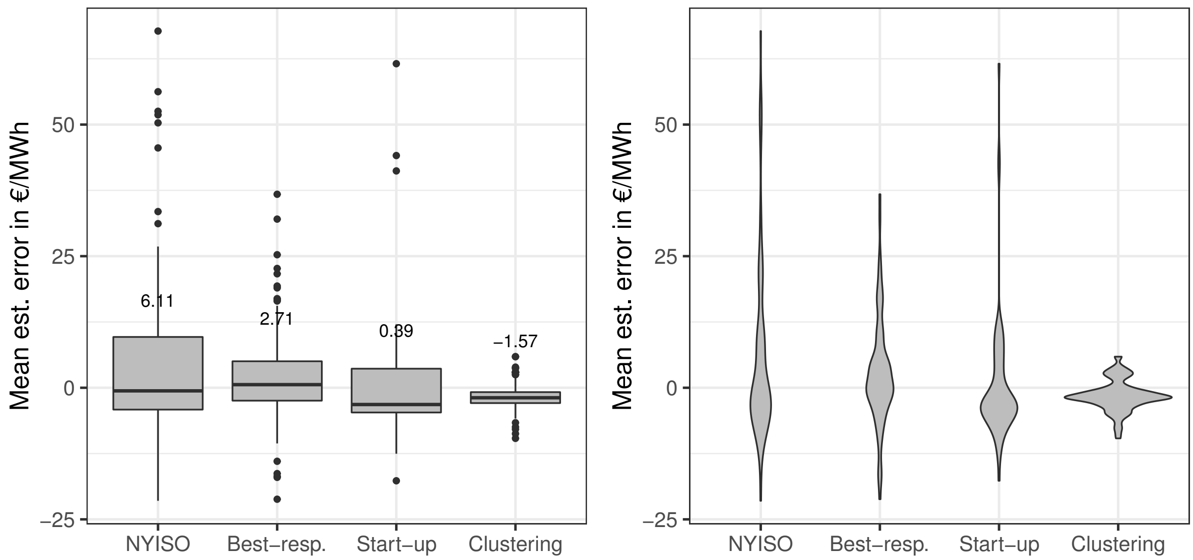


FIGURE 4.6: Accuracy of marginal cost estimation across approaches in relative terms.

Following the model-driven best-response approach leads to more evenly distributed errors and less outliers (see Figure 4.6). This approach performs well, but requires additional information on firms' contract positions within the market. Moreover, it can easily be subject to strategic behavior, as firms are able to influence the reference levels in real time. Among the other three approaches, reference levels are predominantly lower than true marginal cost, indicating a slight structural bias. This bias is driven by coal power plants, for which bid levels often fall short of marginal cost. When firms need to meet certain contract obligations, they often price

[55] Table A.5 in the Appendix displays the outcomes in more detail.

below marginal cost. As coal power plants are situated left of CCGT plants within the merit order, coal power plants are more affected by these strategic considerations. When mitigation is implemented strictly, systematic underestimation of marginal cost would harm producers, as mitigation would enforce bids below true marginal costs. However, this problem could be solved by granting a predefined margin on top of each mitigated bid.

All in all, we find that the current approach to calculate reference levels leaves substantial room for improvement. All alternative methods perform significantly better, with the clustering approach delivering the most promising results. As the application of the clustering approach would moreover reduce the scope for strategic manipulation of the calculation basis, system operators should consider the adoption of this approach for AMP purposes.

4.7 Conclusion

This paper contributes to improved automated mitigation of market power in electricity markets. AMPs find wide application in US power markets and are designed for real-time detection and mitigation of market power exertion. We present novel approaches to estimate underlying marginal cost of producers' supply offers. Improved accuracy of marginal cost estimates allows for both, facilitated detection of market power, as well as refined and more targeted mitigation. Refined mitigation protects consumers from excessive redistribution of rents to producers, but likewise benefits producers by reducing the scope for unjust mitigation of competitive offers.

To test how the existing benchmark approach and our suggested alternative approaches perform, we employ micro-level data from the Iberian day-ahead market. As benchmark approach, we chose the procedure as followed by the NYISO, where marginal cost estimates (also denoted as reference levels) are inferred from past offers of a power plant. For this benchmark approach, we find deviations of marginal cost estimates from true marginal costs to be substantial, with a mean absolute deviation of 11.52 €/MWh.

In contrast, the alternative approaches we propose deliver mean absolute deviations ranging between 2.78 €/MWh for the clustering approach and 8.92 €/MWh for the best-response approach based on Wolak (2003b, 2007), where we reverse-engineer marginal cost from hourly offers instead of past offers of a plant. For the clustering approach we depart from the estimation of marginal cost on the unit-level and estimate marginal cost for clusters of similar power plants.

This approach not only yields the most precise estimates, but likewise counteracts reference creep, i.e the strategic manipulation of bids to evade mitigation.

We show that current AMPs can be improved considerably by adapting the estimation of underlying marginal cost of production. Moreover, our enhanced approaches facilitate research when scholars require cost estimates for empirical analysis in power markets. Our findings are likewise applicable to other use cases and markets, such as monitoring of renewable energy auctions or market power surveillance in air and rail traffic.

5 Findings and Policy Implications

In my thesis, I focus on strategic behavior of electricity producers in wholesale power markets. Wholesale markets for electricity are predominantly organized as multi-unit double auctions, where supply bids by power producers and demand bids by retailers are aggregated to determine the uniform market clearing price. Producers engaging in these markets offer their capacity at prices which, in expectation, maximize their profits. As optimal behavior from a supplier perspective is rarely coincident with optimal behavior from an overall welfare perspective, regulatory intervention is needed. For instance, regulation comes in the form of market design that fosters competition, antitrust policies to limit market concentration, price caps to confine rents from market power exertion, or direct adjustment of offers that are deemed non-competitive. I investigate how regulation and market design shape firms' incentives and corresponding market outcomes. Policy makers can build on my results for more targeted regulations and improved market design. As such, my results contribute to an accelerated and more efficient decarbonization of the electricity sector.

In chapter 2, I focus on market design in form of renewable energy support mechanisms. My essay demonstrates how the choice of renewable support policies affects firm behavior, consequential market prices and, ultimately, policy costs for consumers. When submitting supply schedules to the market, firms take into account how their renewable portfolio is remunerated. In case the renewable production is remunerated "out of the market" via a form of forward contract with the government (feed-in tariff), market size is reduced and pricing at the margin will not affect payments for the renewable portfolio. Firms aim at submitting bids at the margin that balance the chance of realizing a higher mark-up and the chance of pricing the marginal plant out of the market. If higher prices are only realized for conventional production, potential gains from high prices are limited and firms moderate their mark-ups, accordingly. When, on the other hand, remuneration for renewable production is price dependent (e.g. in the form of a feed-in premium), market size and the incentive to raise the clearing price increase, implying higher mark-ups. In brief, I argue that for firms optimality considerations, out-of-market remuneration of renewable energies is equivalent to extended utilization of forward contracts or enhanced vertical integration (Allaz and Vila, 1993, Mansur, 2007, Bushnell et al., 2008). This mitigating effect on market power exertion is clearly an advantage of out-of-market remuneration in the form of feed-in tariffs. My results should be taken into account for the design of optimal and incentive-compatible renewable support mechanisms and are likewise valid when the level of support is determined in renewable tenders.

Apart from achieving emission reductions by a subsidy induced shift in generation technologies, regulators can influence carbon emissions immediately by antitrust policies. In chapter 3, I demonstrate how market structure impacts CO2 emissions in power markets. Previous research has established a link between a firm's size and its ability to follow profit-maximizing bidding behavior (Hortaçsu and Puller, 2008, Hortaçsu et al., 2019). I extend this branch of research by an analysis of associated CO2 emissions. Standard oligopoly theory suggests that small firms stick more closely to marginal cost pricing whereas large firms exercise market power by holding back supply and submitting steeper supply curves. In contrast to this conjecture, but in line with findings of Hortaçsu and Puller (2008), I find that small firms hold back relatively more quantity than large firms. Even though this over-exertion of market power is not desired from a consumer perspective due to inflated prices, it has a diminishing effect on CO2 emissions. This relationship is evidently contingent on a comparable technology mix across firms, requiring detailed analysis on the firm-level. Nevertheless, regulators should take the link between firm size, strategic ability and carbon emissions into account when it comes to potential mergers or acquisitions. At the same time, regulators could control firm size more immediately by enforcing divestitures or splitting up large firms.

As I show in chapter 2 and 3, strategic manipulation of market prices is likewise prevalent in low-carbon power markets and its mitigation continues to pose one of the main challenges for regulatory entities. In fact, power markets are especially prone to the exertion of market power due to limited storing capacity and inelastic short-run demand. There exist plenty of policies to limit undue market power exertion, such as the implementation of price caps, forward contract obligations or antitrust policies to reduce market concentration. In several US markets, regulators intervene immediately in the market by monitoring and mitigating supply bids of generating firms in real time. In chapter 4, I present several suggestions on how to refine the existing mitigation procedures. To assess the level of undue market power exertion of each supply bid, regulatory entities need precise estimates of the underlying marginal production cost. As firms are not incentivized to provide regulators with genuine information on power plant characteristics and input cost, regulators derive marginal cost estimates from observed historical supply bids. I develop alternative and refined approaches to estimate the underlying marginal cost of production. I test the accuracy of both, model-driven, and bid pattern-driven approaches and find all alternatives to outperform the currently applied benchmark method. My approaches not only deliver more precise estimates, but additionally limit the scope for strategic manipulation of estimates by firms. The refined estimates of marginal cost allow for enhanced monitoring and detection of market power by regulators and serve as largely unbiased inputs for effective mitigation procedures.

Appendix

A.1 Renewable Support and Strategic Pricing in Electricity Markets

A.1.1 Data

This appendix provides additional details on our data. To obtain our final sample, we proceed as follows. We first combine the bidding data with power plant lists provided by the market operator (OMIE). The bidding data, i.e. supply and demand curves, are available on the website of the market operator (labeled curva_pbc_uof). Additionally, we use data on aggregate hourly production (labeled pdbc_stot and pdbc_stota) to derive aggregate renewable production supported via the premium and the tariff mechanism, respectively.

We in addition match our sample with information from Electra (Registro de productores de energía eléctrica). Electra publishes data sets on generation capacity in Spain. We also use open power system data that provides information for energy market modeling, including extensive information on European power plants. In combination with the power plant lists provided by OMIE, this matching allows us to extend our sample with the owner of the power plant, the production technology used, and the respective year of commissioning of the plant.

To obtain marginal costs, we use commodity price data from Bloomberg (hard coal and fuel oil) and Thomson Reuters (natural gas). We add EU ETS Phase I prices from Bloomberg. Hard coal prices refer to Australian steam coal (Bloomberg id CLSPAUNE), freight on board in Newcastle with a calorific value of 6000 kc and are updated on a weekly basis. Fuel oil prices reflect daily CIF prices for Milazzo (Italy) with a sulfur content of one percent (Bloomberg id N6M1.OCC).

For natural gas we use Dutch TTF (Title Transfer Facility) prices (Thomson Reuters identifier TRNLTTD) provided on a daily basis. Within our sample, the largest share of natural gas imports stem from Algeria, for which no granular price series exists. We compared available price points for Algerian import prices with the high resolution TTF data we received from Bloomberg, confirming that TTF price data is a good approximation. Furthermore, the TTF price data is in line with the Gazexport-Ruhrgas prices applied by Fabra and Reguant (2014) for the same period.

There was no detailed price data available for lignite as input factor. For our calculations we used a fixed price of 8 €/ton, based on engineering studies. However, we conjecture lignite prices to be rather stable over time.

Power plant efficiency is estimated using the commissioning date as proxy, (see, e.g., Willems et al., 2009). Based on engineering reports (European Commission, 2006, IEA, 2008, 2010, Hussy et al., 2014), we attach fuel efficiency to each power plant conditional on the year of commissioning. In detail, we first determine technology-specific efficiency rates for the years 1960 and 2005 from the sources stated above. Subsequently, we use a linear interpolation to estimate annual efficiency levels for each technology. Combining commodity price data, cost of carbon, power plant efficiency and heating values of the respective fuels, we estimate marginal production cost. We ignore additional marginal cost factors, such as O&M cost in our estimation. According to (IEA, 2015), median levels of variable O&M cost accrue to 2.70 USD/MWh for CCGT and to 3.40 USD/MWh for coal power production, respectively. We assume variable O&M cost to be constant over time. We could not identify reasons for significant changes in O&M cost during our period of observation. Any remaining time-invariant differences in production costs are captured by plant-fixed effects in our analysis.

To determine hourly residual demand curves for each market participant in our sample, we again make use of the supply and demand curves provided by the market operator. To derive residual demand for company i, we first calculate the aggregate supply of all competing market participants $j \neq i$, as well as aggregate demand. Subtracting aggregate supply of all firms j from aggregate demand, we isolate residual demand for firm i. Last, we measure the slope of the residual demand curve at the marginal bid submitted by firm i, making use of the smooth.spline function in R.

A.1.2 Equilibrium Supply Functions

Simplifying equation (2.3) by writing expected profits 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), where renewable energy support in our model replaces the effect of forward contracts.

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:

$$\begin{aligned} H_i(p, S_i) &= Pr\left(S_{-i}(p, x_{-i}^c) + \varepsilon_{-i}(x_{-i}^c) + S_i > D(p) \mid S_i\right) \\ &= Pr\left(\varepsilon_{-i}(x_{-i}^c) > D(p) - S_{-i}(p) - S_i \mid \hat{S}_i\right) \\ &= 1 - F_i\left(D(p) - S_{-i}(p) - S_i \mid S_i\right), \end{aligned} \tag{A.1}$$

where F_i is the cumulative distribution function of ε_{-i}. 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

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

with $m_i(p) = -\frac{\partial}{\partial p}\left(D(p) - S_{-i}(p)\right)$ being the slope of firm i's residual demand. Because the slope of residual demand, $\frac{\partial}{\partial p}\left(D(p) - S_{-i}(p)\right)$ is negative, m_i is positive and measures the steepness of the residual demand curve.

A.1.3 Tables

TABLE A.1: Mark-up regressions when complex bids are used, for morning hours, in levels.

	Mark-up	Mark-up	Mark-up
Renewable output	0.00167***	0.00161***	0.00152***
$\alpha_i x_i^c$	(0.000)	(0.000)	(0.003)
Conventional output	0.00111***	0.00114***	0.000303***
$x_i^e(p^*)$	(0.000)	(0.000)	(0.000)
Demand slope	-0.0337***	-0.0338***	-0.00952***
$m_i(p^*)$	(0.000)	(0.000)	(0.000)
Retail demand	Y	Y	Y
Plant fixed effects	Y	Y	Y
Company fixed effects	Y	Y	Y
Observations	22,130	21,009	4,758
R^2	0.55	0.55	0.66

Notes: Dependant variable is the mark-up by firm i in auction t. Specification (1) uses a sample where firms did not specify complex bids for their power plant at the margin. Specification (2) uses a sample where power plants at the margin have already been running during the previous hour. Specification (3) uses a sample that consists only of observations in morning hours from 5am to 7am, where transmission congestion is unlikely. All samples run from January 2004 to December 2005. All regressions include hour, weekday, week, and month fixed effects, and controls for the level of retail demand by firm i. p-values are in parentheses, * p<0.05, ** p<0.01, *** p<0.001. Standard errors are clustered at the auction level.

Table A.2: IV estimates for mark-ups of Endesa and Iberdrola, all variables in logarithm.

	Mark-up Endesa			Mark-up Iberdola		
	OLS	IV: Rival renewables	IV: Wind speed	OLS	IV: Rival renewables	IV: Wind speed
Renewable output	0.0525***	0.0656***	0.0665***	0.0938***	0.0952***	0.0972***
$\alpha_i x_i^c$	(0.000)	(0.000)	(0.015)	(0.000)	(0.000)	(0.000)
Conventional output	0.727***	1.059***	1.068***	0.587***	0.645***	0.660***
$x_i^e(p^*)$	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Demand slope	-0.341***	-0.449***	-0.455***	-0.424***	-0.437***	-0.434***
$m_i(p^*)$	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Retail demand	Y	Y	Y	Y	Y	Y
Plant fixed effects	Y	Y	Y	Y	Y	Y
Company fixed effects	Y	Y	Y	Y	Y	Y
Observations	7613	7612	7613	7281	7281	7281
R^2	0.47	0.43	0.43	0.75	0.75	0.75

Notes: Dependent variable is the mark-up of Endesa in columns (1), (2), and (3) and of Iberdrola in columns (4), (5), and (6). Columns (1) and (4) show OLS estimates. In columns (2) and (5), we instrument firm i's renewable output sold in the market with aggregate renewable output of all firms. In columns (3) and (6), we use wind speed as instrument. The sample runs from January 2004 to December 2005. All regressions include hour, weekday, week, and month fixed effects. p-values are in parentheses, * p<0.05, ** p<0.01, *** p<0.001. Standard errors are clustered at the auction level.

A.2 Strategic Ability and CO2 Emissions in Electricity Markets

A.2.1 Model and First-order Condition

Rewriting expected profits in equation (3.2) 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 (3.5). 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 p:

$$\begin{aligned} H_i(p, S_i) &= Pr\left(S_{-i}(p) + S_i > D(p) + \varepsilon \mid S_i\right) \\ &= Pr\left(-\varepsilon > D(p) - S_{-i}(p) - S_i \mid \hat{S}_i\right) \\ &= 1 - F_i\left(D(p) - S_{-i}(p) - S_i \mid S_i\right), \end{aligned} \tag{A.2}$$

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.

A.2.2 Tables

Table A.3: 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 Título I, Título 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.º 74/2013 Artigo 1.º; EDP (2018)
Variable O&M costs	Median variable O&M costs per MWh	Coal and gas-fired plants, dataset of 2015	IEA (2015)

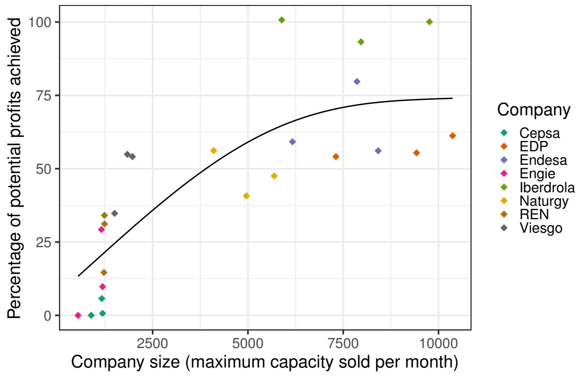
Notes: We abstract from additional variable cost factors that may be attributed to start-up or ramping cost.

TABLE A.4: Overview of magnitudes of parameters applied in the marginal cost estimation.

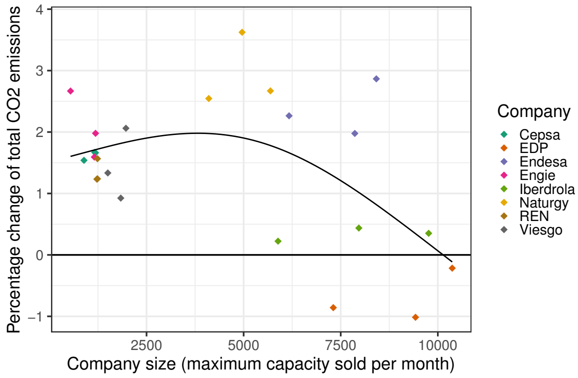
Data type	**Value**	**Source**
Clawback charge Portugal	6.50 € /MWh until 16.11.2017 4.75 € /MWh as of 17.11.2017	Decreto-Lei n.º 74/2013 Artigo 1.º; EDP (2018)
Energy generation tax Spain	7 % of revenue	Ley 15/2012 Título I
Fossil fuel consumption tax Spain	0.65 € /GJ	Ley 15/2012 Título III
Variable 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 Spain's 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.

A.2.3 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.

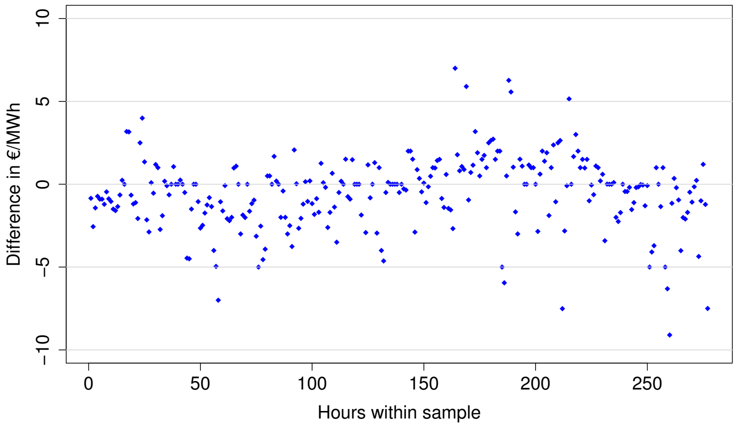


FIGURE A.2: Difference between clearing price in first intraday market and day-ahead market.

A.3 Designing Automated Market Power Mitigation in Electricity Markets

A.3.1 Fuel Price Adjustment

The approach for the adjustment of fuel prices is best explained by an example: We want to derive a reference level of marginal cost r for power plant x at a certain day t. This means that for an exemplary bid b within the calculation basis B, submitted at time $t-20$ for power plant x, we can derive a hypothetical efficiency rate ϵ^* that would justify the observed bid level b under the assumption of competitive bidding. Subsequently we use this efficiency rate ϵ^*, as well as current input prices at time t to calculate an adjusted bid b' which becomes part of the adjusted calculation basis B'. Equation A.3 shows the first step, where we equate the past bid b on the LHS with the marginal cost calculation on the RHS.

$$b(x)_{(t-20)} = \frac{Fuelprice_{(t-20)} + CO2price_{(t-20)} * CO2intensity}{\epsilon^*} + O\&M + Taxes\&Levies \tag{A.3}$$

We solve Equation A.3 for ϵ^*, which captures the level of competitiveness of bid b in $t-20$. We then employ this hypothetical efficiency rate ϵ^* to calculate b' at time t, i.e. the adjusted bid that reflects both, the level of competitiveness of bid b in $t-20$, as well as fuel and emission prices at time t.

$$b'(x)_{(t)} = \frac{Fuelprice_{(t)} + CO2price_{(t)} * CO2intensity}{\epsilon^*} + O\&M + Taxes\&Levies \tag{A.4}$$

We apply this procedure to each bid in B and end up with the adjusted calculation basis B' that incorporates the competitiveness of bids, net of changes in input prices. From this calculation basis, we then derive the reference level r.

A.3.2 Tables

TABLE A.5: Deviations from true marginal costs.

Approach	Mean	Median	Std. dev.	Min.	Max.	Plants
NYISO [€/MWh]	6.11	-0.59	17.33	-21.48	67.76	82
Best response [€/MWh]	2.71	0.59	10.24	-21.18	36.76	85
Start-up [€/MWh]	0.39	-3.18	12.03	-17.67	61.57	72
Clustering [€/MWh]	-1.57	-1.99	2.94	-9.61	5.91	89

Notes: Positive values signify that the respective approach delivers higher values than the bottom-up calculation. Deviation is defined as the difference between derived reference levels and the true marginal cost we calculated bottom-up. In total, there are 89 power plants in our sample.

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