Market Power and Price Exposure:
Learning from Changes in Renewables' Regulation *

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Abstract

We provide theoretical and empirical results regarding the market power implications of different types of renewable support schemes in electricity markets. In particular, we seek to understand how the exposure of renewable energies to wholesale price fluctuations affects the overall degree of market power. Theoretically, we find that shielding renewables from price fluctuations is effective at curbing market power in relatively concentrated markets. Empirically, we leverage several short-lived changes to renewables' support mechanisms in the Spanish electricity market and find that the switch from fixed to market-based pricing caused a 2-4% reduction in the average price-cost markup.

Keywords: market power, forward contracts, arbitrage, price discrimination, renewables.

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1 Introduction

Much has been written about the so-called *merit order effect*, whereby the entry of (almost) zero marginal cost renewables depresses wholesale prices in competitive electricity markets. Yet, as shown by Acemoglu, Kakhbod and Ozdaglar (2017), market power in generation can offset this effect. Is it possible to design renewable support schemes that restore their price-depressing effects despite the presence of market power?

This paper sheds light on this question by bringing together results from the literature on forward contracting (Allaz and Vila, 1993), competition in sequential markets (Ito and Reguant, 2016), and the merit order effect (Acemoglu, Kakhbod and Ozdaglar, 2017). In particular, we analyze how the degree of renewables' exposure to fluctuations in wholesale prices affects market power in electricity markets. This question is particularly important for current policy because regulators are still debating whether the output of the new renewable investments should be paid with fixed prices or with prices that fluctuate with wholesale electricity prices (CEER, 2021).[1] The importance of this question is compounded by the massive renewable investments that have to take place to decarbonize our economies.[2]

We leverage a quasi-experiment that took place in the Spanish electricity market, where the regulator first decided to expose existing wind producers to wholesale market prices, then moved them to fixed prices, and ultimately switched them to market-based prices again. These regulatory changes were taken by surprise at a time when wind already represented an important share of total output. Hence, they provide a unique opportunity to identify the causal effects of changes in the degree of renewables' price exposure on firms' bidding behavior and the resulting impacts on market power in electricity markets.

[1] In the industry jargon, these two schemes are commonly referred to as Feed-in-Tariffs (FiT) and Feed-in-Premia (FiP). The price levels can be set either by the regulator or through renewable auctions. According to IRENA (2019), by the end of 2018 more than 100 countries had adopted auction-based approaches to promoting investment in renewables—a ten-fold increase in just one decade. Many large corporations are also resorting to auctions to procure renewable power. For instance, from 2017-2019 Google procured renewable supplies equivalent to 100% of the company's total electricity use (Google, 2020).

[2] The International Renewable Energy Agency (IRENA) estimates that compliance with the 2017 Paris Climate Agreement will require overall investments in renewables to increase by 76% in 2030, relative to 2014 levels. Europe expects that over two-thirds of its electricity generation will come from renewable resources by 2030, to achieve a carbon-free power sector before 2050 (European Commission, 2019). Likewise, the US plans to achieve carbon neutrality by 2050, with a 90% carbon-free electricity sector by 2035.

Theoretical approach and findings. Electricity markets are commonly organized as a sequence of markets, with a large market that operates one day ahead of the actual delivery, and several smaller sequential markets that operate closer to real-time. In the day-ahead market, generators submit bids indicating how much they are willing to produce at each price, and then have the possibility to fine-tune their day-ahead commitments in the subsequent markets. Evidence shows that generators typically exert market power by withholding part of their production in the day-ahead market, increasing its price, and then selling additional amounts at lower prices in the real-time (or spot) markets. This creates a wedge between day-ahead and spot prices, as the former go up while the latter go down as a consequence of market power (Ito and Reguant, 2016).

In this paper, we develop a simple two-stage game (which mimics the sequence of day-ahead and spot markets) between a dominant firm and a set of fringe firms. The former owns both conventional and renewable generation technologies while the latter own either one of the two. The dominant firm sets prices in the two markets, taking as given the production decisions of the fringe firms, which are assumed to be price-takers.[3] We characterize equilibrium behaviour and market outcomes when renewables are paid with *fixed prices* or with *market prices*.

This model highlights the two channels by which renewables affect the degree of market power in electricity markets. First, as also noted by Ito and Reguant (2016), renewable energies are particularly well suited to arbitrage price differences across sequential markets because they can oversell beyond their true output (they can rarely produce at full capacity depending on the availability of natural resources such as wind and sun).[4] This effect, which we label the 'arbitrage effect', mitigates market power as it makes it harder for the dominant firm to push day-ahead prices up. However, for this effect to be at play, two conditions must be met: renewables must be exposed to *market prices* for them to benefit from arbitrage, and there must be a sufficiently large number of independently owned renewables (the dominant firm does not have incentives to arbitrage with its own renewables as that would curb its market power).

What if these conditions are not satisfied, i.e., if renewables are paid at *fixed prices* and most of the renewable output is in the hands of the dominant producer? Shielding renewable fringe producers from market prices essentially removes their incentives to

[3]This simple dominant-fringe firm model gives rise to similar results as the Cournot model, which we develop in the Appendix. The reason is that the dominant firm best replies to the production decisions of its rivals. Taking these as given, or endogenizing them in equilibrium, does not change the essence of the results.

[4]This arbitrage is purely financial: they oversell in the day-ahead market at a high price and buy their excess commitment in the spot market at a lower price.

serve as arbitrageurs. Nevertheless, *fixed prices* mitigate market power through another channel: they reduce the dominant producer's incentives to withhold output in the day-ahead market as its renewable output would not benefit from the resulting price increase. We label this as the 'forward contract effect' given that *fixed prices* act as a forward contract over the firm's renewable sales (Allaz and Vila, 1993).

We show that the relative strengths of the 'arbitrage' and the 'forward contract' effects depend on the extent to which the dominant firm with conventional (thermal) production also owns renewable generation ('common ownership'). In particular, the lower the degree of common ownership, the stronger the 'arbitrage effect' and the weaker the 'forward contract effect'. In the extreme case in which the dominant firm does not own any renewables, full price exposure is most effective at mitigating market power. On the contrary, if the dominant firm owns all renewables, shielding renewable generation from price fluctuations is more effective.

Under both support schemes, renewables (weakly) depress day-ahead market prices, but the effect is stronger when renewable energies are shielded from wholesale market price fluctuations. Indeed, as also shown by Acemoglu, Kakhbod and Ozdaglar (2017), the merit order effect is fully neutralized when the dominant firm owns all the renewable energies and these are exposed to market price fluctuations. In contrast, we show that under *fixed prices* the merit order effect is never neutralized and it is independent of the degree of common ownership.

These differential effects of the renewable support schemes have welfare and distributional implications. An increase in renewable output reduces the deadweight loss under both support schemes, but efficiency is always greater under *fixed prices*. The reason is that *fixed prices* push spot prices closer to marginal costs, unlike *market prices*. However, the distributional implications –which depend on day-ahead prices– can go either way depending on the degree of common ownership. One of the main results of the paper is that, in markets with high (low) degree of common ownership, consumers are relatively better-off (worse-off) when renewables are shielded from wholesale market prices. It is important to note that this analysis focuses on the market power impacts of renewable support schemes for given capacities, and therefore leaves out some other factors that could also have welfare implications, such as entry and investment incentives, learning externalities and other spillover effects, or the fiscal impacts of the various support mechanisms, among others.

Empirical approach and findings. We test the key predictions of the model using data from the Spanish electricity market from February 2012 to January 2015, which spans three different pricing regimes for renewable energies – market-based pricing, then fixed pricing, and then market-based pricing again. Our empirical approach consists of a structural analysis of bidding incentives and a quasi-experimental analysis of how arbitrage behavior responds to different regulatory pricing regimes. Using results from the structural model, we calculate the price-cost markups in the day-ahead market to assess how the renewable pricing policies affected the degree of market power in the Spanish day-ahead electricity market.

Firstly, our structural analysis of price-setting incentives in the day-ahead market validates the 'forward contract effect'. Namely, taking the slopes of the realized residual demands as given, we show that firms' wind output did not affect their markups under *fixed prices*, in contrast to when their wind output was exposed to *market prices*. This suggests that, all else equal, the 'forward contract effect' reduced firms' market power under *fixed prices*.

Secondly, we rely on a differences-in-differences (DiD) approach to assess how changes in price exposure affected the fringe firms' incentives to arbitrage. Our analysis has two appealing features: (i) we exploit the two regulatory changes, from *market prices* to *fixed prices* and then back to *market prices*, and (ii) we use two plausible control groups, either independent suppliers or renewables other than wind. Our DiD analysis shows that wind producers stopped arbitraging price differences after the switch from *market prices* to *fixed prices*. However, they resumed arbitrage once they were exposed to *market prices* again. These results validate the empirical relevance and robustness of the 'arbitrage effect'.

Thirdly, the interplay between the 'forward contract' and the 'arbitrage' effects is also confirmed by the empirical analysis of the price differences across markets. We show that, under *fixed prices*, an increase in the dominant firm's share of wind output reduced price differences across markets, as expected from the strengthening of the 'forward contract effect'. Instead, under *market prices*, an increase in the fringe firms' wind share enlarged price differences across markets, as expected from the weakening of the 'arbitrage effect'.

Lastly, to understand which of these two effects dominated in shaping market power, we leverage our structural estimates to compute price-cost markups in the day-ahead market. We find that markups were significantly lower while firms were subject to *fixed prices* as compared to *market prices*. The average markup during the fixed price regime was 6.3%, while it was 8.3% and 10.7% under the market-based price regimes, results which are robust to alternative ways of comparing the markups (i.e., by firms, by windy-*vs.*-less-windy hours, by peak-*vs.*-off-peak hours). Based on these findings, we conclude that, given the degree of common ownership in the Spanish electricity market, the 'forward contract effect' dominated over the 'arbitrage effect', which led to weaker market power when renewables were paid at *fixed prices*, relative to when they were exposed to wholesale market price fluctuations.

The remainder of the paper is organized as follows. Section 2 reviews the related literature. Section 3 builds and solves a model of competition across sequential markets when firms are subject either to *market prices* or to *fixed prices*. Section 4 provides an overview of the institutional setting and data used in the analysis. Section 5 performs the empirical analysis and Section 6 concludes. Proofs and extensions are postponed to the Appendix.

2 Related Literature

Our paper relates to several strands of the literature on electricity market design and the role of renewable energies. First, it is closely related to Ito and Reguant (2016) and Acemoglu, Kakhbod and Ozdaglar (2017). From a theoretical point of view, we characterize and compare the equilibria across sequential markets when renewable energies are paid with *fixed prices* or with *market prices*. Ito and Reguant (2016) also document the role of arbitrage in mitigating market power under *market prices*, but the analysis with *fixed prices* and the comparison between the two support schemes are novel. Empirically, our findings give further support to their results regarding the impacts of arbitrage. Moreover, we shed light on how renewable energies support schemes affect their price depressing effects in the presence of market power and under different degrees of common ownership, thus extending Acemoglu, Kakhbod and Ozdaglar (2017)'s and providing empirical support to their theoretical findings.

Second, we complement the existing evidence on the market power impacts of forward contracts in electricity markets (Wolak, 2000; Bushnell, Mansur and Saravia, 2008; Hortaçsu and Puller, 2008; Fabra and Toro, 2005). We contribute by providing new evidence on the impact of firms' price exposure on market power by highlighting the relevance of forward contracting through structural estimates. Our results regarding the existence of market power in the Spanish electricity market are also in line with those of previous studies, despite the differences in the focus and time span of the analyses (Fabra and Toro, 2005; Fabra and Reguant, 2014; Reguant, 2014).

Third, we provide key insights into the ongoing debate about renewable support schemes by focusing on the largely unexplored issue of how they affect firms' bidding incentives for given capacities. This is a required first step towards analyzing the endogenous choice of long-run variables such as entry, exit, or the capacity and location of the new investments. To our knowledge, only a few papers explore the effects of renewables' pricing schemes for given capacities. From a theoretical perspective, Dressler (2016) highlights that Feed-in-Tariffs (FiT) act like forward contracts.[5] From an empirical perspective, Bohland and Schwenen (2021) explore the market power impacts of a voluntary change in the pricing scheme in the Spanish Electricity market during 2005, a period when renewables represented less than 10% in the energy mix.

Nevertheless, firms' price exposure can also have important impacts through capacity investment decisions, an issue which is out of the scope of our paper. For instance, Newbery et al. (2018) and May and Neuhoff (2017) favor the use of pricing schemes with limited price exposure as a way to de-risk the investments, ultimately bringing down the costs of capital and facilitating the entry of more diverse players.[6] Instead, other authors advocate for exposing producers to market price volatility so that they internalize the economic value of their investments (Joskow, 2011), which depends on their production profiles, their correlation with the availability of other installed technologies and with demand, as well as on the costs of the generation technologies that they displace (Callaway, Fowlie and McCormick, 2018). Auctioning fixed-price contracts would select the lowest cost technologies, which need not be the most valuable ones. Instead, auctioning contracts with price exposure would select those investors that are able to produce at times when market prices are higher, as they would require a smaller premium to break even.[7]

Finally, our work complements the growing literature on the short-run and long-run effects of renewables, including their impacts on energy prices (Gowrisankaran, Reynolds and Samano (2016); Genc and Reynolds (2019); Acemoglu, Kakhbod and Ozdaglar (2017)), the nature of competition (Fabra and Llobet (2021)), emissions (Cullen (2013) and Novan (2015)), and profits earned by the conventional producers (Bushnell and No-

[5]However, Dressler (2016) abstracts from the impacts of FiT on price arbitrage and focuses instead on the impacts on forward trading. She finds that FiT might crowd out other forms of forward contracting, in line with Ritz (2016).

[6]As pointed out by Newbery et al. (2018), it is more efficient to share the investment risks across the mass of consumers than to concentrate such risk on a small number of companies. For the former, their share of the construction cost is only a small fraction of their total expenditures, while for the latter the investment might represent a high share of their profits. See Ritzenhofen, Birge and Spinler (2016) for further references. Another interesting, though distinct debate, is whether renewable producers should be supported through investment or output subsidies. Aldy, Gerarden and Sweeney (2018) show that the former led to 10 to 12 percent lower production from wind farms.

[7]Some papers compare renewable support schemes in other dimensions. For instance, Reguant (2019) conducts a simulation that also accounts for the interaction between renewable energy policies and the retail tariff design to compare their efficiency and distributional impacts.

van (2018); Liski and Vehviläinen (2020)). Nonetheless, all these papers apply to settings in which renewables are exposed to *market prices* but do not analyze the effects under *fixed prices*.

3 The Model

We develop a simple model of strategic bidding in electricity markets. Our model combines ingredients in Ito and Reguant (2016), who study bidding behavior in sequential markets, with ingredients in Acemoglu, Kakhbod and Ozdaglar (2017), who study the price impact of renewable energies. Our model adds the analysis of alternative pricing schemes for renewables. Similar to those models, and in line with Allaz and Vila (1993), we abstract from uncertainty and risk aversion.

Markets Electricity is traded in two sequential markets: a day-ahead market ($t = 1$) and a spot market ($t = 2$). Total forecasted demand is inelastically given by A, and it is fully cleared in the day-ahead market. The spot market allows firms to reshuffle their day-ahead commitments, while total demand remains fixed at A. With demand being inelastic, total welfare only depends on productive efficiency, which is a function of spot prices, while consumers' surplus depends on day-ahead market prices only.[8]

Technologies and Firms Electricity is produced by two types of technologies (renewable and conventional) and two types of firms (one dominant firm and a set of fringe firms, respectively denoted by $i = d, f$).[9] Each of the fringe firms owns either renewable or conventional energy, while the dominant firm (might) own both.

The dominant firm's conventional technology has constant marginal costs of production, $c > 0$, while the fringe's conventional technology has increasing marginal costs q/b.[10] In contrast, renewables (generically referred to as *wind*) allow firms to produce at zero marginal costs up to their available capacities. We use k and w to denote wind's maxi-

[8]This is particularly true in the Spanish electricity market, where the default is that households pay a passthrough of the hourly day-ahead market prices (i.e., the Real Time Prices). The default contract provides the price reference for the contracts that are offered in the retail market for those consumers who opt-out of the default. See Fabra et al. (2021) for a description.

[9]Allowing for $n > 1$ Cournot competitors leads to similar results as those reported here. See Appendix A.2 for the full analysis.

[10]We could assume that marginal costs are higher in the spot market, reflecting the fact that the costs of adjusting production tend to be higher close to real-time. The main results remain unchanged.

mum and available capacity,[11] with $k \geq w$. The dominant firm owns a fraction $\delta \in [0,1]$ of k and w, while the fringe owns the remaining $(1-\delta)$ share. We refer to δ as the *degree of common ownership*: if $\delta = 0$ the dominant firm only owns the conventional technology, while it also has an increasing share of renewables the higher δ.

Throughout, we assume that the conventional technology is needed to satisfy total demand, i.e., $D(c) - w > 0$, making c the relevant marginal cost.

Firms' Behavior The dominant firm sets prices in both markets,[12] taking into account the production decisions of the fringe firms, which are assumed to be price-takers. In the day-ahead market, the fringe firms offer their conventional output at marginal cost, i.e., they supply bp_1. In the spot market, if p_2 increases above p_1, they find it optimal to increase their conventional output, i.e., their additional supply in the spot market is $b\left(p_2 - p_1\right)$. In contrast, if p_2 falls below p_1, they find it cheaper to buy back some of their day-ahead commitments instead of satisfying them with their own production, i.e., they demand $b\left(p_1 - p_2\right)$ in the spot market. In turn, since renewable energies have zero marginal costs but limited capacity, the fringe firms have to decide whether to sell their output $(1-\delta)\,w$ in the day-ahead market and/or in the spot market. Their incentives depend on the pricing scheme in place.

Pricing Schemes for Renewables We consider two commonly used pricing schemes: renewable producers receive *fixed prices* for their output, regardless of whether they sell it at $t = 1$ (day-ahead) or $t = 2$ (spot); or renewables are paid at *market prices*, i.e., the prices of the market in which they sell their output, plus a fixed premium.

3.1 No Arbitrage

We first consider the case in which renewable producers are not allowed to arbitrage price differences across sequential markets as they are required to offer all their output in the day-ahead market. The residual demands faced by the dominant firm in the day-ahead

[11] This assumes that firms are able to perfectly predict their available capacities. Fabra and Llobet (2021) report empirical evidence on the wind forecast errors in the Spanish electricity market and show that these tend to be small. Still, the results of the model would not change if one interprets w as expected wind output rather than actual wind.

[12] Since we are dealing with a single dominant firm, results would be the same if the firm chose quantities instead of prices. See Appendix A.2 for details.

market and in the spot market are thus given by

$$D_1(p_1) = A - bp_1 - (1-\delta)\, w \tag{1}$$

$$D_2(p_1, p_2) = b(p_2 - p_1). \tag{2}$$

We solve the game by backward induction. In the spot market, once p_1 is chosen, the dominant firm sets p_2 so as to maximize its profits. Under both pricing rules, the profit maximization problem in the spot market can be written as

$$\max_{p_2} \left[p_2 D_2(p_1, p_2) - c\left(D_1(p_1) + D_2(p_1, p_2) - \delta w\right)\right]. \tag{3}$$

Solving the first order condition for p_2,[13]

$$p_2^* = c + D_2(p_1, p_2^*) \left|\frac{\partial D_2(p_1, p_2^*)}{\partial p_2}\right|^{-1}. \tag{4}$$

This shows that the firm sets a spot price above its marginal cost $p_2^* > c$. The markup is increasing in p_1 given that a higher p_1 enlarges the spot market demand.

In the day-ahead market, under *market prices*, renewable output is paid at p_1 plus a fixed premium $\underline{p}$. Hence, the dominant firm's profit maximization problem is

$$\max_{p_1} \left[p_1 D_1(p_1) + p_2^*\left(p_1\right) D_2\left(p_1, p_2^*\right) - c\left(D_1(p_1) + D_2\left(p_1, p_2^*\right) - \delta w\right) + \delta w \underline{p}\right]. \tag{5}$$

Under *fixed prices*, renewable output is paid at $\overline{p}$. This reduces the dominant firm's price exposure, as shown in the first term of the following profit expression,

$$\max_{p_1} \left[p_1 (D_1\left(p_1\right) - \delta w) + p_2^*\left(p_1\right) D_2\left(p_1, p_2^*\right) - c\left(D_1(p_1) + D_2\left(p_1, p_2^*\right) - \delta w\right) + \delta w \overline{p}\right]. \tag{6}$$

Using the indicator $I = 0$ for *market prices* and $I = 1$ for *fixed prices* allows us to write the solution to the first order condition of profit maximization in the day-ahead market under both pricing rules as follows,

$$p_1^* = p_2^* + \left[D(p_1^*) - w\left(1-\delta\right) - Iw\delta\right] \left|\frac{\partial D(p_1^*)}{\partial p_1}\right|^{-1}, \tag{7}$$

This expression makes it clear that the spot price is the opportunity cost of sales in the day-ahead market. Hence, the dominant firm optimally sets p_1^* with a markup over p_2^*. Such a markup depends on the pricing rule in place. In particular, the marginal gains from increasing p_1 are lower under *fixed prices*, given that the dominant firm's renewable output $(w\delta)$ does not benefit from the price increase.

[13] In the oligopoly model, the residual demands in the first order conditions should be interpreted as net of the rivals' production.

It follows that, all else equal, the markup in the day-ahead market is lower under *fixed prices* than under *market prices.* A lower day-ahead markup reduces the size of the spot market, which in turn implies that the spot price under *fixed prices* is lower than under *market prices*, i.e., $p_2^M > p_2^F > c$ where we have used super-scripts M and F to denote equilibrium outcomes under *market prices* and *fixed prices*, respectively. In turn, these two results imply that the day-ahead price is also lower under *fixed prices*, i.e., $p_1^M > p_1^F > c$. The underlying reason is that *fixed prices* act as a forward contract over the firm's renewable sales. We refer to this as *forward contract* effect.

Our first lemma summarizes these results.

Lemma 1 *Suppose that arbitrage is not allowed. In equilibrium,*
(i) $p_1^M > p_2^M > c$.
(ii) $p_1^F > p_2^F > c$.
(iii) $p_1^M > p_1^F$ *and* $p_2^M > p_2^F > c$.

3.2 Limited Arbitrage

Given the positive differential across the day-ahead and spot prices, there are profitable arbitrage opportunities. These involve selling output in the day-ahead market at a high price and re-buying it in the spot market at a lower price. If there are no limits on arbitrage, and if arbitrage is competitive, the price differential across markets is competed away until the day-ahead and the spot prices convergence, $p_1 = p_2$.

However, in many electricity markets in practice (including the one in our empirical application), market rules impose limits on arbitrage. Typically, all transactions need to be backed by physical assets, thus implying that arbitrage can only come from market agents and only up to their capacities. This leaves some scope for wind producers to engage in arbitrage as the capacity constraint $w \leq k$ is rarely binding. Even though their final production is fixed at $(1-\delta)\,w$, they can thus gain from selling $(1-\delta)\,k$ in the day-ahead market at a high p_1 and buying back their excess commitment $(1-\delta)\,(k-w)$ in the spot market at a low p_2. We refer to this strategy as *overselling.*[14] Throughout, we are going to assume that the arbitrage constraint is binding, i.e., overselling $(1-\delta)\,(k-w)$ does not lead to full price converge between the day-ahead and the spot markets.

When renewables are exposed to *market prices*, the fringe renewable producers have incentives to engage in arbitrage to increase their profits. Hence, the residual demands

[14]Note that this arbitrage is purely financial. The fringe firms' renewable output is fixed at $(1-\delta)w$, but they can gain by deciding which fraction of that output they buy or sell in each market.

faced by the dominant firm in both markets are now given by

$$\begin{aligned} D_1(p_1) &= A - bp_1 - (1-\delta)\,k \\ D_2(p_1, p_2) &= b(p_2 - p_1) + (1-\delta)\,(k-w) \end{aligned}$$

The reduction (increase) in day-ahead (spot) demand implies that the day-ahead (spot) price goes down (up) as compared to the case with no arbitrage (Lemma 1). We refer to this as the *arbitrage effect*.

This effect is not present under *fixed prices*, given that fringe firms have no incentives to engage in arbitrage: they obtain the same price regardless of whether they sell their renewable output in the day-ahead or in the spot market. For this reason, and in line with empirical evidence, we assume that they offer all their renewable output in the day-ahead market.[15] Accordingly, the residual demands faced by the dominant firm remain as in (1) and (2), and equilibrium prices remain as in Lemma 1.

Therefore, the comparison of equilibrium prices across pricing rules essentially boils down to the comparison between the *forward contract* and the *arbitrage effects*: the former applies under *fixed prices* only, the latter applies under *market prices* only.

Proposition 1 *Under limited arbitrage, the comparison of equilibrium prices across pricing schemes shows that:*

(i) $p_1^F < p_1^M$ *if and only if the degree of common ownership is sufficiently high,*

$$\delta > (k-w)/(k+w).$$

(ii) $p_2^F < p_2^M$.

Proposition above shows that the comparison of day-ahead prices depends on the degree of common ownership. The *forward contract effect* under *fixed prices* depends positively on the dominant firm's renewable output, while the *arbitrage effect* under *market prices* depends negatively on the fringe's renewable production. Hence, when common ownership is high (low) the *forward contract effect* under *fixed prices* is strong (weak) while the *arbitrage effect* under *market prices* is weak (strong). It follows that day-ahead prices are relatively lower (higher) under *fixed prices* when the degree of common

[15] Note that it is never in the interest of the dominant firm to engage in arbitrage, as that would only serve to mitigate its own market power.

ownership is sufficiently high (low).[16] On the extremes, if the dominant firm does not own any renewables, the day-ahead market price is unambiguously lower under *market prices*. To the contrary, if it owns them all, the day-ahead market price is unambiguously lower under *fixed prices*.

In contrast, *fixed prices* always give rise to lower spot prices, regardless of the degree of common ownership. Intuitively, the *arbitrage effect* under *market prices* translates into higher spot market demand, which pushes spot prices up. Instead, the *forward contract effect* under *fixed prices* weakens the incentives of the dominant producer to raise the day-ahead price, which leads to a reduction in spot market demand and in spot prices.

Our next proposition provides interesting comparative static results regarding the impact of renewable output w on equilibrium prices, which might depend on the degree of common ownership δ.

Proposition 2 *Comparative statics of equilibrium prices with respect to renewable output show that:*

(i) Equilibrium prices in all markets are strictly decreasing in renewable output under fixed prices, and weakly so under market prices (merit order effect): for $t = 1, 2$,

$$\partial p_t^F / \partial w < 0, \text{ and } \partial p_t^M / \partial w \leq 0.$$

with strict inequality if and only if $\delta < 1$.

(ii) The merit order effect in the day-ahead market is stronger under fixed prices:

$$|\partial p_1^F / \partial w| > |\partial p_1^M / \partial w| \geq 0.$$

(iii) The merit order effect is independent of common ownership under fixed prices. In contrast, under market prices, the merit order effect is mitigated by an increase in common ownership, particularly so in the spot market: for $t = 1, 2$.

$$\partial p_t^F / \partial w \partial \delta = 0, \text{ and } \partial p_2^M / \partial w \partial \delta > \partial p_1^M / \partial w \partial \delta > 0.$$

(iv) Equilibrium price differences across markets are decreasing (increasing) in renewable output under fixed prices, but they are increasing under market prices:

$$\partial \Delta p^F / \partial w < 0, \text{ and } \partial \Delta p^M / \partial w \geq 0,$$

with strict inequality if and only if $\delta < 1$.

[16] In Appendix A.2 we show that with n firms, the threshold on δ is increasing n, from $(k-w)/(k+w)$ for $n = 1$ up to $(k-w)/k$ for $n \to \infty$; see expression (36). Therefore, the more competitors there are, the more likely it is that day-ahead prices will be relatively lower under *market prices*. In any event, note that the threshold on δ is always strictly lower than 1. Hence, even under perfect competition ($n \to \infty$), there are parameter values for which *fixed prices* lead to relatively lower day-ahead prices as compared to *market prices*.

As stated in point (i) of the Proposition, an increase in renewable output pushes day-ahead prices down, independently of the pricing scheme in place. This effect is commonly referred to as the *merit order effect* (Acemoglu, Kakhbod and Ozdaglar, 2017). Our results shed new light on it, as described below.

Point (ii) shows that the merit order effect not only depresses day-ahead prices, but spot prices as well, leading to improved cost efficiency. The reason is that lower day-ahead prices make the spot market smaller, leading to reduced spot prices. It further shows that the intensity of the merit order effect depends on the pricing rule in place. In particular, as wind output increases, day-ahead prices fall more under *fixed prices.* The reason is that, under *fixed prices*, an increase in wind output reduces the degree of market power exercised by the dominant firm while it increases the supply of the fringe wind producers. In contrast, under *market prices,* an increase in wind reduces the fringe's ability to engage in arbitrage. A similar reasoning underlies point (iv), which shows that the merit order effect is decreasing in the degree of common ownership under *market prices*, but it is independent of it under *fixed prices.*

Last, point (iv) shows that renewable energies also affect price differences across markets. Again, and for similar reasons as above, the effects differ across pricing rules: wind output reduces the price differences across markets under *fixed prices*, while it widens those differences under *market prices.*

3.3 Welfare Analysis

Consumer surplus depends on day-ahead prices only,[17] while the deadweight loss depends on spot prices only. Hence, the welfare analysis follows directly from Proposition 1.

Corollary 1 *The welfare comparison across pricing schemes shows that:*

(i) Consumer surplus is higher under fixed prices than under market prices if and only if the degree of common ownership is sufficiently high,

$$\delta > (k - w)/(k + w).$$

Under both pricing rules, consumer surplus is increasing in renewable output w, although under market prices, the increase in consumer surplus is decreasing in common ownership δ.

[17] Consumer payments also depend on the fixed tariff $\overline{p}$ and the fixed premium $\underline{p}$. To compare consumer payments, we are implicitly holding the budget commitment fixed, i.e., $\overline{p}$ and $\underline{p}$ are such that at the competitive solution, consumers would pay the same under both pricing policies.

(ii) The deadweight loss is always lower under fixed prices than under market prices. Under both pricing rules, the deadweight loss is decreasing in renewable output w, although under market prices, the reduction of the deadweight loss is decreasing in the degree of common ownership δ.

Overall, the deadweight loss is lower under *fixed prices* than under *market prices*. However, the difference in consumer surplus depends on the degree of common ownership. When δ is low, prices for consumers are relatively higher under *fixed prices*.

In this case, the choice of pricing rules is thus faced with a standard trade-off as *fixed prices* give rise to greater efficiency but lower consumer surplus. Indeed, for low δ, consumers are better off when renewables are exposed to *market prices*, while firms' profits are higher when paid at *fixed prices*.

For consumers, the ideal world would be one with no common ownership and full market price exposure for renewables. However, if the degree of common ownership is high and regulators cannot reduce it (e.g., by forcing divestitures), such a trade-off disappears as *fixed prices* give rise to both higher efficiency and higher consumer surplus.

Our model helps understand how the renewables' support schemes affect day-ahead and spot prices through the degree of price exposure. However, it does not aim to provide an answer as to which pricing rule should be adopted. There are two main reasons for this. First, our model relies on the comparison of equilibrium outcomes across pricing rules for given capacities. However, pricing rules could also affect investment decisions (how much to invest, which technology to choose), ultimately affecting efficiency beyond the market price impacts. Among the efficiency effects, investments in the various renewable technologies could have distinct impacts on the displaced carbon emissions, on the learning externalities, or on other spillover effects, but these are not captured in the model. Furthermore, we have not compared the prices actually paid by consumers to renewables, which also depend on $\overline{p}$ under *fixed prices* and $\underline{p}$ under *market prices*. These prices are fixed by the time firms bid in the day-ahead and spot markets and therefore do not affect their bidding behaviour. Nonetheless, the values of $\overline{p}$ and $\underline{p}$, which we have assumed exogenous, impact how much consumers end up paying for renewables, possibly through fixed fees or through general taxation. Last but not least, our stylized model leaves some real-life nuances out that could potentially affect market outcomes (e.g., uncertainty and risk aversion).

3.4 Testable Predictions

The actual Spanish market (as well as electricity markets elsewhere) is more complicated than our stylized model. Hence, it is important to first test whether firms actually behave as predicted by the model despite the more complicated real-world market in which they interact. Ultimately, we want to obtain empirical evidence which helps us understand whether consumers are better off or worse off when renewables are paid at *fixed prices* relative to *market prices*. We group our testable predictions in three blocks:

(*i*) **Forward contract effect:** Under *fixed prices*, for given residual demands, day-ahead *market prices* should be decreasing in the strategic firms' wind output. This effect should not be present when firms are fully exposed to *market prices*.

(*ii*) **Arbitrage effect:** Under *market prices*, fringe producers have incentives to oversell in the day-ahead market. Their incentives to do so should be greater as the expected price differential across markets gets larger. This effect should not be present under *fixed prices*. Furthermore, the comparative statics of price differences differ across the two pricing schemes: price differences should decrease (increase) in wind output under *fixed* (*market*) prices.

(*iii*) **Effects on consumers:** Consumer surplus depends on day-ahead prices, which are higher under *market prices* relative to *fixed prices* if the *forward contract effect* dominates over the *arbitrage effect*, and vice-versa, an issue that depends on whether the degree of common ownership is sufficiently high or not. The empirical analysis will reveal which of the two effects dominate in the Spanish electricity market.

Before we take these predictions to our empirical analysis, we first describe some of the institutional details of the Spanish electricity market.

4 Context and Data

In this section, we describe the institutional setting, which is key for understanding the pricing incentives faced by the Spanish electricity producers. We also describe our data sources.

4.1 Market Design and Regulation

The Spanish electricity market is organized as a sequence of markets: the day-ahead market, seven intraday markets that operate close to real-time, and several balancing mechanisms managed by the System Operator. In order to participate in these markets, plants must have offered their output in the day-ahead market first. Electricity producers and consumers can also enter into bilateral contracts and they have to communicate the quantities under those contracts to the Market Operator or auctioneer, on an hourly basis one day ahead.

In our empirical analysis, we analyze bidding in the day-ahead market and arbitrage between the day-ahead market and the first intraday market (which we refer to as the *spot market*). Both markets cover the vast majority of all trades, contributing to approximately 80% of the final electricity price. The day-ahead market opens every day at 12 pm to determine the exchange of electricity to be delivered each hour of the day after. It is organized through a uniform-price central auction mechanism. On the supply side, producers submit price-quantity offers specifying the minimum price at which they are willing to produce with each of their units. The demand side works as a mirror image. The auctioneer ranks the supply bids in an increasing order and the demand bids in a decreasing order to construct the aggregate supply and demand curves, respectively. The market clears at the intersection of the two: the winning supply (demand) units are those that bid below (above) the market-clearing price. All winning units receive (pay) such price.

The intraday markets work in a similar fashion as the day-ahead market, with the difference being that all units—regardless of whether they are supply or demand units—can enter both sides of the market in order to fine-tune their day-ahead commitments. For instance, if a supplier wants to sell less (more) than its day-ahead commitment, it can submit a demand (supply) bid in the intraday markets. The same applies to consumers. The first intra-day market opens at 4pm on the day-ahead, 4 hours after the day-ahead market. Because of their volume of trade, our empirical analysis will focus on comparing the day-ahead market and the first intra-day market. Firms face a fine if their actual production deviates from their final commitment, which provides strong incentives to avoid imbalances.

In some cases, non-strategic reasons can give rise to differences between the day-ahead and the final commitments. For instance, a plant might suffer an outage after the day-ahead market has closed, forcing it to buy back whatever it committed to produce. Similarly, a renewable producer might have to buy or sell additional output if its wind or solar forecasts turn out to be wrong.

In other cases, such differences might be explained by strategic considerations. In particular, if market agents expect a positive price difference between the day-ahead and intraday markets, they might want to engage in arbitrage. Producers oversell in the day-ahead market at a high price and buy back their excess production in the intraday market at a lower price. Similarly, suppliers delay their purchases to the intraday market as much as they can.

As we considered in the theoretical analysis, the rules of the Spanish electricity market impose some constraints on arbitrage. In particular, supply (demand) bids have to be tied to a particular generation (consumption) unit, and the quantity offered (demanded) cannot exceed their maximum production (consumption) capacity. This implies that renewable plants (or big consumers and suppliers) have relatively more flexibility to arbitrage than coal or gas plants, which often operate at full capacity. For instance, renewables can offer to produce at their nameplate capacity in the day-ahead market even when they forecast that their actual available capacity will be lower. Likewise, suppliers can commit to consume below or above their expected consumption knowing that they will have more opportunities to trade in the intraday markets.

Beyond differences in the ability to arbitrage, the regulation also introduces differences in their incentives to do so, across technologies and market agents. Renewable producers' incentives to arbitrage depend on the pricing scheme in place, while big customers and suppliers are always encouraged to arbitrage price differences (since they face full price exposure, they keep any potential profits from arbitrage). We next describe the pricing schemes of Spanish renewables, which are central for our identification strategy.

4.2 Pricing Schemes for Renewables

The pricing schemes for Spanish renewables have been subject to various regulatory changes.[18] In our empirical analysis, we will exploit the occurrence of the two most recent regulatory changes affecting wind producers.

Prior to February 2013, the existing regulation (Royal Decree 661/2007) gave all wind producers the ability to choose between two pricing schemes: either a market-based scheme (Feed-in-Premium or FiP) or a fixed price scheme (Feed-in-Tariff or FiT). Under the FiP option, wind producers had to sell their electricity directly into the wholesale market and would receive a premium payment on top. Under the FiT option, wind producers were obliged to bid their output at a zero price into the wholesale market and would receive a fixed price for it (RD 661/2007; article 31). Since expected payments

[18] See del Rio (2008) for an overview of the changes up to 2007, and Mir-Artiguesa, Cerda and del Rio (2014) for the 2013 reform.

under the FiP option were notably higher than under the FiT option, all wind operators had opted for the former. We label this regime as Regime I - Market Prices. On 2 February 2013 (Royal Decree Law 2/2013), the Government decided to abolish the FiP option "without any former notice",[19] all wind producers were *de facto* moved from FiP to FiT.

The FiT regime—which we label as Regime II - Fixed Prices—only lasted until June 2014, when the government published the details for computing a new remuneration for each type of renewable installation (the Royal Decree 413/2014 was published on June 6, and Ministerial Order IET 1045/2014 that came into force on June 21).[20] In two earlier pieces of legislation (Royal Decree 9/2013 on July 14, 2013, and Law 26/2013 on December 27, 2013), the Government had already announced the main guidelines of the new regulation, but it did not actually implement it until June 2014.[21]

In general terms, the new scheme that was introduced in June 2014 (labelled as Regime III - Market Prices) moved all renewable producers to FiP. Under this regulation, which is still in place, renewables have to sell their production into the Spanish electricity wholesale market and receive the market price for such sales plus additional regulated payments.[22] The latter is based on technology and vintage specific standards, and are thus independent of the actual market revenues made by each firm. In particular, the old wind farms (i.e., those that were commissioned before 2005) do not receive any additional payment under the premise that they had previously received enough revenues to cover their construction costs. Hence, there exist some differences between the pre-February 2013 regulation (Regime I) and the post-June 2014 regulation (Regime III), mainly in the level of support. Nonetheless, the two regulations have one thing in common: they expose renewable producers to market-based prices, which is our focus.

[19] The quotes are taken from 'Pain in Spain: New Retroactive Changes Hinder Renewable Energy', published in April 2013 at www.renewableenergyworld.com. Similar quotes can be found in other industry publications.

[20] Various reasons explained these changes, including the regulator's lack of a forward-looking understanding of market performance as well as the attempt to hide payment cuts under the change of pricing format. Prior to 2013, market prices were relatively higher as compared to the *fixed prices*. Hence, the regulator thought that by moving wind producers to the fixed price regime their payments would be reduced. The opposite occurred prior to the 2014 regulatory change.

[21] We have ran placebo tests with these announcement dates, which show that these laws had no influence on firms' bidding behavior.

[22] These include a remuneration per MW of installed capacity (meant to compensate those construction costs that cannot be reasonably recovered through the market) and a remuneration per MWh produced (meant to cover the costs of operating the plants). These two regulated payments are based, not on the actual construction costs or market revenues of the plant, but rather on those of a so-called *efficient and well-managed company* subject to technology-specific standards.

4.3 Data

We use different sources of data on bids, marginal costs, renewable production (actual and forecasts), and weather data. First, we use detailed bid data from the Iberian market operator (OMIE), which reports all the supply and demand functions submitted by all plants, every hour, in the day-ahead market as well as in the intraday markets. We match the bid data with the plant characteristics data to obtain information on their owners and types (e.g., for supply units, we know their technology and maximum capacity; for demand units, we know whether they are big customers with direct market access, suppliers of last resort, or liberalized suppliers). With these bid data, we can construct each firm's residual demand by subtracting the supply functions of all its competitors from the aggregate demand curve. We also observe the market-clearing price, the marginal unit that set that price, and the units that submitted prices close to that price.

Second, we have data on the cost characteristics of all the coal plants and Combined Cycle Gas Turbines (CCGTs), including their efficiency rates (i.e., how much fuel they burn per unit of electricity) and their emission rates (i.e., how much carbon they emit per unit of electricity). Together with Bloomberg daily data on coal prices (API2), gas prices (TTF), and CO2 prices (ETS), we compute engineering-based estimates of each thermal plant's marginal cost on a daily basis.[23] While these are reliable cost data sources,[24] we cannot rule out measurement errors. For instance, the price of coal and gas in international markets need not reflect the correct opportunity cost firms face when burning their fossil fuels. This might be due to transaction costs, transportation costs, or contractual constraints on firms' ability to resell the gas bought through long term contracts. Indeed, large disparities between the load factors of various CCGTs in the market suggest that one of the strategic firms might have had access to gas prices below

[23]A 7% tax was levied at the start of 2013 on all electricity producers, including both conventional and renewables. We take this into account when computing marginal costs in our empirical analysis.

[24]The cost parameters were provided to us by the Spanish System Operator (REE) and were previously used in Fabra and Toro (2005) and Fabra and Reguant (2014). We have recently updated them to include the new capacity additions. The efficiency and emission rates are in line with standard measures for each technology, but incorporate finer heterogeneity across plants, e.g., reflecting their vintage, or, for the coal plants, incorporating the exact type of coal they burn which affects both their efficiency as well as their emission rate.

the ones in the international exchanges.[25]

Third, we use publicly available data provided by the System Operator (REE) on the hourly production of all the plants in the Spanish electricity market, including the fractions that were sold through the market or through bilateral contracts.[26] These data allow us to compute, on an hourly basis, the market shares by technologies (including renewables) and by firms. Since we observe the supply and demand allocated to the vertically integrated firms, we can compute their hourly net positions, i.e., their production net of their bilateral contracts and vertical commitments.[27] Furthermore, by computing each plants' day-ahead and final commitments, we can assess whether firms engaged in arbitrage across markets. The System Operator also provides detailed information on the hourly demand and wind forecasts one day ahead, right before the market opens.

Last, we also use publicly available daily weather data (including temperature, wind speed, and precipitation) provided by the Spanish Meteorological Agency (AEMET).

In order to encompass the two main regulatory changes affecting renewables in the Spanish electricity market, the time frame of our empirical study runs from February 2012 until January 2015. During this period, there were no major capacity additions or other relevant changes in the market structure. There were three main vertically-integrated firms, which we refer to as the *strategic firms*: Iberdrola (firm 1), Endesa (firm 2), and Gas Natural (firm 3). They all owned various technologies, with differences in the weight of each technology in their portfolios. Notably, Iberdrola was the largest wind producer, while Gas Natural was the main owner of CCGTs.[28] There was also a fringe of conventional producers, renewable producers, and independent suppliers. The market share for the strategic firms was relatively lower in the renewable segment than

[25] For instance, as reported by REE, in 2014 Gas Natural's CCGTs had the highest load factors (22% on average, as compared to 4% of all the other CGGTs). Notably, this was true also for twin CCGTs (i.e., at the same location and same vintage, owned by different companies). For instance, Besos 4 owned by Gas Natural operated at a 65% load factor, while Besos 3 owned by Endesa operated at an 8% load factor. The same was true for San Roque 1 (owned by Gas Natural, 59% load factor) and 2 (owned by Endesa, 12% load factor).

[26] One drawback of these data is that it does not include information on the units located in Portugal. However, as these plants were not affected by the regulatory changes implemented by the Spanish Government, we exclude them from the analysis.

[27] We do not include those vertical commitments that are due to regulated sales since these are simply passed-through to final consumers.

[28] This explains why Gas Natural is the price-setter during a large fraction of the time. Differences could also be due to the different degree of market power of the vairous players. Together with the fact that Gas Natural had long-term contracts for gas at prices below the international spot price for gas, explains (together with the contract clauses that often do not allow for resale) why we sometimes find negative markups in the day-ahead market prices.

in the conventional segment. Annual renewable production ranged from 42% to 45% of total generation, and the rest came from nuclear (19%), hydro (10% to 18%), coal (13% to 15%) and CCGTs (3% to 9%).

Table 1 reports the summary statistics. We use hourly data in all of our analyses: there were a total of 26,304 hourly observations, split into 8,784 observations for the first period with *market prices* (Regime I, from 1 February 2012 to 31 January 2013), 12,120 observations for the period with *fixed prices* (Regime II, from 1 February 2013 to 21 June 2014) and 5,400 observations for the second period with *market prices* (Regime III, from 22 June 2014 to 31 January 2015). The day-ahead price ranged between 38 to 52 Euro/MWh, being lower on average but also more volatile during Regime II. This could partly be explained by the higher wind availability (the average hourly wind forecast was 6.5 GWh during Regime II, above the 5.7 GWh and 5.0 GWh for Regimes I and III).[29] The spot market price was consistently lower than the day-ahead price. The average price differential across the two markets ranged between 0.3 and 1.2 Euro/MWh, being smaller during Regime III. Demand net of wind forecasts was similar on average across all three periods, if anything only slightly higher under Regime I.

A first look at the data. It is illustrative to provide a first look at the raw data. The upper panel of Figure 1 plots the difference between the day-ahead and the final output commitments for wind plants belonging to the fringe and to the strategic firms (positive numbers reflect overselling in the day-ahead market, while negative numbers reflect withholding). As can be seen, when paid according to *fixed prices* (Regime II), the fringe wind producers did not engage in arbitrage (i.e., on average, they sold all of their output in the day-ahead market). They also behaved fairly similarly as the strategic firms. Instead, when paid according to *market prices* (Regimes I and III), the fringe wind producers actively engaged in arbitrage by overselling their wind output in the day-ahead market.[30] The smaller amount of arbitrage by wind plants during Regime III is likely due to price differences across markets being narrower (see Table 1). The change in the pricing schemes also had a strong impact on the strategic producers' behavior. The strategic producers withheld more wind output across markets when exposed to market prices, notably so after the switch from Regime II to III.[31] This is paralleled by a sharp

[29] Also, coal and gas prices were more volatile during Regimes II and III relative to Regime I.

[30] This is consistent with Ito and Reguant (2016), who showed that fringe firms stopped arbitraging after the switch from *market prices* to *fixed prices* (from Regime I to II). Our results further show that they resumed arbitrage after the switch from *fixed* to *market prices* (from Regime II to III).

[31] Figure 4 in Appendix B shows that these effects showed up not only on average, but also across all hours of the day, particularly so at peak times.

Table 1: Summary Statistics

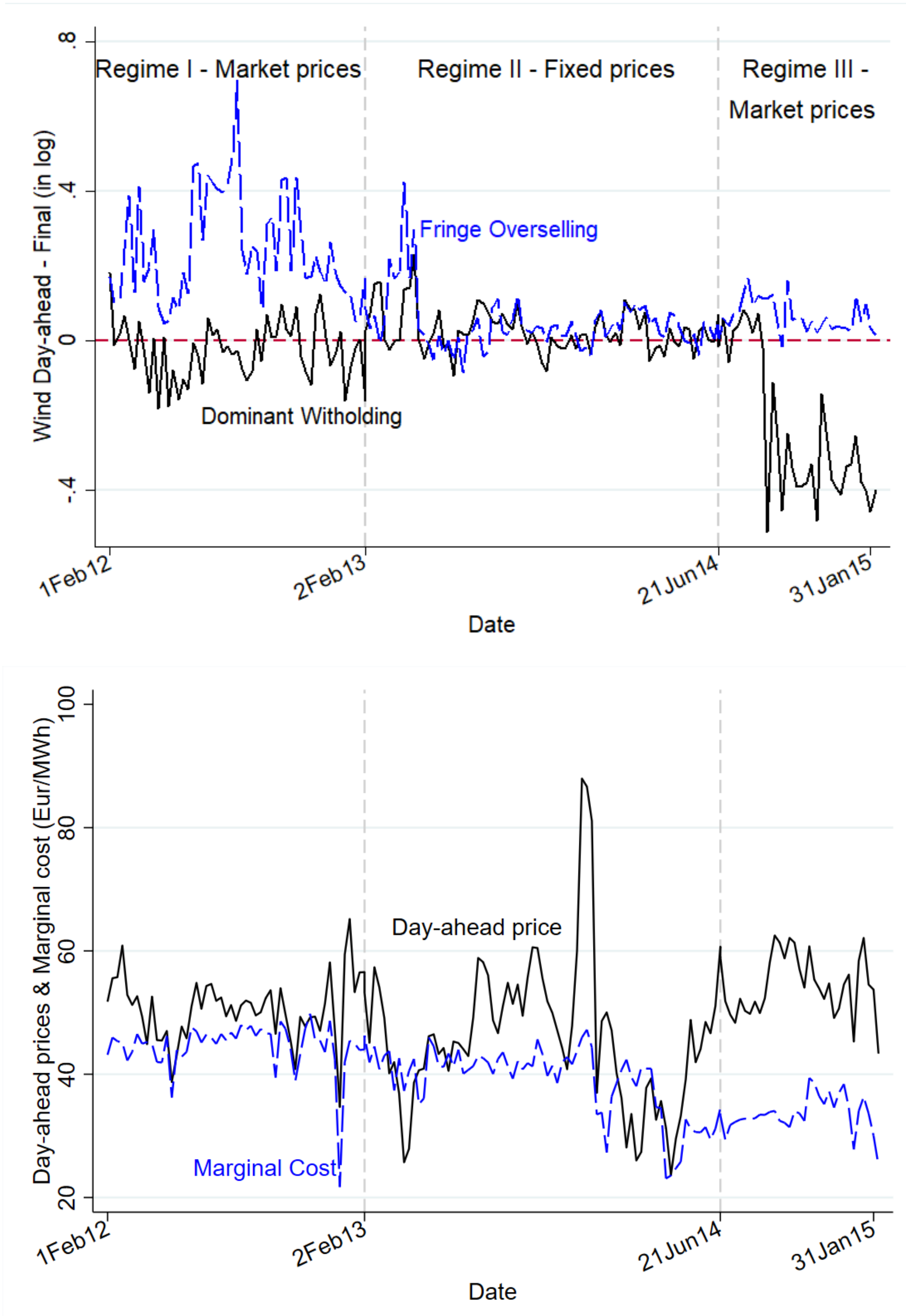
	Regime I		Regime II		Regime III	
	Mean	SD	Mean	SD	Mean	SD
Price day-ahead	50.2	(13.8)	38.1	(22.2)	52.0	(11.2)
Price intra-day 1	48.9	(14.2)	37.2	(22.1)	51.7	(11.7)
Price premium	1.2	(5.0)	1.0	(5.6)	0.3	(3.9)
Marginal cost	47.5	(6.6)	42.3	(7.2)	37.0	(3.8)
Demand forecast	29.8	(4.8)	28.5	(4.6)	28.1	(4.3)
Wind forecast	5.7	(3.4)	6.5	(3.6)	5.0	(3.2)
Dominant wind share	0.6	(0.0)	0.7	(0.0)	0.6	(0.0)
Fringe wind share	0.4	(0.0)	0.3	(0.0)	0.4	(0.0)
Installed capacity wind	22.76		23.01		23.03	
Dominant non-wind share	0.8	(0.0)	0.8	(0.1)	0.8	(0.1)
Fringe non-wind share	0.2	(0.0)	0.2	(0.1)	0.2	(0.1)
Installed capacity non-wind	99.82		100.16		100.08	

Notes: Sample from 1 February 2012 to 31 January 2015. Regime I is from 1 February 2012 to 31 January 2013; Regime II is from 1 February 2013 to 21 June 2014; Regime III is from 22 June 2014 to 31 January 2015. Prices and marginal cost are expressed in Euro/MWh. The marginal cost refers to the marginal cost of the last unit produced. Demand forecasts and wind forecasts express the average hourly values during each Regime, in GWh. Installed capacities are expressed in GW.

increase in the price-cost margin in the day-ahead market during Regime III, as can be seen in the lower panel of Figure 1.

In sum, these figures suggest that changes in the pricing schemes had a strong impact on firms' bidding behavior, and the resulting degree of market power in the day-ahead market. In the next sections, we undertake an empirical analysis to uncover the channels by which renewables' price exposure affected market power in the day-ahead market as well as their incentives to arbitrage across markets. This analysis will further reveal whether, in the Spanish case, consumers were better off or worse off when renewables were exposed to changes in market prices.

Figure 1: Wind sales across markets, day-ahead prices and marginal costs



Notes: The upper figure shows the day-ahead production commitments relative to final production. If the day-ahead commitment exceeds (is lower than) the final production, the value reported is greater (lower) than 0 and we refer to this as overselling (withholding). Data are reported for the wind producers belonging to the strategic firms (solid line) and to the fringe firms (dash line). The lower figure shows the weekly average of hourly day-ahead prices (solid line) and the engineering estimates of marginal costs (dash line). The vertical lines date the changes in the pricing schemes for renewables.

5 Empirical Analysis

In this section, we perform an empirical analysis of the market impacts of renewables' pricing schemes. To disentangle the mechanisms at play, we decompose the analysis in four steps. First, we perform a structural analysis of the determinants of the strategic firms' price-setting incentives in the day-ahead market. Second, we use a differences-in-differences approach to assess the effects of pricing schemes on the fringe's incentives to engage in arbitrage. Third, we analyze whether the determinants of price differences across markets are consistent with the model's predictions. Last, to assess the overall impact of the pricing regulation on market power in the day-ahead market, we leverage on our structural estimates to construct estimates of day-ahead price-cost markups under the two pricing schemes.

5.1 Price-Setting Incentives in the Day-Ahead Market

We use a structural approach to assess whether the changes in the renewable energies' pricing schemes affected the price-setting incentives of the strategic producers in the day-ahead market. Our focus is on whether the strategic firms take into account changes in their wind output when setting prices, and whether this depends on the pricing scheme in place, as predicted by our theoretical model.

Empirical Approach. Building on the first-order condition of profit maximization in the day-ahead market, equation (7), we estimate the following empirical equation in hours t in which firm i is bidding at or close to the market-clearing price:

$$b_{ijt} = \rho \hat{p}_{2t} + \beta \left| \frac{q_{it}}{DR'_{it}} \right| + \sum_{R=1}^{3} \theta^s \left| \frac{w_{it}}{DR'_{it}} \right| I_t^s + \alpha_{ij} + \gamma_t + \epsilon_{ijt}, \tag{8}$$

where b_{ijt} is the marginal bid of firm i when bidding at or close to the market-clearing price with unit j at time t; $\hat{p}_{2t}$ is the expected spot price at time t; q_{it} is firm i's total sales at time t; DR'_{it} is the slope of firm i's residual demand at time t at the market-clearing price; w_{it} is firm i's wind output at time t; I_t^s are three indicator variables for each pricing scheme s (Regimes I, II, and III);[32] α_{ij} are unit fixed effects, and γ_t are time fixed effects. We include unit, quarter, and hour fixed-effects in all specifications, while

[32] We define the indicator variables for Regimes I, II, III using the February 1, 2013 and June 22, 2014 cutoffs, respectively, which is when the regulatory changes were fully implemented, as described in Section 4.2.

linear and quadratic time trends are added in a cumulative fashion. Last, ϵ_{ijt} is the error term clustered at the plant level to allow errors to be correlated within the same plant.[33]

Variables Description. On the left hand side of equation (8), we include the bids of all price-setting units belonging to one of the strategic firms,[34] plus those within a 5 Euro/MWh range as they have an ex-ante positive probability of setting the market price. We exclude (i) hydro units (since it is difficult to assess the true opportunity costs of using their stored water), as well as (ii) units that operate on either the first or last step in their bidding functions (since their constraints for reducing or increasing their output might be binding, invalidating the use of the first-order in equation (7)).[35]

On the right hand side of (8), two variables require further explanations. First, to compute the expected spot market price ($\hat{p}_{2t}$), we use information available to firms at the time the day-ahead market opens. In particular, we regress demand and wind forecasts, hourly dummies, and date dummies on the observed spot market price, and use the estimated coefficients to predict $\hat{p}_{2t}$.[36] Second, to build the realized residual demand curve faced by each firm (DR_{it}), we fit a quadratic function to the residual demand curve and calculate its slope at the market-clearing price (see Figures 8 in Appendix B for an illustration).[37]

Identification. When estimating equation (8), there are at least two identification challenges. First, the slope of the residual demand at the market-clearing price (DR_{it}) is likely endogenous, thus making the markup terms endogenous as well.[38] Second, other

[33]Our results are robust to several ways of clustering, such as at firm-day, firm-month-year, and firm-week levels (see Table 6 in Appendix B).

[34]If a strategic firm owns more than one unit with these characteristics, we include them all in the analysis.

[35]We follow a similar approach as Fabra and Reguant (2014) and Reguant (2014).

[36]The estimating equation is $p_{2t} = \alpha D_t^{fc} + \beta w_t^{fc} + X_t + Y_t + \epsilon_t$, where the two first regressors are the demand and wind forecasts. We allow all the coefficients to vary across pricing regimes, so the relationship between the spot price, demand, and wind forecasts need not be the same across regimes. The errors are clustered within day.

[37]Approximating the slope of residual demand is common in the existing literature, see also Wolak (2003); Reguant (2014); Fabra and Reguant (2014); Ito and Reguant (2016). To avoid the flat region of the inverse residual demand curve occurred at zero price, which makes our linear approximation poorly predict the local slopes, we truncate the residual demand to the minimum quantity that firms are willing to serve at zero price. Note that we also explore the other alternative methods such as kernel smoothing around the market price (Reguant, 2014) and fitting linear splines with 10 knots to the residual demand curve. Our conclusions are similar regardless the method of approximation we use.

[38]Note that, since we use the predicted spot price ($\hat{p}_{2t}$) based on the public information available to firm at day-ahead, it is exogenous.

factors may influence the bids, and hence not properly controlling for them could lead to omitted variable bias.

To address the first challenge, we instrument DR'_{it} using wind speed and precipitation (and each of them interacted with three dummies for the pricing scheme) as residual demand shifters. The exclusion restriction holds under the assumption that, conditional on unit and time fixed effects, wind speed and precipitation affect firms' marginal bids only through our markup parameters. This assumption is plausible and common in the literature (Fabra and Reguant, 2014; Ito and Reguant, 2016) because wind speed and precipitation may influence the firm's inframarginal quantity, but they are unlikely to influence the marginal bid directly. We then use Two-Stage Least Squares (2SLS) to estimate equation (8). To address the second challenge, we add a set of flexible controls, such as time trends, and quadratic time trends, on the top of a set of fixed effects discussed earlier.

Since we want to understand whether firms' markups are affected by their wind output, our parameter of interest in equation (8) is θ^s. We expect it to take a negative value under *fixed prices* (Regime II), but we expect it to be not significantly different from zero under *market prices* (Regimes I and III). This would reflect that firms do not (do) take into account the price effects on their wind output when it is paid at *fixed* (*market*) prices.

Results. The results are shown in Table 2. In columns (1)-(3), we constrain the coefficient on the firm's markup over its total output to be equal to one. In all specifications, the $\hat{p}_2$ coefficients are positive, as expected. The results confirm that wind output has a significant price-depressing effect when renewable output is paid at fixed prices, but it has a small and noisy effect otherwise, consistently with our predictions. Moreover, these coefficients are stable across the different specifications, reassuring robustness regardless of the set of flexible controls we use. In column (4), we allow the coefficient for the firm's total output markup to vary. The estimated coefficient for the Regime II indicator variable is still very similar. The sign of the coefficient for the firm's total output markup is positive as expected,[39] given that greater output and a steeper residual demand enhance

[39] While the sign of the coefficient is as expected, we do not attempt to interpret the magnitude of the coefficient. The coefficient of $\frac{q_{it}}{DR'_{it}}$ may be inflated as $\frac{q_{it}}{DR'_{it}}$ is correlated with $\frac{w_{it}}{DR'_{it}}$, with a correlation coefficient equal to 0.36.

market power.[40]

It would be misleading to compare the coefficients on the various variables given that their means are very different. To get some orders of magnitude of the *forward contract effect*, one can take for instance the mean of a strategic firm's hourly wind production during Regime II, 317.5 MWh, over the mean of the slope of its residual demand, 404.9 Euro/MWh. Using the estimates in column (1) for instance, an increase in wind output of ten percent over its mean would imply a price reduction of 1.2 Euro/MWh (approximately, a 3.1 percent reduction over the average price) during Regime II.

5.2 Arbitrage across Markets

Since day-ahead prices were systematically higher than prices in the spot market, fringe producers could gain by engaging in arbitrage under Regimes I and III, when they were exposed to market prices; in particular, by overselling in the day-ahead market at high prices and buying back their excess supply at the lower spot price. However, differences between the day-ahead and the final commitments could also be explained by non-strategic reasons, such as wind or demand forecast errors. What distinguishes arbitrage from non-strategic reasons is that the former are linked to price differences across markets, whereas the latter are not. Accordingly, in order to understand whether pricing rules affected firms' incentives to engage in arbitrage, we examine whether the response of overselling to the predicted price differential differed when renewables were paid according to *fixed prices* (Regime II) or *market prices* (Regimes I and III).

Empirical Approach. Following a DiD approach, we regress the differences between the day-ahead and the final output commitments on the price differential, interacted with a dummy variable for each pricing regime. Using this approach, we limit the concern that other unobservable time-variant factors may also influence arbitrage through the price differential, therefore leading to an omitted variable bias. Our treatment group is wind producers and our two possible control groups are: (1) non-wind renewable producers

[40] The firms included in this analysis are vertically integrated. Hence, one could conjecture that they set prices to maximize the profits of the vertical chain. Table 7 in Appendix B reports the results accounting for vertical integration. Note that we observe the day-ahead sales and purchases by firms belonging to the same vertically integrated group, but we do not have information about the forward (sale or purchase) contracts they may have. Using these data, our main predictions remain valid. However, relative to the results in Table 2, the coefficients under the Regimes I and III go up, with the former becoming slightly significant. This is consistent with two hypothesis: firms were only maximizing their supply-side profits as market power is under-estimated when we take account firms' net sales; or they had forward contracts (which we do not observe) that muted the effect of vertical integration.

Table 2: The Forward Contract Effect

	2SLS			
	(1)	(2)	(3)	(4)
Regime I $\times \frac{w_{it}}{DR'_{it}}$	6.35	9.31	9.10	5.54
	(5.03)	(6.28)	(6.10)	(5.47)
Regime II $\times \frac{w_{it}}{DR'_{it}}$	-14.2***	-14.5***	-14.9***	-14.3***
	(3.03)	(2.88)	(3.02)	(3.24)
Regime III $\times \frac{w_{it}}{DR'_{it}}$	1.72	0.049	0.60	5.69
	(4.10)	(3.42)	(3.21)	(5.24)
$\hat{p}_{2t}$	0.77***	0.78***	0.77***	0.38***
	(0.057)	(0.062)	(0.062)	(0.15)
$\frac{q_{it}}{DR'_{it}}$				4.81***
				(1.25)
Linear Trends	N	Y	Y	Y
Quad. Trends	N	N	Y	Y
Observations	19,805	19,805	19,805	19,805

Notes: This table shows the estimation results of equation (8) using 2SLS. All regressions include unit, firm and quarterly dummies. In columns (2)-(4) we add day-of-the-week dummies, hour fixed effects, and quadratic time trends in a cumulative fashion. We constrain the coefficient for the markup for firms' total output to be one in columns (1) to (3), and we relax this by allowing the markup coefficient to vary in column (4). We limit hourly prices to be within 5 Euro/MWh range relative to the market price and exclude the outliers (bids with market prices below the 1st percentile and above the 99th percentile). We instrument our markups with wind speed, precipitation, and each of them interacted with the three pricing scheme indicators. The standard errors are clustered at the plant level. See Table 6 for alternative ways of clustering.

(i.e., solar, small hydro and cogeneration units), and (2) suppliers in the liberalized market.

We split the sample in two, each of which contains one regulatory change. The first sample ($d = 1$), which ranges from February 1, 2012, to February 1, 2014, contains the change from *market prices* to *fixed prices* that took place on February 1, 2013. The second sample ($d = 2$), which ranges from February 1, 2013, to January 31, 2015, contains the change from *fixed prices* to *market prices* that took place on June 22, 2014.

We run three separate OLS regressions, one for each sample $d = 1, 2$ and one for each

each control group $g=$ non-wind renewables, suppliers. Note that for sample $d=2$, we cannot use other renewables as the control group given that they were also affected by the regulatory change. We estimate the following equation, for $d=1,2$,

$$\begin{aligned}\Delta \ln q_t =& \alpha + \beta_1 W I_t^d \Delta\hat{p}_t + \beta_2 W \Delta\hat{p}_t + \beta_3 W I_t^d + \beta_4 I_t^d \Delta\hat{p}_t + \beta_5 \Delta\hat{p}_t + \\ & \beta_6 W + \beta_7 I_t^d + \rho \mathbf{X}_t + \eta_t\end{aligned} \tag{9}$$

In equation above, I_t^1 is an indicator for *fixed prices* (Regime II)—the switch from *market prices* to *fixed prices*. Similarly, I_t^2 is an indicator for *market prices* (Regime III)—the switch from *fixed prices* to *market prices*. For both samples, W is an indicator for wind fringe producers. We include a set of control variables such as weather controls (daily solar radiation time and precipitation), the hourly demand forecast error, the hourly wind forecast error, week of sample fixed effects, and day-of-week fixed effects, all captured in $\mathbf{X}_t$. Standard errors are clustered at the week of sample.

Our coefficient of interest, β_1, captures the change in the price response of arbitrage by wind producers relative to the control group. We expect the sign of this coefficient to be negative using sample 1, as the switch from *market prices* to *fixed prices* should reduce the wind producers' incentives to engage in arbitrage. On the contrary, we expect the coefficient for β_1 to be positive using sample 2, as the switch from *fixed prices* to *market prices* should induce wind producers to engage in arbitrage again.

A Key Variable. To capture how fringe firms reacted to changes in the price differential across markets that they could forecast at the time of bidding, we construct the forecasted price premium ($\Delta\hat{p}_t$) as follows. First, we use two exogenous variables that were available to firms prior to bidding: demand and wind forecasts. Similar to how we compute the expected spot price in Section 5.1, we regress demand and wind forecasts, hourly dummies, and date dummies on the price premium.[41] We then use the regression coefficients to obtain the forecasted price premium at time t, $\Delta\hat{p}_t$. Using $\Delta\hat{p}_t$ rather than the actual price difference is important to rule out potential endogeneity concerns between arbitrage and price differences.

Parallel Trends. Before we move forward with our DiD estimation in equation (9), it is important to test if the parallel trends assumption holds. Non-wind renewable producers were subject to *fixed prices* under Regimes I and II, and were then exposed to

[41] The estimating equation is $\Delta p_t = \alpha D_t^{fc} + \beta w_t^{fc} + X_t + Y_t + \epsilon_t$, where the two first regressors are the demand and wind forecasts. We also allow all the coefficients to vary across pricing regimes. The regressions have an R-squared ranging from 0.3 to 0.4.

market prices under Regime III. Hence, their incentives to engage in arbitrage should be similar to those of wind during Regimes II and III regimes. For this reason, one should observe parallel trends for wind vs. non-wind renewables during Regimes II and III. The regulation impact on wind overselling is captured by the difference between wind vs. non-wind renewables during Regime I. For suppliers, they have incentives to engage in arbitrage in all periods as they were not subject to price regulation. Hence, we expect suppliers to engage in arbitrage just like wind under Regimes I and III. For this reason, one should observe parallel trends for wind vs. suppliers during those regimes. The regulation impact on wind overselling is captured by the difference between wind vs. suppliers during Regime II.

To compare the price response of wind producers, non-wind renewable producers, and suppliers, we first document the response of each group's arbitrage to the predicted price premium on a quarterly basis. We regress the forecasted price premium, $\Delta\hat{p}_t$, on the difference between the logs of the day-ahead and the final commitments of firms in group g (wind producers, non-wind renewable producers, and suppliers), $\Delta \ln q_{tg}$. Our sample includes 13 quarters, from Q1 2012 to Q1 2015. We control for demand and wind forecast errors, denoted D_t^{er} and w_t^{er}, as these could give rise to differences between day-ahead and final commitments which are unrelated to arbitrage.[42] We also control for seasonality (i.e., using dummies for days-of-the-week and week of sample), for daily solar radiation time, daily precipitation, and temperature, all captured in $\mathbf{X}_t$. The estimating equation is

$$\Delta \ln q_{tg} = \alpha + \sum_{q=1}^{13} \theta_{qg} \Delta\hat{p}_t + \gamma D_t^{er} + \delta w_t^{er} + \rho \mathbf{X}_t + \eta_{tg} \tag{10}$$

where η_{tg} is the error term. Our coefficients of interest are θ_{qg}, which capture the response of arbitrage by group g at quarter q to the predicted price differential. We cluster standard errors at the week of sample.

Figures 2 plots the θ_{qg} coefficients from equation (10) for each quarter.[43] As expected, in Figure 2 (a) one can observe that during Regime II (Q1 2013 to Q2 2014), the price response of arbitrage by the non-wind renewable producers is similar to that of wind producers and not significantly different from zero. Similarly, Figure 2 (b) shows that

[42]Demand and wind forecast errors are computed by subtracting the hourly forecast and the observed values. The forecast values are publicly available to firms the day before.

[43]For this graphical evidence, hours when the predicted price differential gives a poor prediction for the observed price differential are excluded (i.e., when the difference between predicted and observed price differential is above the 50th percentile). Figure 5 in Appendix B shows that, in some hours, the predicted price differential departs substantially from the observed one, probably due to some unobservables not included in our estimating equation.

during Regime II (Q1 2013 to Q2 2014), the price response of the suppliers' arbitrage is positive and very similar to that of the wind producers during Regimes I and III (2012 and Q3 2014 onwards). Therefore, Figure 2 serves as graphical evidence on the parallel trend between wind and each of the control groups, during the relevant periods. Table 8 in the Appendix, shows three parallel trend tests: (1) for sample $d = 1$, during Regime I the wind producers and the suppliers behave similarly in response to the predicted price differential (p-value of 0.529); (2) for sample $d = 1$, during Regime II wind and non-wind renewables behave similarly (p-value of 0.151); (3) for sample $d = 2$, during Regime III, wind and suppliers behave similarly (p-value of 0.503).[44]

Results. We report the DiD results (β_1 coefficients from equation (9)) in Table 3. The impact of the switch from *market prices* (Regime I) to *fixed prices* (Regime II) is shown in columns (1) and (2), depending on whether we use non-wind renewables or suppliers as the control group, respectively. In both cases, the negative coefficients show that this switch reduced arbitrage relative to both control groups, and by a similar magnitude. In contrast, the impact of the switch from *fixed* (Regime II) to *market prices* (Regime III), shown in column (3), was positive, thus indicating that this switch brought wind fringe producers back to arbitrage.[45] Overall, these results are all consistent with our predictions.

Having confirmed the empirical relevance of the *forward contract* and the *arbitrage* effects, we next provide further evidence showing that the resulting price differences across markets responded to changes in the renewables' market structure, as predicted by the model.

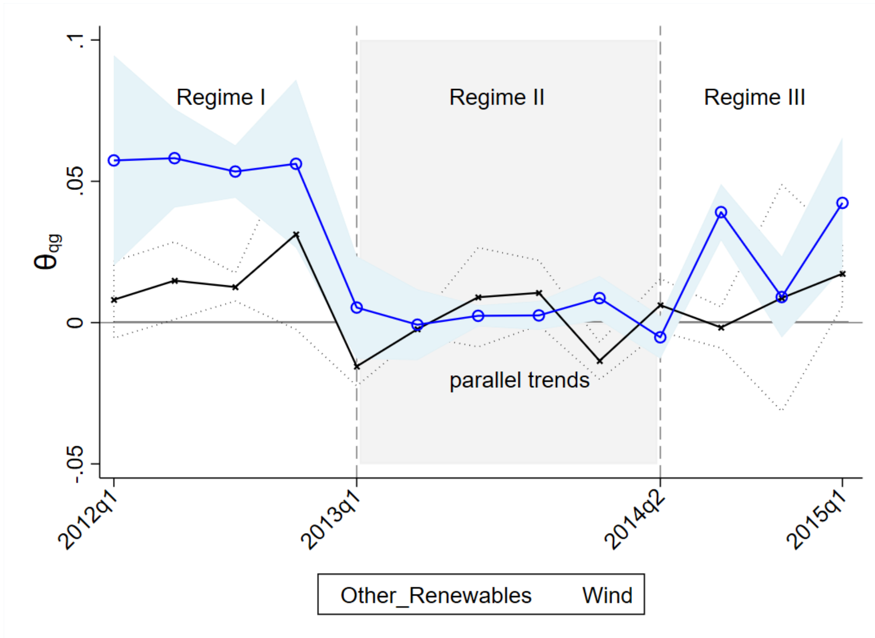
5.3 Price Differences across Markets

Empirical Approach. Our model predicts that price differences across markets respond differently to changes in the wind production market shares depending on whether wind producers are paid at *fixed prices* or exposed to *market prices*. To test for this, we

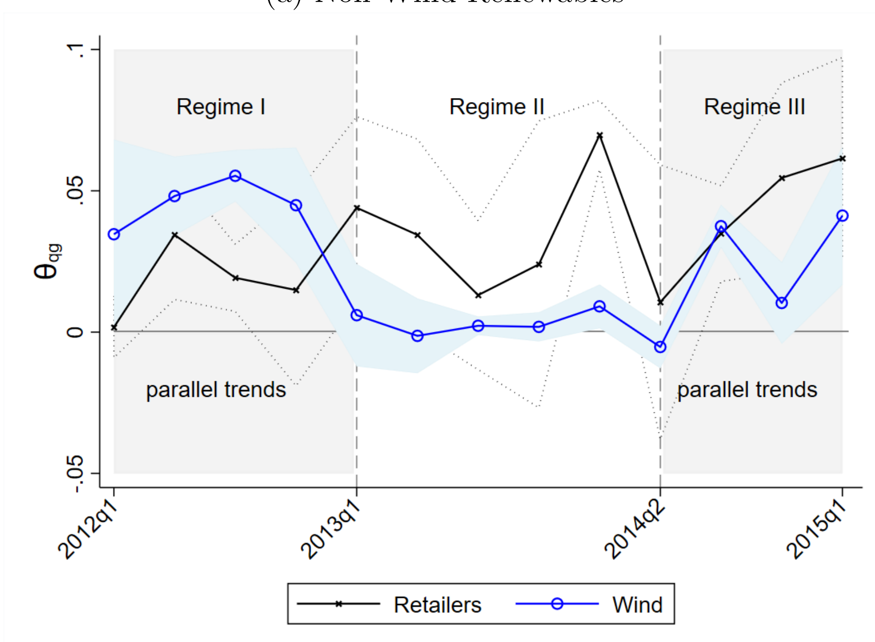
[44]The complete results with the overselling response to the price premium (and its corresponding p-values) are reported in Appendix B, Table 8.

[45]As mentioned earlier, during Regime III, all renewables are exposed to market prices, hence we expect to see their price responses are not very different with that of wind. Here, we do not report the effect of the move from Regime II to III as the other renewables were also affected by it. The treatment effect is also positive, but smaller than that on column (3). See Appendix B, Table 8.

Figure 2: Arbitrage Trends by the Fringe (Wind, Non-Wind Renewables, and Suppliers)



(a) Non-Wind Renewables



(b) Suppliers

Notes: This figure plots the coefficients of the OLS regression in equation (10) for (a) wind vs. other non-wind renewable producers and (b) wind vs. suppliers. It captures the response of overselling to the predicted price differential. Positive numbers suggest that overselling was increasing in the predicted price differential. A zero coefficient shows no attempt to arbitrage. The parallel trends are shown by the shaded areas: during Regime II for (a), and during Regimes I and III for (b). The sample includes hours from 1 January 2012 to 31 March 2015 to ensure a similar number of observations in each quarter. Hours when the predicted price differential is poorly predicted are excluded.

Table 3: Impacts of Changing the Pricing Schemes on Overselling by Wind

	Non-wind renewables	Suppliers	
	(1)	(2)	(3)
$\Delta\hat{p}\times$ Wind $\times$ Regime II	-0.071***	-0.069***	
	(0.0068)	(0.014)	
$\Delta\hat{p}\times$ Wind $\times$ Regime III			0.059***
			(0.011)
Observations	41,080	41,080	34,194

Notes: This table shows the β_1 coefficients from equation (9). Each column is a different regression using the log of overselling as the dependent variable. Non-wind renewables is the control group in column (1), and suppliers is the control group in columns (2)-(3). Columns (1) and (2) use sample $d = 1$ from 1 February 2012 to 1 February 2014, with the Regime II indicator equal to one for days after 1 February 2013, while column (3) uses the sample from 1 February 2013 to 31 January 2015, with the Regime III equal to one for days after 22 June 2014. All regressions include seasonality controls, hour of day, and week fixed effects. Note that, under Regime III, non-wind renewables are also affected by the regulation. Hence, we prefer not to use it as a control group in our analysis during Regime III. The standard errors are clustered at the week of sample.

use 2SLS and estimate the following empirical equation for our second stage:

$$\Delta p_t = \alpha + \sum_{s=1}^{2} \beta_1^s I_t + \beta_2 \frac{w_{dt}}{W_t} + \sum_{s=1}^{2} \beta_3^s I_t \frac{w_{dt}}{W_t} + \alpha_1 D\hat{R}'_{1t} + \alpha_2 D\hat{R}'_{2t} + \gamma \mathbf{X}_t + \epsilon_t \tag{11}$$

where Δp_t is the price premium at time t; I_t takes two values (1 for Regime I, 2 for Regime III, and therefore 0 for Regime II serves as the reference point); the wind share w_{dt}/W_t captures the wind share of the strategic firms as it is computed as the ratio between the strategic firms' wind output over total wind output; $D\hat{R}'_{1t}$ and $D\hat{R}'_{2t}$ capture the (instrumented) slopes of the residual demands faced by the strategic firms in the day-ahead and intraday markets, respectively, from our first stage regression. We follow a approach similar as in Section 5.1 as the slopes of the residual demands are potentially endogenous. Therefore, we instrument these two slopes (DR'_1 and DR'_2) with daily and hourly weather variables (daily average, minimum, and maximum temperature, and average temperature interacted with hourly dummies).[46] $\mathbf{X}_t$ is a set of controls, such as demand forecasts,[47] wind forecasts, and dummy variables (i.e., hourly dummies, peak-

[46] We compute the aggregate hourly residual demand faced by the strategic firms in the day ahead and in the intraday markets and their slopes using the same approach as discussed in footnote 37.

[47] The demand forecast is predetermined before the day-ahead market opens. It is therefore exogenous.

hour dummy, weekend dummy); last, ϵ_t is the error term. We use bootstrap standard errors with 200 replications.

The coefficient β_1 compares price differences across pricing schemes. Coefficients β_2 and β_3 capture the impacts of changes in the wind shares on the price difference. Our theoretical model predicts that an increase in the strategic firms' wind share should reduce the price differential when renewables are subject to *fixed prices*, but it should increase the price differential when exposed to *market prices*. Regarding the other coefficients, we expect that all the variables that enhance market power—a higher demand and a steeper (flatter) demand at day-ahead (spot)—also enlarge the price differences across markets.

Results. Table 4 reports our main coefficients of interest: β_2, β_3^1, and β_3^2 from equation (11). The remaining coefficients are all broadly consistent with our theoretical predictions.[48] We can see that the price difference is smaller when the wind share of the strategic firms increases (see coefficients of $\frac{w_{dt}}{W_t}$ in all columns). Also, price differences are higher under the regimes with *market prices* relative to the *fixed prices* regime when the wind share of the strategic firms increases, as reflected by the positive coefficients of Regime I $\times \frac{w_{dt}}{W_t}$ and Regime III $\times \frac{w_{dt}}{W_t}$ in all columns. This evidence is consistent with the predictions of the model, giving further support to the relevance of the *forward contract effect* under *fixed prices* (which is strengthened as w_d increases) and the *arbitrage effect* under *market prices* (which is weakened as w_d increases).

5.4 Market Power in the Day-Ahead Market

Our results in section 5.1 showed that, given the observed residual demands, firms had weaker incentives to increase day-ahead prices when their renewable output was shielded from fluctuations in market prices. However, this alone does not allow us to conclude that reducing firms' price exposure mitigated market power in the day-ahead market, thus benefiting consumers. As our previous results also indicate, the pricing schemes might have also affected firms' residual demands through the impacts on arbitrage across markets. Therefore, taking into account the changes in the residual demands, in this section we compute and compare firms' markups across pricing regimes to evaluate the overall impact of the pricing schemes on market power in the day-ahead market.

[48] See the complete list of coefficients is in Appendix B, Table 9. The sign of the other coefficients, such as those on total demand and the slopes of the residual demands in the day-ahead and in the intraday markets, are respectively positive, negative, and positive, as expected. Results are very similar if we instead define the market share variable as a ratio between the strategic's wind and the fringe's wind output (w_{dt}/w_{ft}).

Table 4: The Impact of Pricing Schemes on Price Differences across Markets

	2SLS			
	(1)	(2)	(3)	(4)
$\frac{w_{dt}}{W_t}$	-0.59***	-0.50***	-0.59***	-0.50***
	(0.18)	(0.17)	(0.18)	(0.18)
Regime I $\times$ $\frac{w_{dt}}{W_t}$	0.44**	0.46**	0.44**	0.46**
	(0.21)	(0.19)	(0.21)	(0.21)
Regime III $\times$ $\frac{w_{dt}}{W_t}$	0.46**	0.41**	0.46***	0.41**
	(0.18)	(0.17)	(0.16)	(0.17)
Weekend FE	N	N	Y	Y
Peak Hour FE	N	Y	N	Y
Observations	25,334	25,334	25,334	25,334

Notes: This table shows only our coefficients of interest: β_2 and β_3 from equation (11). The complete list of coefficients is in Appendix B, Table 9. R I is an indicator for Regime I periods, R III for Regime III periods, and Regime II periods are the reference periods. We use bootstrap standard errors with 200 replications.

Using the first-order condition of profit-maximization—represented by equations (7) in the theory analysis and (8) in the empirical analysis—markups in the day-ahead market can be expressed as

$$\frac{p_{1t} - \hat{p}_{2t}}{p_{1t}} = \left| \frac{\partial DR_{i1t}}{\partial p_{1t}} \right|^{-1} \frac{q_{i1t} - I_t w_{i1}}{p_{1t}}$$

where, leveraging on the structural estimates obtained in Section 5.1, we set $I_t = 1$ under Regime II (*fixed prices*) and $I_t = 0$ under Regimes I and III (*market prices*).

Results. The first and third rows of Table 5 report firms' average markups in the day-ahead market (using either the simple average or the demand-weighted average). Figure 3 shows their distribution. Markups are always relatively lower under *fixed prices*: the average markup during Regime II was 6.3%, while it was 8.3% and 10.7% under Regimes I and III regimes, respectively. A two-sample Kolmogorov–Smirnov test rejects at 1% significance level the hypothesis that the markup distributions are the same across pricing regimes. A similar conclusion applies when comparing the markups of each strategic firm individually, for off-peak versus on-peak hours, or for more windy or less windy hours.[49] This evidence on the markups comparison is also consistent with the slopes

[49]See Figures 6 and 7 in Appendix B.

of the residual demands being relatively larger under *fixed prices*, thus indicating that the weaker incentives to exercise market power induced firms to submit flatter supply functions (see the last row of Table 5). This effect seems to have played a stronger role than the absence of significant arbitrage.

Table 5: Average markups across pricing regimes

	Regime I		**Regime II**		**Regime III**	
	Mean	SD	Mean	SD	Mean	SD
Markups (in %) – Simple average						
Day-Ahead (structural)	8.3	(3.3)	6.3	(3.3)	10.7	(3.7)
Overall (engineering)	8.6	(23.1)	8.1	(29.4)	29.7	(14.0)
Markups (in %) – Demand weighted average						
Day-Ahead (structural)	8.3	(3.2)	6.4	(3.3)	10.7	(3.6)
Overall (engineering)	10.0	(22.8)	9.2	(29.6)	30.4	(13.5)
Slope of day-ahead residual demand (in MWh/euros)	524.2	(78.2)	553.6	(120.7)	418.2	(73.0)

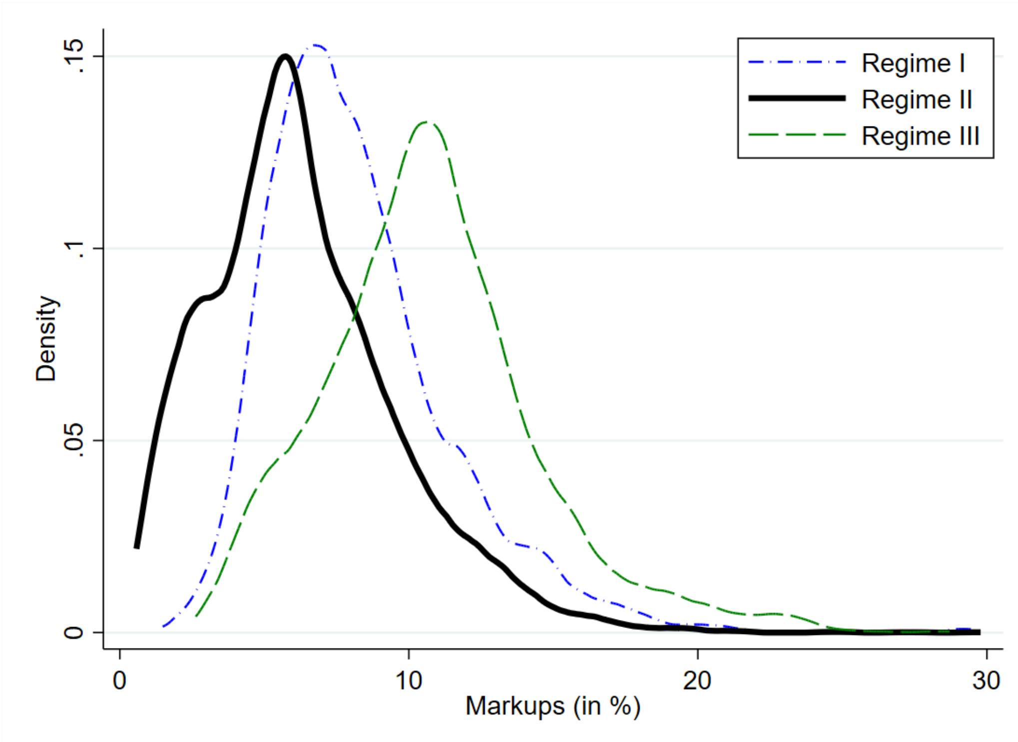
Notes: It reports the mean and standard deviation of markups and slopes of the day-ahead residual demand using the sample from February 2012 to February 2015. Regime I (*market prices*) is from 1 February 2012 to 31 January 2013; Regime II (*fixed prices*) is from 1 February 2013 to June 13 2014; Regime III (*market prices*) is from June 14 2014 to January 2015, for three strategic firms. It only includes marginal bids around 5 Euro/MWh range and bids with prices above 25 Euro/MWh.

These results are a lower bound on the degree of market power actually exercised by firms, given that the expected spot market price (which we have used as the shadow cost of day-ahead sales) might also include a markup over the firm's marginal costs. To compute firms' markups over their actual marginal costs, we rely on engineering estimates for marginal costs. This approach, which is common in the literature,[50] leads to noisier markups due to potential measurement errors in the marginal cost estimates.[51] Nonetheless, as shown in Table 5, the results are consistent with our main result; namely, market power as measured by the price-cost markups was weaker when renewables were paid according to *fixed prices*. Also note that the price-cost markups are larger on average

[50] For example, see Borenstein, Bushnell and Wolak (2002), Fabra and Toro (2005), or Fabra and Reguant (2014), among others.

[51] For instance, we see some negative markups which could be explained by firms buying coal and gas through long-term bilateral contracts at prices below the spot market price, which we use to compute our marginal cost estimates.

Figure 3: Distribution of day-ahead markups



Notes: This figure plots the distributions of day-ahead markups for all firms by pricing regimes, for hours with prices above 25 Euro/MWh. Plots by firms (Figure 6) in Appendix B show a very similar pattern. To absorb some seasonal variation in the markups, Figure 7 by wind quartiles in Appendix B suggests that markups are indeed lower during Regime II.

than the markups in the day-ahead market, given that the expected spot market price includes a markup over marginal costs.

6 Conclusions

In this paper, we have analyzed how the degree of price exposure faced by renewable energies impacts market power in electricity markets, taking into account two countervailing incentives (*forward contract effect*). On the one hand, in line with Allaz and Vila (1993), reducing renewables' price exposure mitigates firms' incentives to increase prices. On the other hand, if renewables are insulated from price changes, firms face weaker incentives to arbitrage price differences, which enhances the strategic producers' market power (*arbitrage effect*).

This trade-off is particularly relevant for a key policy debate in electricity markets; namely, how to pay for renewables. Since compliance with the environmental targets requires massive investments in renewables, it is paramount to understand how alternative renewable support schemes impact market prices and efficiency. One of the key messages of the paper is that understanding the impact of renewable policy requires an analysis of the interaction between conventional and renewable generation technologies, and not just of renewables alone. The interplay between the two very much depends on the degree of common ownership, which drives much of the outcomes and efficiency results of the paper.

We have used the Spanish electricity market as a lab to explore the trade-off between the *forward contract* and the *arbitrage* effects. Our empirical analysis confirms that the strategic producers attempted to exercise market power by withholding output in the day-ahead market. When exposed to *market prices*, independent wind producers made the withholding strategy more costly by overselling their idle capacity in the day-ahead market in order to arbitrage price differences across markets. Instead, paying renewables according to *fixed prices* reduced arbitrage, but also mitigated the dominant producers' incentives to withhold output in the first place. The latter effect dominated, giving rise to relatively lower markups in the day-ahead market when renewables were not exposed to *market prices*. This was particularly important for consumers, as it allowed them to pay lower electricity prices.

There are reasons to expect that market power concerns in electricity markets will diminish over time (as demand response and storage facilities become more widely spread). However, there are also compelling reasons to remain vigilant as the expansion of renewable energies will make it increasingly important to understand how renewables' support schemes affect market performance.[52] The long-run impacts of such differences on investment decisions are left for future research.

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[52]Furthermore, there might be concerns regarding the market power impact of storage depending on who owns and operates he storage facilities (Andrés-Cerezo and Fabra, 2020).

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Appendix

Appendix A: Additional Results and Proofs

A.1 Proofs

In this section we provide closed-form solutions for the equilibrium prices of the model described in Section 3. All proofs for the lemmas and propositions in the main text follow from these expressions.

No Arbitrage We first solve the profit maximization problems in (3) for the spot market, and (5) under *market prices* and (6) under *fixed prices* for the day-ahead market. We do so by backward induction, with $D_1(p_1) = A - bp_1 - (1-\delta)\,w$ and $D_2(p_1, p_2) = b\Delta p$. For given p_1, the spot market solution is given by, under both pricing rules,

$$p_2 = \frac{p_1 + c}{2}, \text{ implying } q_2 = b\frac{p_1 - c}{2}. \tag{12}$$

To solve the day-ahead market problem, we first consider *market prices* and then *fixed prices*.

Under ***market prices***, plugging (12) into the day-ahead problem (5), one can find the day-ahead market solution

$$p_1^M = \left[2\left(A - (1-\delta)\,w\right) + bc\right]/3b$$

implying

$$q_1^M = \left(A - (1-\delta)\,w - bc\right)/3.$$

Plugging this back into the spot market solution gives

$$p_2^M = \left[A - (1-\delta)\,w + 2bc\right]/3b$$

implying

$$q_2^M = \left(A - (1-\delta)\,w - bc\right)/3.$$

Taking the difference between the two prices,

$$\Delta p^M \equiv p_1^M - p_2^M = \left(A - (1-\delta)\,w - bc\right)/3b.$$

Since we have assumed $A - w - bc > 0$, it follows that $q_1^M > 0$, and $p_1^M > p_2^M > \delta w/3b + c > c$. Note that the solution is the same as Ito and Reguant (2016)'s Result 1, with $A - (1-\delta)\,w$ here in the place of A there.

Under ***fixed prices***, plugging (12) into the day-ahead problem (6), one can find the day-ahead market solution,

$$\begin{aligned} p_1^F &= [2(A-w)+bc]/3b \\ &= p_1^M - 2\delta w/3b \end{aligned} \tag{13}$$

implying

$$\begin{aligned} q_1^F &= \frac{(A+w(3\delta-1)-bc)}{3} \\ &= q_1^M + 2\delta w/3. \end{aligned}$$

Plugging this back into the spot market solution gives

$$\begin{aligned} p_2^F &= [A-w+2bc]/3b \\ &= p_2^M - \delta w/3b \end{aligned} \tag{14}$$

implying

$$\begin{aligned} q_2^F &= (A-w-bc)/3 \\ &= q_2^M - \delta w/3. \end{aligned}$$

Taking the difference between the two prices,

$$\begin{aligned} \Delta p^F &= (A-w-bc)/3b \\ &= \Delta p^M - \delta w/3b > 0. \end{aligned} \tag{15}$$

Last, using the above expressions, we obtain

$$\begin{aligned} q_2^F &= (A-w-bc)/3 \\ &= q_2^M - \delta w/3 > 0. \end{aligned}$$

The comparative statics of prices with respect to w and δ are:

$$\begin{aligned} \frac{\partial p_1^F}{\partial w} &= -2/3b < 0 \text{ and } \frac{\partial p_1^F}{\partial \delta} = 0 \\ \frac{\partial p_2^F}{\partial w} &= -1/3b < 0 \text{ and } \frac{\partial p_2^F}{\partial \delta} = 0 \\ \frac{\partial \Delta p^F}{\partial w} &= -1/3b < 0 \text{ and } \frac{\partial \Delta p^F}{\partial \delta} = 0 \\ \frac{\partial p_1^F}{\partial w \partial \delta} &= \frac{\partial p_2^F}{\partial w \partial \delta} = \frac{\partial \Delta p^F}{\partial w \partial \delta} = 0. \end{aligned}$$

Unlimited Arbitrage We now solve the profit maximization problem under ***market prices*** with unlimited arbitrage s adjusted so that the two prices converge. We again proceed by backward induction. For given p_1, the spot market solution is given by, under both pricing rules,

$$p_2 = \frac{p_1 + c}{2} + \frac{s}{2b}, \text{ implying } q_2 = b\frac{p_1 - c}{2} + \frac{s}{2}. \tag{16}$$

Plugging (16) into the day-ahead problem (5), one can find the day-ahead market solution

$$p_1^M = \left[2\left(A - (1-\delta)\, w\right) + bc - s\right]/3b \tag{17}$$

implying

$$q_1^M = \left(A - (1-\delta)\, w - bc - 2s\right)/3.$$

Plugging this back into the spot market solution gives

$$p_2^M = \left[A - (1-\delta)\, w + 2bc + s\right]/3b \tag{18}$$

implying

$$q_2^M = \left(A - (1-\delta)\, w - bc + s\right)/3.$$

Taking the difference between the two prices,

$$\Delta p^M \equiv p_1^M - p_2^M = \left(A - (1-\delta)\, w - bc - 2s\right)/3b.$$

Setting $p_1^M = p_2^M$, we find

$$s^M = \left(A - (1-\delta)\, w - bc\right)/2.$$

Plugging this back into the price expressions,

$$p_1^M = p_2^M = \left[A - (1-\delta)\, w + bc\right]/2b.$$

Limited Arbitrage If arbitrage is limited, the degree of arbitrage needed to achieve full price convergence exceeds the fringe's idle capacity, $s^M > (1-\delta)(k-w)$. The solution under limited arbitrage is found by simply plugging $s = (1-\delta)(k-w)$ into equations (17) and (18) above. This gives rise to the following equilibrium prices

$$p_1^M = \left[2A - (1-\delta)(k+w) + bc\right]/3b \tag{19}$$

$$p_2^M = \left[A + (1-\delta)(k-2w) + 2bc\right]/3b \tag{20}$$

$$\Delta p^M = \left[A - (1-\delta)(2k-w) - bc\right]/3b. \tag{21}$$

The comparative statics of prices with respect to w and δ are:

$$\begin{aligned}
\frac{\partial p_1^M}{\partial w} &= -\left(1-\delta\right)/3b \leq 0 \text{ and } \frac{\partial p_1^M}{\partial \delta} = \left(k+w\right)/3b > 0 \\
\frac{\partial p_2^M}{\partial w} &= -2\left(1-\delta\right)/3b \leq 0 \text{ and } \frac{\partial p_2^M}{\partial \delta} = -\left(k-2w\right)/3b \\
\frac{\partial \Delta p^M}{\partial w} &= \left(1-\delta\right)/3b \geq 0 \text{ and } \frac{\partial \Delta p^M}{\partial \delta} = \left(2k-w\right)/3b > 0 \\
\frac{\partial p_1^M}{\partial w \partial \delta} &= \frac{1}{2}\frac{\partial p_2^M}{\partial w \partial \delta} = 1/3b > 0.
\end{aligned}$$

We can now compare the equilibrium outcomes under limited arbitrage across pricing rules under the assumption that the arbitrage constraint is binding.

Comparing the expressions for p_1, (13) and (19):

$$p_1^M - p_1^F = \left[-\left(1-\delta\right)\left(k-w\right) + 2\delta w\right]/3b.$$

Hence, $p_1^M > p_1^F$ if and only if $\delta w > \left(1-\delta\right)\left(k-w\right)/2$. Solving for δ,

$$\delta > \widehat{\delta} \equiv \frac{k-w}{k+w} \in [0,1].$$

Comparing the expressions for p_2, (14) and (20):

$$p_2^M - p_2^F = \left[\left(1-\delta\right)\left(k-w\right) + \delta w\right]/3b > 0.$$

A.2 Extensions: Cournot Competition

In the main text we have assumed that there is a single dominant firm. We now analyze the case with $n > 1$ strategic firms competing *à la* Cournot. Our solution in the main text can be recovered by setting $n = 1$.

We use q_{it} to denote firm i's production in market t, $q_{-it} = \sum_{j\neq i}^{n} q_{jt}$ to denote its rivals' production in market t, and $q_t = q_{it} + q_{-it}$ to denote total production in market t, for $i = 1, ..., n$ and $t = 1, 2$. Each strategic firm owns a fraction δ/n of the renewable capacity, where $\delta \in [0,1]$. They can all produce conventional output at constant marginal costs c.

We first solve the baseline case (denoted by B) with *market prices* and no arbitrage, and then solve the games with *market prices* and limited arbitrage, and the game with *fixed prices*.

Baseline. The problem of the strategic firms $i = 1, ..., n$ is solved by backwards induction. In the spot market, firm i chooses q_{i2} so as to maximize its profits, taking as given the quantities chosen by its rivals in the spot market as well as the day-ahead quantities. We can express the spot market problem as in (3), but we now express it as a function of firms' quantities,

$$\max_{q_{i2}} \left[p_2\left(q_1, q_2\right) q_{i2} - c\left(q_{i1} + q_{i2} - \delta w/n\right)\right], \tag{22}$$

where, using (2), spot market demand can be expressed as $p_2\left(q_1, q_2\right) = p_1\left(q_1\right) - q_2/b$.

Solving the FOC, each firm's reaction function in the spot market is

$$q_{i2}\left(q_{-i2}\right) = b\frac{p_1 - c}{2} - \frac{1}{2}q_{-i2}.$$

In a symmetric equilibrium,

$$q_{i2}^*\left(q_1\right) = \frac{b}{n+1}\left(p_1\left(q_1\right) - c\right) \text{ and } p_2^*\left(q_1\right) = \frac{p_1\left(q_1\right) + cn}{n+1}. \tag{23}$$

The day-ahead market problem becomes

$$\max_{p_1} \left[p_1\left(q_1\right) q_1 + p_2^*\left(q_1\right) q_2^*\left(q_1\right) - c\left(q_{i1} + q_{i2} - \delta w/n\right) + \underline{p}\delta w/n\right] \tag{24}$$

where, using (1), the day-ahead demand can be expressed as

$$p_1\left(q_1\right) = \left(A - w\left(1 - \delta\right) - q_1\right)/b. \tag{25}$$

Solving the FOC, each firm's reaction function in the day-ahead market is

$$q_{i1}\left(q_{-i1}\right) = \frac{\left(n^2 + 2n - 1\right)}{2n\left(n+2\right)}\left[A - w\left(1 - \delta\right) - bc - q_{-i1}\right].$$

In a subgame-perfect symmetric equilibrium under the baseline case,

$$q_{i1}^B = \Delta\left(n\right)\left(n^2 + 2n - 1\right)\left(A - w\left(1 - \delta\right) - bc\right),$$

where to simplify notation, we have used $\Delta\left(n\right) = \left(n^3 + 3n^2 + n + 1\right)^{-1} > 0$.

The equilibrium price p_1^B can be found by plugging $q_1 = nq_{i1}^B$ into (1). The spot price p_2^B can be found by plugging p_1^B into (23). Using the resulting equilibrium expressions, the price difference across markets is given by

$$\Delta p^B \equiv p_1^B - p_2^B = \Delta\left(n\right) n\left(n+1\right)\left(A - w\left(1 - \delta\right) - bc\right)/b.$$

Market Prices with Limited Arbitrage. The spot market problem is the same as in (22), but the demand is now given by $p_2(q_2) = p_1 + (k-w)(1-\delta)/b - q_2/b$ since the fringe has incentives to arbitrage $(k-w)(1-\delta)$.

Each firm's reaction function in the spot market becomes

$$q_2(q_{-i2}) = b\frac{p_1 - c}{2} + \frac{(k-w)(1-\delta)}{2} - \frac{1}{2}q_{-i2}.$$

In a symmetric equilibrium,

$$\begin{aligned} q^*_{i2}(q_1) &= \frac{b}{n+1}(p_1(q_1) - c) + \frac{(k-w)(1-\delta)}{n+1} \\ p^*_2(q_1) &= \frac{p_1(q_1) + cn}{n+1} + \frac{1}{b}\frac{(k-w)(1-\delta)}{n+1}. \end{aligned}$$

The day-ahead market problem is the same as in (24), but demand is now given by $p_1(q_1) = (A - k(1-\delta) - q_1)/b$ since the fringe offers its full renewable capacity $k(1-\delta)$. After some algebra, the solution is given by

$$\begin{aligned} p^M_1 &= p^B_1 - \Delta(n)\left(n^2+1\right)(1-\delta)(k-w)/b && (26) \\ p^M_2 &= p^B_2 + \Delta(n)\,n(n+1)(1-\delta)(k-w)/b && (27) \\ \Delta p^M &= \Delta p^B - \Delta(n)\left(2n^2+n+1\right)(1-\delta)(k-w)/b. \end{aligned}$$

Performing comparative statics with respect to w,

$$\begin{aligned} \frac{\partial p^M_1}{\partial w} &= -2\Delta(n)\,n(1-\delta)/b \leq 0 && (28) \\ \frac{\partial p^M_2}{\partial w} &= -\Delta(n)(n+1)^2(1-\delta)/b \leq 0 && (29) \\ \frac{\partial \Delta p^M}{\partial w} &= \Delta(n)\left(n^2+1\right)(1-\delta)/b \geq 0. && (30) \end{aligned}$$

All the inequalities are strict for $\delta < 1$.

Computing the cross-derivatives with respect to δ,

$$\frac{\partial p^M_2}{\partial w \partial \delta} \geq \frac{\partial p^M_1}{\partial w \partial \delta} > 0 \geq \frac{\partial \Delta p^M}{\partial w \partial \delta}.$$

Fixed Prices. The solution to the spot market problem is the same as in the baseline model, (22). In the day-ahead market, the problem becomes

$$\max_{q_{i1}} \left[p_1(q_1)(q_{i1} - \delta w/n) + p_2(p_1)\,q_2(p_1) - c(q_{i1} + q_{i2} - \delta w/n) + \overline{p}\delta w/n\right]$$

where $p_1(q_1) = (A - w(1-\delta) - q_1)/b$. Following the same steps as before, the solution is given by

$$\begin{aligned} p_1^F &= p_1^B - \Delta(n)(n+1)^2 w\delta/b && (31) \\ p_2^F &= p_2^B - \Delta(n)(n+1) w\delta/b && (32) \\ \Delta p^F &= \Delta p^B - \Delta(n)(n+1) nw\delta/b \end{aligned}$$

Performing comparative statics with respect to w,

$$\begin{aligned} \frac{\partial p_1^F}{\partial w} &= -(n+1)^2 \Delta(n)/b < 0 && (33) \\ \frac{\partial p_2^F}{\partial w} &= -(n+1)\Delta(n)/b < 0 && (34) \\ \frac{\partial \Delta p^F}{\partial w} &= -n(n+1)\Delta(n)/b < 0 && (35) \end{aligned}$$

All the cross-derivatives with respect to δ equal 0.

Comparison across Pricing Rules. We are now ready to prove the analogous of Proposition 1 for the case $n > 1$.

(i) Comparing the expressions for p_1, (26) and (31):

$$p_1^F - p_1^M = \Delta(n)\left[\left(n^2+1\right)(1-\delta)(k-w) - (n+1)^2 w\delta\right]/b.$$

Hence, $p_1^F < p_1^M$ if and only if the term in brackets is positive. Solving for δ,

$$\delta > \widehat{\delta}(n) \equiv \frac{k-w}{k + \frac{2n}{n^2+1} w}. \tag{36}$$

Since $\widehat{\delta}(n)$ is increasing in n, it follows that

$$\widehat{\delta}(n) \in \left[\frac{k-w}{k+w}, \frac{k-w}{k}\right].$$

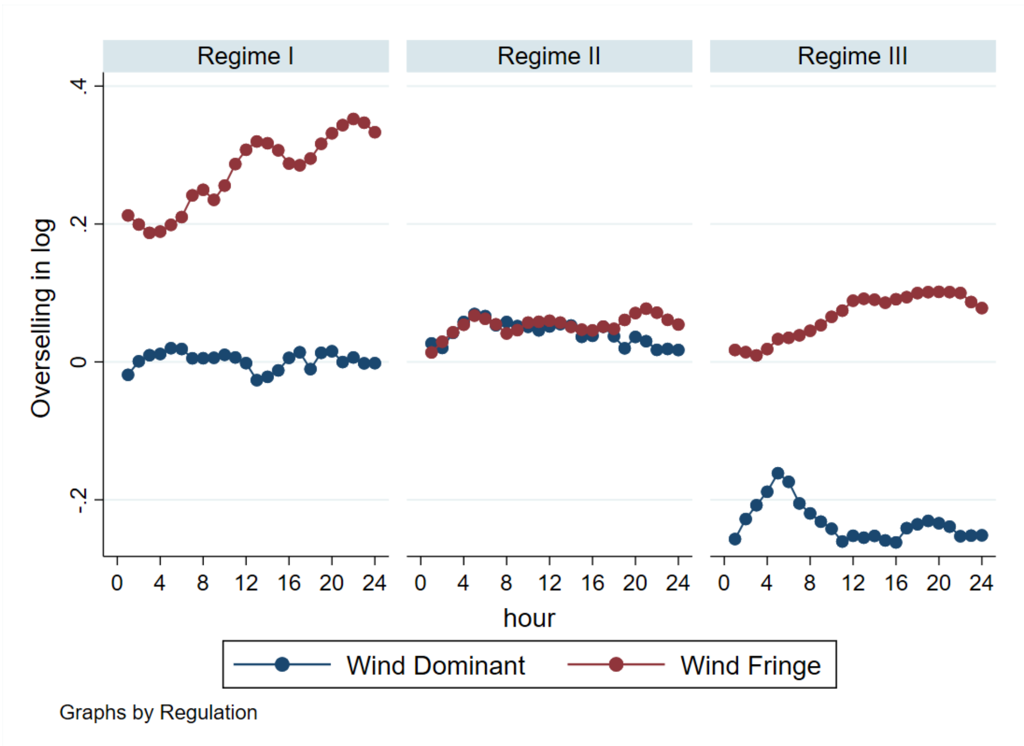
(ii) Comparing the expressions for p_2, (27) and (32):

$$p_2^F - p_2^M = -w\frac{(n+1)}{b\left(k + kn^2 + 2nw\right)}(k-w) < 0.$$

Similarly, the analogous of Proposition 2 for the case $n > 1$ follows from the comparative statics reported above.

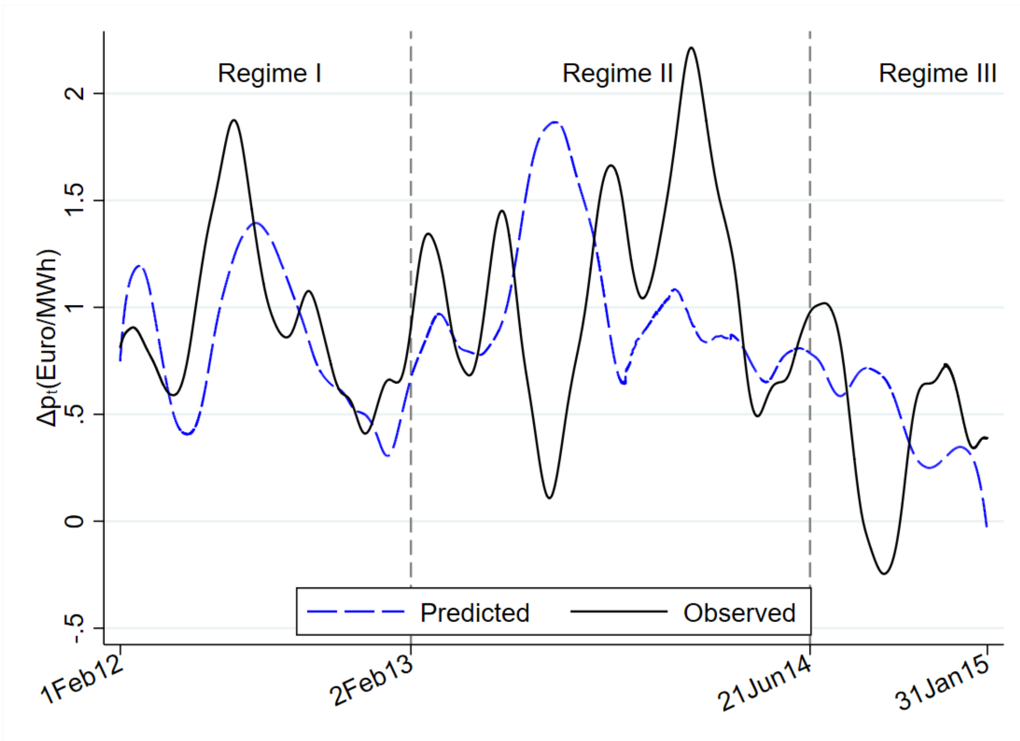
Appendix B: Additional Figures and Tables

Figure 4: Overselling and Withholding by Wind Producers



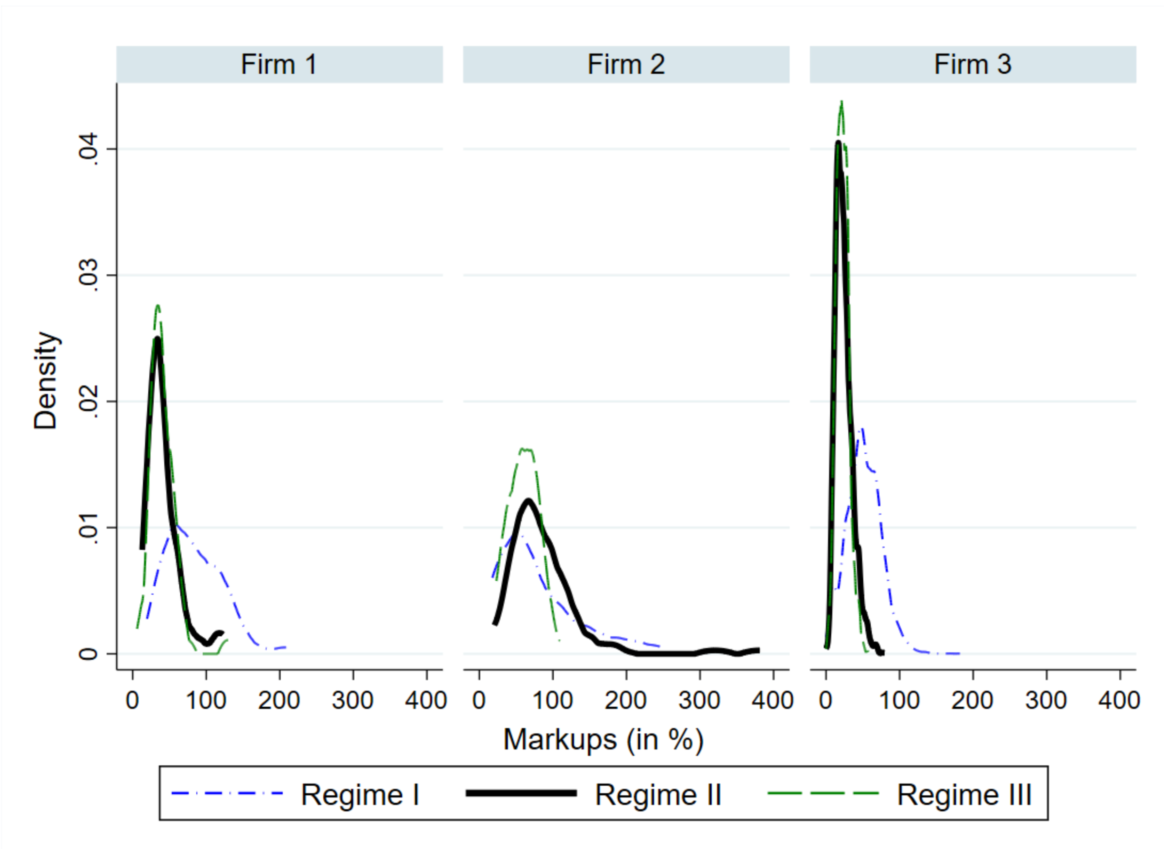
Notes: This figure shows the weekly average of the day-ahead commitments relative to the final commitments of the wind producers, split in three regulatory regimes. Sample is from February 2012 to February 2015. Regime I - Market Prices is from 1 February 2012 to 31 January 2013; Regime II - Fixed Prices is from 1 February 2013 to 21 June 2014; Regime III - Market Prices is from 22 June 2014 to 31 January 2015.

Figure 5: Predicted and Observed Price Premium



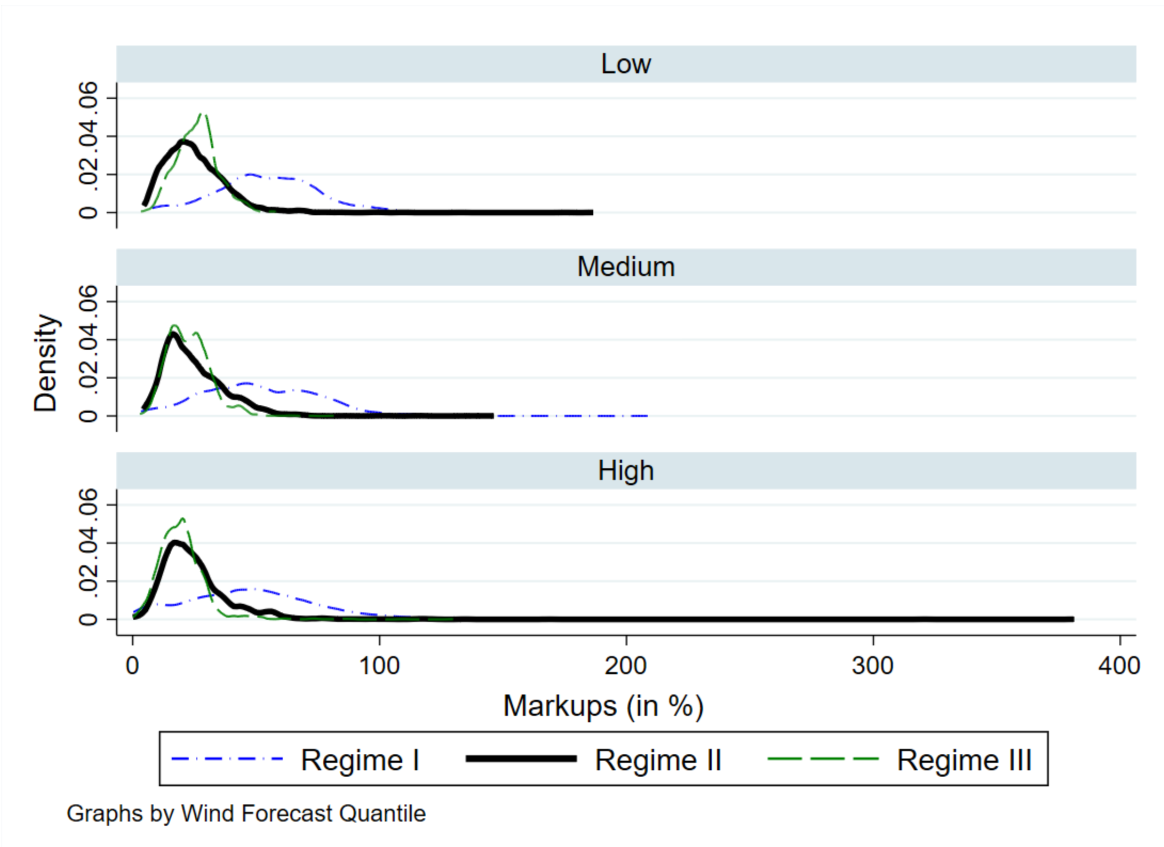
Notes: This figure shows locally weighted linear regressions of $\Delta\hat{p}_t$ (predicted) and Δp_t (observed) from February 2012 to February 2015. The weights are applied using a tricube weighting function (Cleveland, 1979) with a bandwidth of 0.1. The predictions ($\Delta\hat{p}_t$) are done using the estimated coefficients obtained from equation in footnote 41. These $\Delta\hat{p}_t$ are used in equation 10.

Figure 6: Markup Distribution by Firm



Notes: This figure plots the markup distributions for each of the strategic firms by their pricing regimes for hours with prices above 25 Euro/MWh.

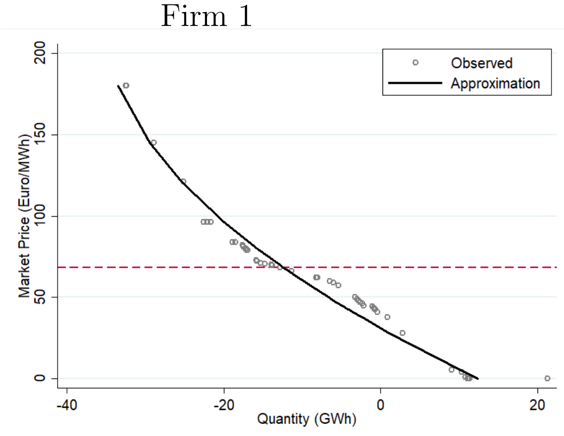
Figure 7: Markup Distribution by Wind Quartiles



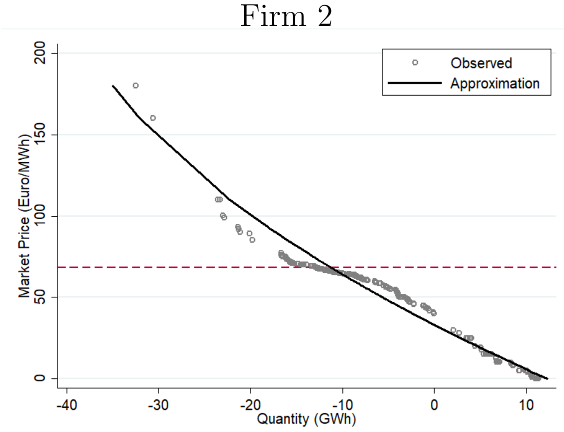
Notes: This figure compares markups distribution by wind forecast quartiles (low, medium, and high wind days) in three different pricing regimes for hours with prices above 25 Euro/MWh.

Figure 8: Approximating the slopes of the residual demands

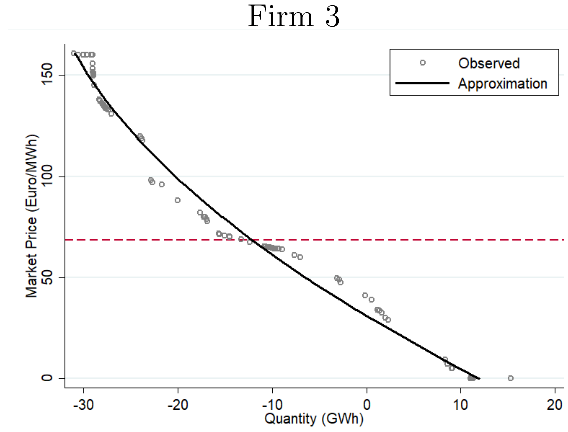
Firm 1



Firm 2



Firm 3



Notes: This figure illustrates how we use quadratic approximation to compute the local slope around the market clearing price (the horizontal line) for each of the dominant firm's residual demand curve. Here, we show each firm's the residual demand curve in October 10, 2014, 18.00.

Table 6: The Forward Contract Effect with Various Clusterings

	2SLS			
	(1)	(2)	(3)	(4)
RI $\times \frac{w_{it}}{DR'_{it}}$	6.35	9.31	9.10	5.54
Firm-month-year	(8.58)	(9.20)	(8.70)	(7.43)
Firm-week	(7.12)	(7.20)	(6.98)	(6.97)
Firm-day	(5.35)	(5.50)	(5.37)	(5.58)
RII $\times \frac{w_{it}}{DR'_{it}}$	-14.2**	-14.5**	-14.9**	-14.3
Firm-month-year	(6.43)	(6.16)	(6.30)	(8.68)
Firm-week	(7.11)	(7.05)	(7.17)	(8.24)
Firm-day	(7.22)	(7.15)	(7.24)	(8.46)
RIII $\times \frac{w_{it}}{DR'_{it}}$	1.72	0.049	0.60	5.69
Firm-month-year	(6.81)	(5.87)	(5.56)	(7.67)
Firm-week	(6.71)	(5.98)	(5.81)	(8.50)
Firm-day	(4.04)	(3.45)	(3.32)	(6.84)
Linear Trends	N	Y	Y	Y
Quad. Trends	N	N	Y	Y
Observations	19,805	19,805	19,805	19,805

Notes: See the notes in Table 2 which uses plant level clustering. Here we report three different standard errors from three alternative clusterings: firm-day, firm-month-year, and firm-week levels.

Table 7: The Forward Contract Effect Accounting for Vertical Integration

	2SLS			
	(1)	(2)	(3)	(4)
RI $\times \frac{w_{it}}{DR'_{it}}$	11.9*	12.5*	12.4*	18.5**
	(6.45)	(6.59)	(6.41)	(8.79)
RII $\times \frac{w_{it}}{DR'_{it}}$	-14.1***	-12.7***	-13.1***	-7.48**
	(3.47)	(2.83)	(2.97)	(3.48)
RIII $\times \frac{w_{it}}{DR'_{it}}$	1.09	1.15	1.78	7.57*
	(3.91)	(3.74)	(3.43)	(4.18)
$\hat{p_{2t}}$	0.94***	0.96***	0.96***	1.18***
	(0.064)	(0.067)	(0.067)	(0.10)
$\frac{q_{it}}{DR'_{it}}$				3.36***
				(0.93)
Linear Trends	N	Y	Y	Y
Quad. Trends	N	N	Y	Y
Observations	19,805	19,805	19,805	19,805

Notes: This table shows the estimation results of equation (8) using 2SLS. All regressions include unit, firm and quarterly dummies, time trends, while in columns (2)-(4) we add day-of-the-week dummies, hour fixed effects, and quadratic time trends are added in a cumulative fashion. We constrain the coefficient for markups from firms' total output to be one in columns (1) to (3), and we relax this by allowing the markup coefficient to vary in column (4). We limit hourly prices to be within 5 Euro/MWh range relative to the market price and exclude the outliers (bids with market prices below the 1st percentile and above the 99th percentile). We instrument our markups with wind speed, precipitation, and each of them interacted with the three pricing scheme indicators. The standard errors are clustered at the plant level.

Table 8: The Response of Overselling to the Price Premium

	Wind	Non-wind Renewables	Retailers	Diff	
	(1)	(2)	(3)	(1)-(2)	(1)-(3)
R I	0.064	0.008	0.079	-0.076	-0.006
	(0.000)	(0.000)	(0.000)	(0.000)	(0.529)
R II	-0.001	-0.004	0.086	-0.005	0.063
	(0.882)	(0.004)	(0.000)	(0.151)	(0.000)
R III	0.032	-0.006	0.053	-0.036	0.004
	(0.000)	(0.000)	(0.000)	(0.000)	(0.503)
R I→R II	-0.065	-0.013	0.008	-0.071	-0.069
	(0.000)	(0.000)	(0.334)	(0.000)	(0.000)
R II→R III	0.026	-0.000	-0.049	0.03	0.059
	(0.000)	(0.812)	(0.000)	(0.000)	(0.000)

Notes: This table reports the coefficient of $\Delta\hat{p}_t$ from 25 different regressions similar to equation (10). Columns (1)-(3) only use overselling quantity from each group on the corresponding column header. The two columns on the right compare the difference in overselling from either columns (1) and (2) or columns (1) and (3). The last two rows compare two pricing regimes, either from Regime I to II or from Regime II to III. The corresponding P-values for each coefficient are in parentheses. Pre-trend assumptions are supported by the p-values in columns (1)-(2) row 2 – under Regime II, wind and non-wind renewables face the same incentives to oversell – and columns (1)-(3) row 1 or row 3 – under Regime III, wind, and suppliers face the same incentives to oversell. The impact on the price response of overselling can be seen in the last two rows in columns (1)-(2) and (1)-(3), and it is similar to numbers reported in Table 3.

Table 9: The Impact of Pricing Schemes on Price Differences across Markets

	2SLS			
	(1)	(2)	(3)	(4)
DR'$_1$	-0.014**	-0.0080	-0.014**	-0.0080
	(0.0058)	(0.0061)	(0.0062)	(0.0066)
DR'$_2$	0.091***	0.089***	0.091***	0.089***
	(0.024)	(0.024)	(0.024)	(0.025)
Wind Forecast (GWh)	0.060	0.0029	0.060	0.0029
	(0.046)	(0.050)	(0.049)	(0.056)
$\frac{w_{dt}}{Wt}$	-0.59***	-0.50***	-0.59***	-0.50***
	(0.18)	(0.17)	(0.18)	(0.18)
R I	-0.46***	-0.52***	-0.46***	-0.52***
	(0.16)	(0.16)	(0.15)	(0.17)
R II	-1.16***	-1.01***	-1.16***	-1.01***
	(0.21)	(0.22)	(0.23)	(0.23)
R I $\times$ $\frac{w_{dt}}{Wt}$	0.44**	0.46**	0.44**	0.46**
	(0.21)	(0.19)	(0.21)	(0.21)
R II $\times$ $\frac{w_{dt}}{Wt}$	0.46**	0.41**	0.46***	0.41**
	(0.18)	(0.17)	(0.16)	(0.17)
Demand Forecast (GWh)	-0.0029	0.079***	-0.0029	0.079***
	(0.017)	(0.024)	(0.019)	(0.027)
Weekend FE	N	N	Y	Y
Peak Hour FE	N	Y	N	Y
Observations	25334	25334	25334	25334

Notes: This table shows the coefficients from equation (11). The slopes of the residual demands DR'_1 and DR'_2 are instrumented using daily average, minimum, and maximum temperature, and average temperature interacted with hourly dummies. Regime I is an indicator for Regime I periods, R III$_t$ for Regime III periods, with Regime II periods used as the reference point. We use bootstrap standard errors with 200 replications.

Table 10: Average Markups in the Day-ahead Market

	R I		R II		R III	
	Mean	SD	Mean	SD	Mean	SD
Markups (in %) – Simple average						
All	8.3	(3.3)	6.3	(3.3)	10.7	(3.7)
Firm 1	7.0	(2.2)	7.0	(2.6)	12.1	(4.4)
Firm 2	12.3	(4.1)	8.2	(5.1)	14.7	(4.4)
Firm 3	7.7	(2.3)	6.0	(3.3)	10.3	(3.3)
Slope of day-ahead residual demand (in MWh/euros)						
All	524.2	(78.2)	553.6	(120.7)	418.2	(73.0)
Firm 1	506.6	(50.5)	458.4	(72.7)	411.0	(62.4)
Firm 2	508.5	(71.8)	556.4	(165.0)	453.8	(99.8)
Firm 3	538.2	(88.7)	573.3	(117.2)	418.0	(73.2)

Notes: Sample from February 2012 to January 2015, includes the markups for those units bidding within a 5 Euro/MWh range around the market price, for hours with prices above 25 Euro/MWh. Regime I is from 1 February 2012 to 31 January 2013; Regime II is from 1 February 2013 to 21 June 2014; Regime III is from 22 June 2014 to 31 January 2015.