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

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Abstract

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Market Power and Price Exposure:
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Abstract

In many regulatory settings, regulators often debate whether to pay producers at fixed prices or at market-based prices. In this paper, we assess how firms' price exposure affects the degree of market power. We find that fixed prices mitigate market power by directly affecting the dominant firms' incentives to exert market power, while market-based prices do so indirectly by promoting the fringe firms' incentives to engage in arbitrage. To empirically identify these effects, we exploit a natural experiment that took place in the Spanish electricity market, where the regulator switched back and forth from paying renewable energies according to fixed or to market-based prices. Overall, we find that fixed prices were relatively more effective in weakening firms' market power, even though the market-based price regime led to more active price arbitrage.

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

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1 Introduction

Ambitious environmental targets, together with decreasing investment costs, have fostered the rapid deployment of renewable energy around the world. However, the goal to fully decarbonize the power sector will require further investments to replace conventional power plants with renewable energy resources.[1] To achieve this objective, regulators are increasingly resorting to auctions for renewable investments.[2] The idea is simple: they set a target level of investment in renewable energy capacity and then allocate long-term energy contracts to the lowest bidders at the resulting auction-based prices.

In designing these auctions, regulators have to make several decisions, ranging from the auction format to the bidders' eligibility requirements, to name just two.[3] However, one dimension of auction design stands out for its key impact on electricity markets: whether the auctioned contracts expose renewable investors to the volatility of short-run electricity prices, or not. To provide full price insurance, regulators have the option of auctioning off fixed prices per unit of output –these are the so-called Feed-in-Tariffs (FiT). Instead, to provide full price exposure, regulators have the option of allowing producers to sell their output at the short-run electricity market price, to which they add an auction-based fixed premium –these are the so-called Feed-in-Premia (FiP).[4] This paper aims to analyze how these choices regarding the degree of renewables' price exposure affect

[1]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, with the goal of achieving a carbon-free power sector before 2050 (European Commission, 2019). Likewise, at the time of writing this paper, Joe Biden has announced his plans to achieve carbon neutrality by 2050, with a 90% carbon-free electricity sector by 2035.

[2]According to IRENA (2019), by the end of 2018 more than 100 countries had adopted auction-based approaches to promoting investment in renewables, i.e., 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).

[3]See IRENA (2019) for the full list of auction design choices, as well as for country-specific examples of where such choices have been used in practice.

[4]This premium can take several forms; it can be a direct payment by the regulator, it can be a tax credit (as the Federal Production Tax Credit in the US), or it might derive from the sale of renewable energy credits to electricity providers that are required to procure a proportion of their sales with renewable energy (as the system of Revenue Obligation Certificates (ROCs) in the UK, or the Renewable Portfolio Standard (RPS) in the US). See Newbery (2016) for a description of the ROCs, and Greenstone, McDowell and Nath (2019) for an analysis of RPS.

the performance of electricity markets once the investments have taken place.[5] The importance of this question is compounded by the massive renewable investments that will have to take place in the future.

One approach for analyzing this question would be to use actual bidding data of renewable projects with varying degrees of price exposure. However, those projects must have accessed the market through different auctions, possibly at different times and in different countries, which would likely confound the true market impact of price exposure. To avoid this, we leverage a quasi-experiment that took place in the Spanish electricity market, where the regulator first decided to pay existing wind producers at market-based prices (FiP), then moved them to fixed prices (FiT), and ultimately switched them back to market-based prices again (FiP).[6] These regulatory changes provide a unique opportunity to identify the impacts of renewables' price exposure on market performance. It is important to point out that these changes were implemented by surprise, that wind already represented a significant share of total output, and that no other changes in market rules or market structure took place during that time. Access to very detailed wholesale market bid data thus allows us to conduct an empirical analysis of the causal effects of changes in the degree of renewables' price exposure on firms' bidding behavior in electricity markets and the resulting impacts on market power.

Theoretical approach and findings In electricity markets, 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 markets that operate closer to real-time. Fully exposing renewables to electricity market prices encourages them to arbitrage the resulting price differences, which reduces the dominant firms' incentives to exercise market power in the day-ahead market (Ito and Reguant, 2016). We refer to this effect as the 'arbitrage effect'.

Instead, shielding renewable producers from short-run electricity market prices essentially bars them from serving as arbitrageurs as they receive the same price regardless of where they sell their output. However, even if this limits arbitrage, it also mitigates market power through another channel: fixed prices reduce the dominant producer's in-

[5] In between these two extremes, there are hybrid solutions. For instance, producers could receive fixed prices for a shorter time and then sell their output at market prices until the end of their lifetimes. Alternatively, the auctioneer could pay the renewable output at a weighted average of a fixed price (to be determined through the auction) and the short-run market price.

[6] The FiT or the FiP were not set through auctions, but were instead determined by the regulator. However, for our study, this difference is irrelevant as once the investments are in place, price *levels* do not affect bidding incentives (as long as they are above marginal costs, which was always the case).

centives to increase market prices as fixed prices act as a forward contract over the firm's renewable sales (Allaz and Vila, 1993).[7] We refer to this as the 'forward contract' effect.

While the 'arbitrage' and the 'forward contract' effects act in opposite directions, we show that their relative strengths depend on market structure. In particular, the higher the share of wind output in the hands of the dominant producers, the stronger the 'forward contract' effect and the weaker the 'arbitrage effect'. Hence, shielding renewable producers from market prices is relatively more effective for mitigating market power in highly concentrated markets, which are the ones where market power concerns are likely to be higher.[8]

Empirical approach and findings To test these predictions, we first estimate a structural model of price-setting incentives in the Spanish day-ahead market. On the one hand, taking the slopes of the realized residual demands as given, we show that when firms received fixed prices, they did not internalize the market price increases on their wind output. On the other, under market-based prices, firms internalized the price effects on their total output, including wind. This suggests that, all else equal, the 'forward contract effect' reduced firms' markups under fixed prices.

Second, we analyze how changes in price exposure affected the fringe firms' incentives to arbitrage. To ensure that time-varying changes in unobservable variables do not confound the effects, we rely on a differences-in-differences (DiD) approach. Two appealing features of our analysis are that: (i) we exploit the two regulatory changes, from market-based prices to fixed prices and then back to market-based prices, and that (ii) we use two control groups, either independent retailers that faced the same arbitrage incentives as renewables before the first and after the second regulatory change, or renewables other than wind that faced similar arbitrage incentives as wind after the first regulatory change. Our DiD analysis shows that wind producers stopped arbitraging price differences after the switch from market-based prices to fixed prices. However, they resumed arbitrage once they were exposed to market-based prices again. This confirms the empirical relevance and robustness of the 'arbitrage effect'.

The interplay between the 'forward contract' and the 'arbitrage' effects is also con-

[7]Empirically, the market impacts of forward contracts in electricity markets have been analyzed by several authors (Wolak, 2000; Bushnell, Mansur and Saravia, 2008; Hortaçsu and Puller, 2008; Fabra and Toro, 2005).

[8]Acemoglu, Kakhbod and Ozdaglar (2017) and Genc and Reynolds (2019) also point out the relevance of market structure in shaping the price depressing effects of renewables in a Cournot model. However, they do not assess the effects of market structure on the relative performance of market-based versus fixed prices simply because they only consider the former.

firmed by the empirical analysis of the price differences across markets. We show that, under fixed prices, an increase in the dominant firm's wind share reduced price differences across markets, as expected from the strengthening of the 'forward contract effect'. Instead, under market-based prices, an increase in the fringe firms' wind share enlarged price differences across markets, as expected from the weakening of the 'arbitrage effect'.

In order to understand which of these two effects dominated in shaping market power, we leverage our structural estimates to compute markups in the day-ahead market. We find that markups were significantly lower while firms were subject to fixed prices as compared to market-based 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. Our results 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 market structure of 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 market-based prices.

Our contribution Our contribution is to capture the effects of price exposure on market power, an issue that is relevant in electricity markets and beyond. We provide a tractable model and a structural analysis comparing firms' market behavior subject to different degrees of price exposure. This analysis could well apply to many other markets that are also organized sequentially (e.g., gas, oil, emission allowances, bonds, or stocks, among others) where firms face different degrees of price exposure depending on whether they are subject to short or long-term contracts. To our knowledge, this article is also the first to provide a causal impact of price exposure on market power, taking into account the countervailing incentives.

From a theoretical point of view, we also contribute to the literature by characterizing and comparing the equilibria under fixed-prices and market-based prices. Ito and Reguant (2016), who also analyze the latter, document the role of arbitrage in mitigating market power. However, the analysis with fixed prices and the comparison between the two cases are novel. From an empirical point of view, we provide new evidence on the impact of firms' price exposure on market power and the price differences across markets by highlighting the relevance of forward contracting through structural estimates. We use a differences-in-differences approach to capture the magnitude of the arbitrage effect while avoiding potential confounding effects. Using two regulatory changes, our findings give further support to the results in Ito and Reguant (2016) regarding the impacts of arbitrage.

Our results provide key insights to the ongoing debate about how to support the deployment of renewables at least cost. We focus on the largely unexplored issue of how renewables' pricing schemes affect firms' bidding incentives for given capacities, an important determinant of the performance of electricity markets. 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 FiT acts like forward contracts.[9] From an empirical perspective, Bohland and Schwenen (2020) attempt to 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. 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.[10] 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.[11]

Finally, our work complements the growing literature exploring 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

[9] 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).

[10] 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 investment 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.

[11] 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.

Ozdaglar (2017)), on the nature of competition (Fabra and Llobet (2019)), on emissions (Cullen (2013) and Novan (2015)), and on the profits earned by the conventional producers (Bushnell and Novan (2018); Liski and Vehviläinen (2017)), among others. Nonetheless, these papers apply to settings in which renewables are exposed to market prices but do not analyze whether the effects of renewables would differ if they were subject to fixed prices instead.

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

2 The Model

In this section, we develop a simple model of strategic bidding that mimics some of the key ingredients of electricity markets. In line with Allaz and Vila (1993), we abstract from uncertainty and risk aversion in order to focus on the impact of pricing schemes on market power.

We assume that total demand is downward sloping, $D(p)$. This demand can be thought of as the sum of the demand of households, which tends to be price unresponsive, and the demand of large energy consumers and retailers, which is price responsive.[12] Both types of consumers are assumed to be myopic.[13]

Sequential markets Transactions take place in two sequential markets: a day-ahead market ($t = 1$) and a spot market ($t = 2$). Total demand is determined in the second market at the spot price, $D(p_2)$. It can be decomposed as the sum of the day-ahead market demand, $D(p_1)$, plus the unserved demand which is traded in the spot market,

[12] As in Ito and Reguant (2016), an equivalent micro foundation for demand elasticity is that $D(p)$ is total demand net of the demand of a myopic competitive fringe with increasing marginal costs.

[13] In reality, the demand of households is inelastically cleared in the day-ahead market. Hence it is reasonable to assume that they are myopic. Large consumers and retailers can participate in both markets and could thus wait to buy in the spot market if they expect that prices will be lower than in the day-ahead market. We allow for this possibility in the empirical analysis. The theory model would easily allow to add financial arbitrageurs.

$D(p_2) - D(p_1)$.[14] Let $\Delta p \equiv p_1 - p_2$ denote the price difference across markets.

Technologies and Firms Electricity is produced by two types of technologies (renewable and conventional) and two types of firms (fringe and dominant, respectively denoted by $i = f, d$). The fringe firms only own renewable assets, in contrast to the dominant firm that also owns conventional assets. While fringe firms are price-takers, the dominant firm sets prices in both markets, taking into account the decisions of the fringe players.

Renewables, which we generically refer to as *wind*, allow firms to produce at zero marginal costs up to their available capacities. We use w_i and k_i to respectively denote firm i's available and maximum wind capacity, with $w_i \leq k_i$, $i = d, f$. Without loss of generality, we assume that firms are able to perfectly predict their available capacities so w_i is indistinctively used to refer to both actual or expected wind availability.[15] The dominant firm's conventional technology has constant marginal costs of production, $c > 0$.

Throughout, we assume that the conventional technology is needed to satisfy total demand, i.e., $D(c) - w_d - w_f > 0$. This implies that the dominant firm's relevant marginal cost is c. Relaxing this assumption would require considering several subcases, without altering the main insights of the analysis.

Pricing rules We consider two commonly used pricing schemes for renewables:[16] (i) under market-based or variable prices (FiP), renewable producers receive the price of the market where they sell their output, plus a premium; (ii) under fixed prices (FiT), renewable producers receive a fixed price for their output regardless of the market at which they sell it.

[14]The model can be solved under the assumption that demand in the spot market becomes more inelastic. This would not affect the main results of the analysis. In the empirical analysis of section 4.3, we incorporate the elasticities of the demands in the day-ahead and the spot market as two separate variables.

[15]Fabra and Llobet (2019) report empirical evidence on the wind forecast errors in the Spanish electricity market and show that these tend to be small. Still, they show that uncertainty and private information over available capacities impacts equilibrium bidding behavior when renewables are exposed to market-based prices. However, if this uncertainty is small, the impact is second-order as compared to the impact of changes in the pricing rules.

[16]We focus on these two schemes since these are the ones used in the Spanish electricity market, which is the subject of our empirical investigation. However, for completeness, in the appendix, we also characterize the equilibrium under an alternative pricing scheme: Contracts-for-Differences (CfDs).

2.1 No Arbitrage

We first consider the case in which renewable producers are required to offer all their output in the day-ahead market. This will serve as a benchmark to assess the effects of allowing for arbitrage across markets. The residual demands faced by the dominant firm in the day-ahead market and in the spot market are thus given by

$$q_1(p_1) = D(p_1) - w_f \tag{1}$$

$$q_2(p_1, p_2) = D(p_2) - D(p_1). \tag{2}$$

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

$$\max_{p_2} \left[p_2 q_2(p_1, p_2) - c\left(q_1(p_1) + q_2(p_1, p_2) - w_d\right)\right]. \tag{3}$$

Solving the first order condition for p_2,

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

As it is standard, the firm adds a mark-up over its marginal cost c. This mark-up is increasing in p_1 as a higher p_1 implies a larger spot market demand.

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

$$\max_{p_1} \left[p_1 q_1(p_1) + p_2^*\left(p_1\right) q_2\left(p_1, p_2^*\right) - c\left(q_1(p_1) + q_2\left(p_1, p_2^*\right) - w_d\right) + w_d \underline{p}\right]. \tag{5}$$

Under fixed prices, the profit maximization problem in the day-ahead market changes, as renewable output is now paid at $\overline{p}$.[17] This reduces the dominant firm's price exposure, as shown in the first term of the following profit expression,

$$\max_{p_1} \left[p_1(q_1\left(p_1\right) - w_d) + p_2^*\left(p_1\right) q_2\left(p_1, p_2^*\right) - c\left(q_1(p_1) + q_2\left(p_1, p_2^*\right) - w_d\right) + w_d \overline{p}\right]. \tag{6}$$

The first order conditions of the profit maximization problems (5) and (6) illustrate the drivers of our main results. Using the Envelope Theorem and solving for p_1,

$$p_1^* = p_2^* + \left(D(p_1^*) - w_f - I w_d\right)\left|\frac{\partial D(p_1^*)}{\partial p_1}\right|^{-1}, \tag{7}$$

[17] The values of the fixed premium and the fixed price do not affect bidding incentives and therefore equilibrium market prices. Hence, one could well them set them so that total payments to wind are the same, i.e., $\overline{p} = \underline{p} + p_1^*$.

where $I = 0$ under variable prices and $I = 1$ under fixed prices. From this expression, it is clear that the spot price becomes the opportunity cost of sales in the day-ahead market. Hence, the dominant firm optimally sets p_1^* with a mark-up over p_2^*. Such a mark-up depends on the pricing rule in place, given that under fixed prices, increasing the day-ahead price does not increase the price for its renewable output. As this implies lower marginal gains from increasing p_1, the day-ahead market price is lower under fixed prices as compared to variable prices. Furthermore, since a lower day-ahead price reduces spot market demand, the spot price under fixed prices is lower as well.

Our first lemma illustrates these results (we use super-scripts V and F to denote equilibrium outcomes under variable and fixed prices, respectively).

Lemma 1 *Suppose that arbitrage is not allowed. In equilibrium,*

(i) $p_1^V > p_2^V > c$ *and* $p_1^F > p_2^F > c$.

(ii) $p_1^V > p_1^F > c$ *and* $p_2^V > p_2^F > c$.

2.2 Limited Arbitrage

Given the positive price differential across markets, there are profitable opportunities to engage in arbitrage. 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 both prices converge, $p_1 = p_2$.

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 if their capacity constraint $w_f \leq k_f$ is not binding. They can thus arbitrage by selling k_f in the day-ahead market to then buy $(k_f - w_f)$ back in the spot market. We refer to *overselling* as the difference between the day-ahead sales of wind producers and their final allocation, $\Delta q_f = k_f - w_f$.

Under variable prices, fringe firms have incentives to engage in arbitrage given that they are paid at the market price where they sell their output. Hence, the residual demands faced by the dominant firm in both markets are now given by[18]

$$
\begin{aligned}
q_1(p_1) &= D(p_1) - k_f \\
q_2(p_1, p_2) &= D(p_2) - D(p_1) + (k_f - w_f)
\end{aligned}
$$

[18]In these expressions we are implicitly assuming that arbitrage $(k_f - w_f)$ is not large enough to close the price gap.

Since pricing incentives are directly linked to market size, arbitrage pushes the day-ahead price down and the spot price up as compared to the case with no arbitrage (Lemma 1). We refer to this as the *arbitrage effect*.

Instead, under fixed prices, fringe firms have no incentives to engage in arbitrage as they obtain the same price regardless of where they sell their output. Given this indifference, and in line with empirical evidence, we assume that they offer all their renewable output in the day-ahead market. Accordingly, the residual demands faced by the dominant firm remain as in (1) and (2), and equilibrium prices remain as in Lemma 1.

The following lemma summarizes these results.

Lemma 2 *Allowing for limited arbitrage implies that, relative to Lemma 1, in equilibrium p_1^V goes down while p_2^V goes up. In contrast, equilibrium prices p_1^F and p_2^F remain unchanged.*

It follows that the comparison between fixed prices versus variable prices essentially bolts down to the comparison between the *forward contract* and the *arbitrage effects*. As shown in our next proposition, this trade-off depends on the renewables' ownership structure.[19]

Proposition 1 *Assume linear demand of the form $D(p) = A - bp$. If the arbitrage constraint is binding, the comparison of equilibrium outcomes across pricing schemes shows that:*

(i) $p_1^F < p_1^V$ *if and only if* $w_d > (k_f - w_f)/2$.
(ii) $p_2^F < p_2^V$.
(iii) $\Delta q_f^F = 0$ *and* $\Delta q_f^V = (k_f - w_f)$.
(iv) Δp^F *is decreasing in* w_d*, while* Δp^V *is increasing in* w_f.

Proof. See the Appendix. ■

First, the proposition shows that day-ahead prices are relatively lower under fixed prices when the dominant firm owns a big share of renewables. The reason is that the *forward contract effect* under fixed prices is channeled through the dominant firm's renewable output, while the *arbitrage effect* under variable prices is channeled through the fringe firms' ability to arbitrage, which depends negatively on its own renewable production (as shown in point *(iii)*).

[19] The proposition assumes linear demand to obtain closed form solutions. Similar results would apply under more general functional forms.

Second, the proposition shows that fixed prices ambiguously give rise to lower spot prices than variable prices. Intuitively, the *arbitrage effect* under variable prices translates into a higher demand in the spot market, 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. This in turn reduces the extent of unserved demand, leading to lower spot prices.

Last, all the factors that enhance market power in the day-ahead market also strengthen the price differences across markets. Since the determinants of market power differ under the two pricing schemes, so do the comparative statics of the price differences. While the price differences under variable prices increase in w_f (as it reduces the amount of idle capacity that firms can use to arbitrage) the price differences under fixed prices decrease in w_d (as it mitigates the dominant producer's market power).

Proposition 1 leads to an important conclusion: within this model, overall welfare is greater under fixed prices than under variable prices.[20] However, the choice between the two might have distributional consequences between firms and consumers and across consumer groups.[21] Even though this issue is outside of this model, let us note that in practice, households' demand is typically cleared in the day-ahead market, whereas energy retailers and large energy consumers often buy a fraction of their demands in the spot market. Hence, changes in day-head and spot prices do not affect all consumers equally. The reduction in day-ahead market prices is particularly relevant, not only because of the relatively larger volume of day-ahead transactions, but also because it directly translates into lower prices for households.

2.3 Testable Predictions

The above analysis provides theoretical predictions which will be tested in the empirical section of the paper. We group them in three blocks:

(i) **Price-setting incentives in the day-ahead market:** Under fixed prices, the *forward contract effect* implies that, for given residual demands, the dominant firms

[20] Jha and Wolak (2019) find that financial arbitrage can reduce costs by improving the scheduling of power plants in the day-ahead market. This can be due to cost complementarities across hours. This source of efficiency does not show up in our model as we model hours independently of each others.

[21] To see the impacts on consumers, note that we can write the difference in consumer surplus as:

$$CS^F - CS^V = \int_{p_2^F}^{p_2^V} D(\rho)\, d\rho - \left[q_1^F \Delta p^F - q_1^V \Delta p^V\right]. \tag{8}$$

While the first term is positive, the second term can be positive or negative depending on parameter values.

do not internalize the price impact on their own wind output. This is unlike the case in which firms are exposed to variable prices.

(*ii*) **Arbitrage across markets:** Under variable prices, the *arbitrage effect* implies that fringe producers oversell in the day-ahead market as compared to their final commitments. Their incentives to do so are greater the larger the price differential across markets. Since this effect is not present under fixed prices, any differences between the renewable fringe producers' day-ahead and final commitments should be orthogonal to the price differential.

(*iii*) **Price differences across markets:** the comparative statics of prices differences differ under the two pricing schemes: they increase in w_f under variable prices, but decrease in w_d under fixed prices.

Last, the interplay between the *forward contract* and the *arbitrage* effects determines whether market power in the day-ahead market is larger under variable prices relative to fixed prices, or vice-versa. The resulting estimates will serve to determine the relative strength of these two effects.

Before we take these predictions to the data, we move on to describing some of the institutional details of the Spanish electricity market.

3 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.

3.1 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 whose quantities have to be communicated 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 concentrate 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 and the first intra-day market (which we will refer to as the *spot 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.

However, 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, retailers delay their purchases to the intraday market as much as they can.

However, 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 retailers) have relatively more flexibility to arbitrage than coal or gas plants, as these are more often operating at 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, retailers 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. Big customers and retailers face full price exposure, as they pay the market price and can keep any potential profits from arbitrage. Instead, the incentives of renewable producers to arbitrage depend on the pricing scheme they are subject to. We next describe the pricing schemes of Spanish renewables, which are key for our identification strategy.

3.2 Pricing schemes for renewables

The pricing schemes for Spanish renewables have been subject to various regulatory changes.[22] In our empirical analysis, we will exploit the occurrence of the two most recent regulatory changes affecting wind operators.

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 Feed-in-Premium (FiP) or a Feed-in-Tariff (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 under the FiP option were notably higher than under the FiT option, the vast majority of wind operators opted for the former. We will label this regime as R I. When, on 2 February 2013 (Royal Decree Law 2/2013), the Government decided to abolish the FiP option "without any former notice",[23] all wind producers were *de facto* moved from FiP to FiT.

The FiT regime – which we label as R II – 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 Minis-

[22]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.

[23]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.

terial Order IET 1045/2014 that came into force on June 21).[24] 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.[25]

In general terms, the new scheme that was introduced in June 2014 – which we label as R III – moved all renewable generators 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.[26] 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 investment costs. Hence, there exist some differences between the pre-February 2013 FiP (R I) and the post-June 2014 FiP (R III) regimes, mainly in the level of support. Nonetheless, they both have one thing in common: they expose renewable producers to market-based prices, which is the key difference our analysis focuses on.

3.3 Data

We use different sources of data on bids, costs, actual and forecast renewable production, 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 plants' bid codes with the plants' names 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, retailers of last resort, or liberalized retailers). With these bid data, we can construct each firm's

[24] 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 tariffs. 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.

[25] We have ran placebo tests with these dates, which show that these laws had no effect.

[26] These include a remuneration per MW of installed capacity, meant to compensate those investment 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 investment costs or market revenues of the plant, but rather on those of a so-called *efficient and well-managed company* subject to technology-dependent standards.

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 it, and the units that submitted prices close to it.

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.[27] While these are reliable cost data sources,[28] 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 they buy on long term contracts. Indeed, large disparities between the load factors of various CCGTs in the market suggest that one of the dominant firms might have had access to cheaper gas, well below the price of gas in the international exchanges.[29]

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 fraction that they sold through the market or through bilateral contracts.[30] These data allow us to compute, on an hourly basis, the market shares of the various technologies (including renewables) and firms. Since we observe the supply and demand allocated to the vertically integrated firms, we can compute their hourly net positions, i.e., their

[27] 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.

[28] 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.

[29] 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).

[30] 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.

production net of their bilateral contracts and vertical commitments.[31] Furthermore, by computing each plants' day-ahead and final commitments, we can assess whether firms engaged in arbitrage 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 *dominant 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.[32] There was also a fringe of conventional producers, renewable producers, and independent retailers. The market structure in the renewable segment was more fragmented than in the conventional segment. The market share for the dominant firms was relatively lower in the renewable segment than 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 analysis and there were a total of 26,304 hourly observations, split into 8,784 observations for the first period with FiP (R I, from 1 February 2012 to 31 January 2013), 12,120 observations for the period with FiT (R II, from 1 February 2013 to 21 June 2014) and 5,400 observations for the second period with FiP (R 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 the R II period. 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 the R III period. Demand net of wind forecasts was similar on average across all three periods, if anything only slightly higher under R III.

[31] We do not include vertical commitments due to regulated sales since these are simply pass-through market prices to the final consumers.

[32] This explains why Gas Natural is the price-setter during a large fraction of the time. This, together with the fact that Gas Natural had long-term contracts for gas at prices below the international spot price for gas, explains why we sometimes find negative markups in the day-ahead market prices.

Table 1: Summary Statistics

	R I		R II		R 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	

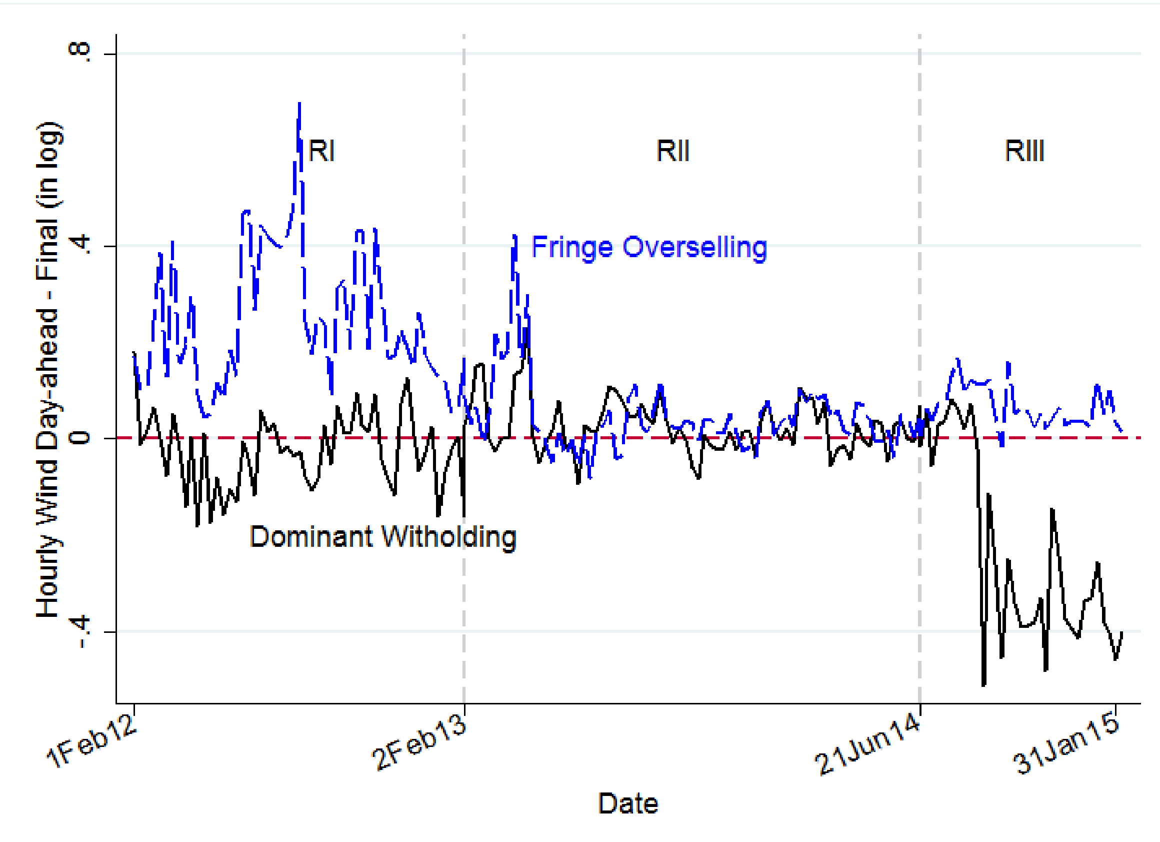
Notes: Sample from 1 February 2012 to 31 January 2015. R I is from 1 February 2012 to 31 January 2013; R II is from 1 February 2013 to 21 June 2014; R III is from 22 June 2014 to 31 January 2015. Prices are in Euro/MWh. Demand forecasts, wind forecasts and installed capacities are in GWh. Installed capacities are in GW.

A first look at the data It is illustrative to provide a first look at the raw data. Figure 1 plots the difference between the day-ahead and the final output commitments for wind plants belonging to the fringe and to the dominant 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 (R 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 dominant firms. Instead, when paid according to variable prices (R I and R III), the fringe wind producers actively engaged in arbitrage by overselling their wind output in the day-ahead market.[33] The smaller amount of arbitrage by wind plants during R III is likely due to the smaller price differences across markets (see Table 1). The change in the pricing schemes also had a

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

strong impact on the dominant producers' behavior. The dominant producers withheld more wind output across markets when exposed to variable prices, notably so after the switch from R II to R III.[34]

Figure 1: Overselling and withholding across markets by wind producers



Notes: This figure shows the day-ahead relative to the final commitments of wind producers belonging to both the dominant and the fringe firms. The values greater than 0 reflect overselling, while values less than 0 reflect withholding. The vertical lines date the changes in the pricing schemes for renewables.

While this figure suggests that changes in the pricing schemes had a strong impact on firms' bidding behavior, it would be misleading to derive further conclusions from these figures alone. First, price differences, overselling, and withholding across markets are all jointly determined in equilibrium, thus implying that they cannot be assessed in isolation. Furthermore, one needs to take into account the dominant firms' overall behavior, not just the one that is reflected in the supply of their wind plants. Since wind represents only a fraction of the dominant firms' assets, and given the noise in the series, it is difficult to visualize large differences across time in their overall withholding

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

behaviour. Last but not least, exogenous changes in some of the relevant variables (e.g., wind availability, or demand factors, among others) could be confounding some of the effects. Without controlling for those factors, one cannot obtain robust conclusions.

Therefore, to properly analyze the impacts of renewables' price exposure on market power, we undertake a deeper empirical analysis in the rest of the paper.

4 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 dominant 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, we leverage on our structural estimates to construct estimates of market power under the two pricing schemes.

4.1 Price-setting incentives in the day-ahead market

We use a structural approach to assess whether the changes in the renewables' pricing schemes affected the price-setting incentives of the dominant producers in the day-ahead market. Our focus is on whether the dominant firms internalize the 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:

$$b_{ijt} = \rho \hat{p}_{2t} + \beta \left| \frac{q_{it}}{DR'_{it}} \right| + \sum_{R=1}^{3} \theta^s \left| \frac{w_{it}}{DR'_{it}} \right| I_t^s + \alpha_{ij} + \gamma_t + \epsilon_{ijt}, \tag{9}$$

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 (R I, R II, and R III);[35] α_{ij} are unit fixed effects, and γ_t are time fixed effects. We include unit, quarter, and hour fixed-effects, while 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.[36]

Variable Description First, on the left hand side of equation (9), we include the bids of all price-setting units belonging to one of the dominant firms,[37] 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).[38]

On the right hand side of (9), in order to compute the expected spot market price, 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 $\hat{p}_{2t}$.[39] Also, in order to build the realized residual demand curve faced by each firm, we fit a quadratic function to the residual demand curve and calculate its slope at the market-clearing price (see Figures 8 in the Appendix for an illustration).[40]

[35] We define the R I, R II, and R III indicator variables using the February 1, 2013 and June 22, 2014 cutoffs, respectively, which is when the regulatory changes were fully implemented, as described in Section 3.2.

[36] 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 the Appendix).

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

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

[39] 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.

[40] 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.

Identification When estimating equation (9), 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.[41] Second, other 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 the slope of the day-ahead residual demand, 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 (9). 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 (9) is θ^s. We expect it to take a negative value under fixed prices (R II), but we expect it to be not significantly different from zero under variable prices (R I and R II). This would reflect that firms do not (do) internalize the price effects on their wind output when it is paid at fixed (variable) 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 R II indicator variable is still very similar. The sign of the coefficient for the firm's total output markup is positive as expected, given that greater output and a steeper residual demand enhance market

[41] 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.

power.[42]

Table 2: The Forward Contract Effect

	2SLS			
	(1)	(2)	(3)	(4)
RI × $\frac{w_{it}}{DR'_{it}}$	6.35	9.31	9.10	5.54
	(5.03)	(6.28)	(6.10)	(5.47)
RII × $\frac{w_{it}}{DR'_{it}}$	-14.2***	-14.5***	-14.9***	-14.3***
	(3.03)	(2.88)	(3.02)	(3.24)
RIII × $\frac{w_{it}}{DR'_{it}}$	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 (9) using 2SLS. All regressions include linear time trends, 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.

It would be misleading to compare the coefficients on the various variables given

[42]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 the Appendix reports the results accounting for vertical integration. The main predictions remain valid. However, relative to the results in Table 2, the coefficients under R I and R III go up, with the former becoming slightly significant. This is an indication that firms were only maximizing their supply-side profits as market power is under-estimated when we take account firms' net sales.

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 dominant firm's hourly wind production during R 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 the R II period.

4.2 Arbitrage across markets

Since day-ahead prices were systematically higher than prices in the spot market, fringe producers under R I and R III could gain by engaging in arbitrage; 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 (R II) or variable prices (R I and R III).[43]

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 (i.e., solar, small hydro and cogeneration units), and (2) retailers 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 variable 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 to variable 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

[43] Our results are consistent with Ito and Reguant (2016), who show that after the first regulatory change, from R I to R II, fringe producers stopped arbitraging. We further show that the second regulatory change, from R II to R III, had the opposite effect. Also, we rely on a differences-in-differences approach using two possible control groups.

each control group $g=$ non-wind renewables, retailers. 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 $d=1,2$,

$$\begin{aligned}\Delta \ln q_t =& \alpha + \beta_1 W I_t^d \Delta\hat{p}_t + \beta_2 W \Delta\hat{p}_t + \beta_3 W I_t^d + \beta_4 I_t^d \Delta\hat{p}_t + \beta_5 \Delta\hat{p}_t + \\ & \beta_6 W + \beta_7 I_t^d + \rho \mathbf{X}_t + \eta_t\end{aligned} \tag{10}$$

In equation above, I_t^1 is an indicator for fixed prices (R II) –the switch from variable to fixed prices. Similarly, I_t^2 is an indicator for variable prices (R III) –the switch from fixed to variable 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. 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 variable 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 to variable 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 4.1, we regress demand and wind forecasts, hourly dummies, and date dummies on the price premium.[44] 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 Non-wind renewable producers were subject to fixed prices in R I and R II, and were then moved to variable prices in R III. Hence, their incentives to engage in arbitrage should be similar to those of wind during the R II and the R III regimes. For

[44] 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.

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

To compare the price response of wind producers, non-wind renewable producers, and retailers, 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 retailers), $\Delta\ln q_{tg}$. 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.[45] 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

$$\Delta\ln q_{tg} = \alpha + \sum_{q=1}^{13} \theta_{qg}\Delta\hat{p}_t + \gamma D_t^{er} + \delta w_t^{er} + \rho\mathbf{X}_t + \eta_{tg} \tag{11}$$

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 (11) for each quarter.[46] As expected, in Figure 2 (a) one can observe that during the R II regime (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 during the R II regime (Q1 2013 to Q2 2014), the price response of the retailers' arbitrage is positive and very similar to that of the wind producers during the R I and R

[45]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.

[46]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 the Appendix 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.

III regimes (2012 and Q3 2014 onwards). Therefore, Figure 2 provides graphical evidence on the parallel trend between wind and each of the control groups, during the relevant periods. The statistical test for each of the parallel trends, Table 8 in the Appendix, shows three parallel trend tests: (1) for sample $d = 1$, during R I the wind producers and the retailers behave similarly in response to the predicted price differential (p-values 0.529); (2) for sample $d = 1$, during R II wind and non-wind renewables behave similarly (p-values 0.151); (3) for sample $d = 2$, during R III, wind and retailers behave similarly (p-values 0.503).

Results We report the DiD results (β_1 coefficients from equation (10)) in Table 3.[47] The impact of the switch from variable prices (R I) to fixed prices (R II) is shown in columns (1) and (2), depending on whether we use non-wind renewables or retailers 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 (R II) to variable prices (R III), shown in column (3), was positive, thus indicating that this switch brought wind fringe producers back to arbitrage.[48] 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.

4.3 Price differences across markets

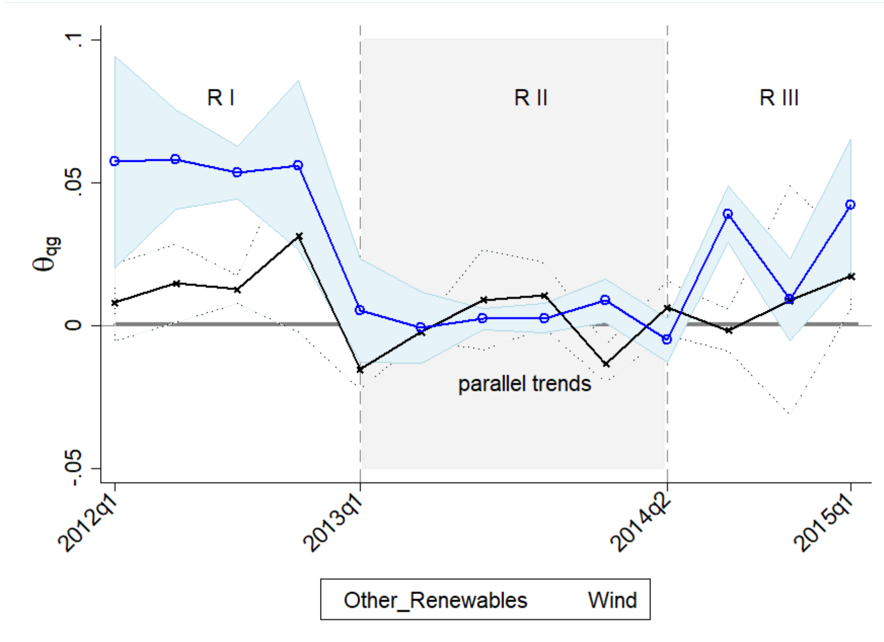
Empirical Approach Our model predicts that price differences across markets respond differently to changes in the wind production market shares depending on whether wind producers are subject to fixed or variable prices. To test for this, we use 2SLS and estimate the following empirical equation for our second stage:

$$\Delta p_t = \alpha + \sum_{s=1}^{2} \beta_1^s I_t + \beta_2 \frac{w_{dt}}{W_t} + \sum_{s=1}^{2} \beta_3^s I_t \frac{w_{dt}}{W_t} + \alpha_1 D\hat{R}'_{1t} + \alpha_2 D\hat{R}'_{2t} + \gamma \mathbf{X}_t + \epsilon_t \qquad (12)$$

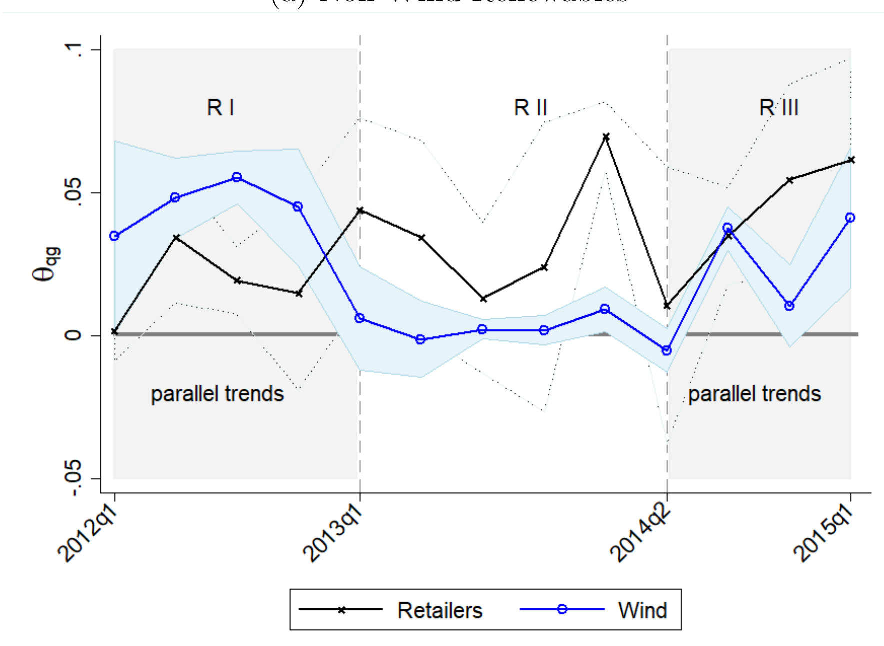
[47] The complete results with the overselling response to the price premium (and its corresponding p-values) are reported in the Appendix Table 8.

[48] As mentioned earlier, during R 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 R II to R III as the other renewables were also affected by it. The treatment effect is also positive, but smaller than that on column (3). See the Appendix Table 8.

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



(a) Non-Wind Renewables



(b) Retailers

Notes: This figure plots the coefficients of the OLS regression in equation (11) for (a) wind vs. other non-wind renewable producers and (b) wind vs. retailers. 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 R II for (a), and during R I and R 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	Retailers	
	(1)	(2)	(3)
$\Delta\hat{p}\times$ Wind $\times$ R II	-0.071***	-0.069***	
	(0.0068)	(0.014)	
$\Delta\hat{p}\times$ Wind $\times$ R III			0.059***
			(0.011)
Observations	41,080	41,080	34,194

Notes: This table shows the β_1 coefficients from equation (10). Each column is a different regression using the log of overselling as the dependent variable. Non-wind renewables is the control group in columns (1), retailers in columns (2)-(3). Columns (1) and (2) use sample $d = 1$ from 1 February 2012 to 1 February 2014, with the R 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 R 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 R 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 R III period. The standard errors are clustered at the week of sample.

where Δp_t is the price premium at time t; I_t takes two values (1 for R I, 2 for R III, and therefore 0 for R II serves as the reference point); the wind share w_{dt}/W_t captures the wind share of the dominant firms as it is computed as the ratio between the dominant 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 dominant firms in the day-ahead and intraday markets, respectively, from our first stage regression. We follow a approach similar as in Section 4.1 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).[49] X_t is a set of controls, such as demand forecasts,[50] wind forecasts, and dummy variables (i.e., hourly dummies, peak-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

[49] We compute the aggregate hourly residual demand faced by the dominant firms in the day ahead and in the intraday markets and their slopes using the same approach as discussed in footnote 40.

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

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 dominant firms' wind share should reduce the price differential when renewables are subject to fixed prices, but it should increase the price differential under variable 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 (12). The remaining coefficients are all broadly consistent with our theoretical predictions.[51] We can see that the price difference is smaller when the wind share of the dominant firms increases. Also, price differences are higher under variable prices (R I and R III) relative to fixed prices (R II) when the wind share of the dominant firms increases, as reflected by the positive coefficients of R I $\times$ w_{dt}/W_t and R III $\times$ 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 the higher w_d) and the *arbitrage effect* under variable (which is weakened the higher w_d).

4.4 Market power in the day-ahead market

Our results in 4.1 showed that, given the observed residual demands, firms had weaker incentives to increase day-ahead prices when their renewable output was paid according to fixed rather than variable prices. However, this alone does not allow us to conclude that reducing firms' price exposure mitigated market power in the day-ahead market, which is the most relevant market given its size. As our previous results also indicate, the pricing schemes might have also affected firms' residual demands through the impacts on arbitrage across markets. Therefore, to evaluate the overall impact of the pricing schemes on market power in the day-ahead market, in this section we compute and compare firms' markups across pricing regimes.

Using the first-order condition of profit-maximization –represented by equations (7) in the theory analysis and (9) in the empirical analysis– markups in the day-ahead market

[51] See the complete list of coefficients is in the Appendix, 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 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)
R I $\times$ $\frac{w_{dt}}{W_t}$	0.44**	0.46**	0.44**	0.46**
	(0.21)	(0.19)	(0.21)	(0.21)
R 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	25334	25334	25334	25334

Notes: This table shows only our coefficients of interest: β_2 and β_3 from equation (12). The complete list of coefficients is in the Appendix, Table 9. R I is an indicator for R I periods, R III for R III periods, and R II periods are the reference periods. We use bootstrap standard errors with 200 replications.

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 4.1, we set $I_t = 1$ under R II and $I_t = 0$ under R I and R III.

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 the R II regime was 6.3%, while it was 8.3% and 10.7% under the R I and R 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 dominant firm individually, for off-peak versus on-peak hours, or for more windy or less windy hours.[52] This evidence on the markups comparison is also consistent with the slopes 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

[52]See Figures 6 and 7 in the Appendix.

than the absence of significant arbitrage.

Table 5: Average markups across pricing regimes

	R I		R II		R 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)

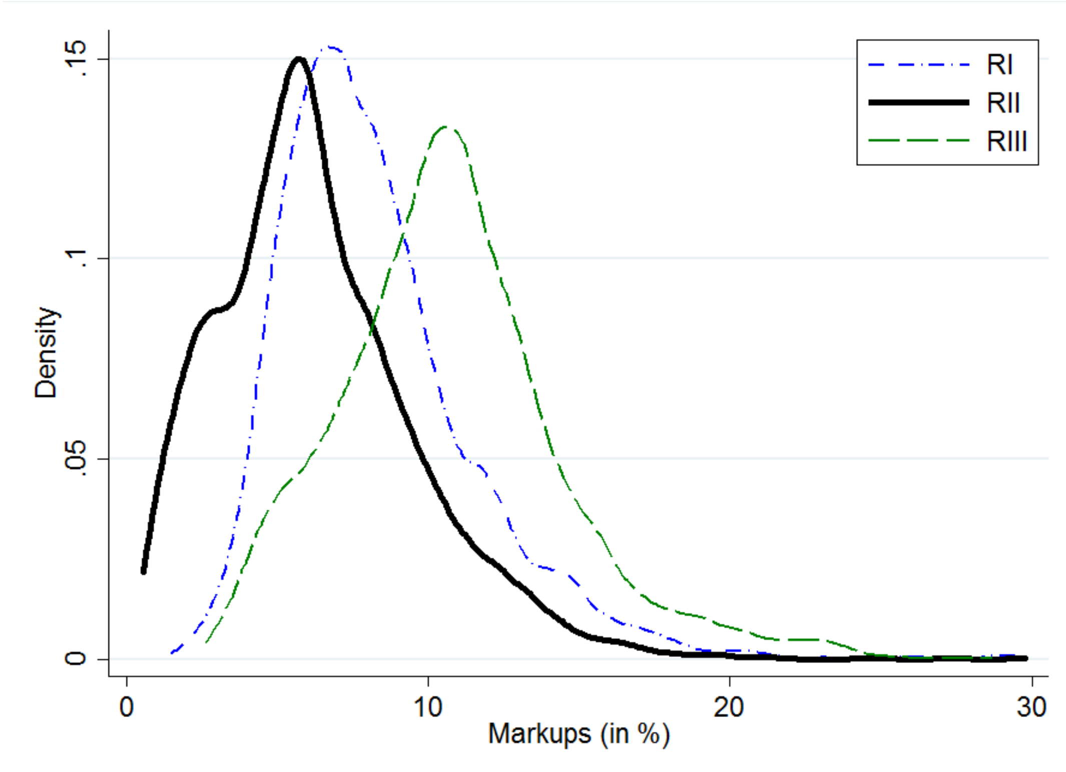
Notes: It reports the mean and standard deviation of markups and slopes of the day-ahead residual demand using the sample from February 2012 to February 2015. R I is from 1 February 2012 to 31 January 2013; R II is from 1 February 2013 to June 13 2014; R III is from June 14 2014 to January 2015, for three dominant 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,[53] leads to noisier markups due to potential measurement errors in the marginal cost estimates.[54] Nonetheless, as shown in Table 5, the results are consistent with our main result; namely, market power as measured by the price-cost mark-ups was weaker when renewables were paid according to fixed prices. Also note that the price-cost markups are larger on average than the markups at day-ahead, given that the expected spot market price includes a markup over marginal costs.

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

[54]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 the Appendix show a very similar pattern. To absorb some seasonal variation in the markups, Figure 7 by wind quartiles in the Appendix suggests that markups are still lower during R II, although they are relatively lower during windy hours than low-wind hours.

5 Conclusions

In this paper, we have analyzed how the degree of firms' price exposure impacts market power, taking into account two countervailing incentives. On the one hand, as first pointed out by Allaz and Vila (1993), reducing firms' price exposure mitigates firms' incentives to increase prices. On the other hand, if firms are insulated from price changes, they face weaker incentives to arbitrage price differences, which enhances the dominant producers' market power.

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 pricing schemes for renewables 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 suppliers, and not just of renewables alone. The interplay between the two types of suppliers 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 dominant producers attempted to exercise market power by withholding output in the day-ahead market. When exposed to variable 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 tariffs reduced arbitrage, but it also mitigated the dominant producers' incentives to withhold output in the first place. The latter effect dominated, giving rise to relatively lower markups under fixed 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 increase in renewables' penetration in the hands of the dominant producers will make it increasingly important to understand how renewables' pricing rules affect market performance. The long-run impacts of such differences on investment decisions are left for future research.

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Appendix

Appendix A: Additional Results and Proofs

A.1. Contracts for Differences (CfDs)

Suppose now that renewables are paid according to Contracts-for-Differences (CfDs) by which, (i) firms receive market prices (similarly to variable prices), but (ii) their payments are settled by differences between the contract's price, $\overline{p}$, and the day-ahead market price (similarly to fixed prices). Point (i) implies that the fringe renewables have the same incentives to arbitrage as under variable prices, giving rise to the same residual demands for the dominant firm. In turn, point (ii) implies that the dominant firm's day-ahead profit maximization problem is the same as under fixed prices.

Our last lemma characterizes, under limited arbitrage, the solution when firms are subject to contracts-for-differences, which we denote with the super-script C (for Contracts). As it is clear, the solution combines elements from Lemmas 1 and 2.

Lemma 3 *Suppose that renewable producers are subject to contracts-for-differences, and assume linear demand $D(p) = A - bp$. Under limited arbitrage, the day-ahead and spot market equilibrium prices are given by*

$$\begin{aligned} p_1^C &= p_1^F + \beta (k_f - w_f) > c \\ p_2^C &= p_2^F + \beta (k_f - w_f) > c \end{aligned}$$

or equivalently to

$$\begin{aligned} p_1^C &= p_1^V - 2\beta w_d > c \\ p_2^C &= p_2^V - \beta w_d > c \end{aligned}$$

leading to a positive price differential

$$\Delta p^C = \Delta p^F - \beta w_d = \Delta p^V - 2\beta (k_f - w_f) > 0,$$

where $\beta = (3b)^{-1} > 0$, and p_1^F, p_2^F and Δp^F are those in Lemma 1.

Proof. It follows the same steps as the proofs of Lemmas 1 and 2, and it is therefore omitted ■

The above characterization allows us to compare equilibrium outcomes across all three pricing schemes.

Proposition 2 *Under limited arbitrage, the comparison of equilibrium outcomes across pricing schemes (contracts-for-differences, fixed prices and variable prices) shows that:*
(i) $p_1^C < p_1^F$ and $p_1^C < p_1^V$.
(ii) $p_2^F < p_2^C < p_2^V$.
(iii) $\Delta p^C < \Delta p^F$ and $\Delta p^C < \Delta p^V$.

Proof. It follows from comparing Lemmas 1, 2 and 3. ■

A.2. Proofs

The proofs of Lemmas 1 and 2 are included in the main text. Here we provide closed-form solutions for all results under linear demand, $D(p) = A - bp$.

We first solve the profit maximization problems in (3) for the spot market, and (5) under variable prices and (6) under fixed prices for the day-ahead market. We do so by backward induction, with $q_1(p_1) = A - bp_1 - w_f$ and $q_2(p_1, p_2) = b\Delta p$. For given p_1, the spot market solution is given by, under both pricing rules,

$$p_2 = \frac{p_1 + c}{2}, \text{ implying } q_2 = b\frac{p_1 - c}{2}. \tag{13}$$

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

(i) Under variable prices, plugging (13) into the day-ahead problem (5), one can find the day-ahead market solution

$$p_1^V = [2(A - w_f) + bc]/3b, \text{ implying } q_1^V = (A - w_f - bc)/3.$$

Plugging this back into the spot market solution gives

$$p_2^V = [A - w_f + 2bc]/3b, \text{ implying } q_2 = (A - w_f - bc)/3.$$

Taking the difference between the two prices,

$$\Delta p^V \equiv p_1^V - p_2^V = (A - w_f - bc)/3b.$$

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

(ii) Under fixed prices, plugging (13) into the day-ahead problem (6), one can find the day-ahead market solution,

$$p_1^F = [2(A - w_d - w_f) + bc]/3b = p_1^V - 2w_d/3b \tag{14}$$

implying

$$q_1^F = \frac{(A + 2w_d - w_f - bc)}{3} = q_1^V + 2w_d/3$$

Plugging this back into the spot market solution gives

$$p_2^F = [A - w_d - w_f + 2bc]/3b = p_2^V - w_d/3b$$

implying

$$q_2^F = (A - w_d - w_f - bc)/3 = q_2^V - w_d/3$$

Taking the difference between the two prices,

$$\Delta p^F = (A - w_d - w_f - bc)/3b = \Delta p^V - w_d/3b > 0.$$

Since we have assumed $A - w_d - w_f - b > 0$, it follows that $p_1^F > p_2^F > c$. The price differential is increasing in A, and it is decreasing in w_f, w_d and b.

Last, using the above expressions, we obtain

$$q_2^F = (A - w_f - w_d - bc)/3 = q_2^V - w_d/3 > 0.$$

This implies that total quantity is

$$q_1^F + q_2^F = q_1^V + q_2^V + w_d/3.$$

We now solve the profit maximization problem under variable 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,

$$p_2 = \frac{p_1 + c}{2} + \frac{s}{2b}, \text{ implying } q_2 = b\frac{p_1 - c}{2} + \frac{s}{2}. \tag{15}$$

Plugging (15) into the day-ahead problem (5), one can find the day-ahead market solution

$$p_1^V = \left[2\left(A - w_f\right) + bc - s\right]/3b, \text{ implying } q_1^V = \left(A - w_f - bc - 2s\right)/3. \tag{16}$$

Plugging this back into the spot market solution gives

$$p_2^V = \left[A - w_f + 2bc + s\right]/3b, \text{ implying } q_2^V = \left(A - w_f - bc + s\right)/3. \tag{17}$$

Taking the difference between the two prices,

$$\Delta p^V \equiv p_1^V - p_2^V = \left(A - w_f - bc - 2s\right)/3b.$$

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

$$s^V = \left(A - w_f - bc\right)/2.$$

Plugging this back into the price expressions,

$$p_1^V = p_2^V = \left[A - w_f + bc\right]/2b$$

If arbitrage is limited, so that $k_f - w_f < \left(A - w_f - bc\right)/2$, the solution is found by simply plugging $s = k_f - w_f$ in equations (16) and (17) above.

With the above results, we can now prove Proposition 1.

Proof of Proposition 1. We compare the equilibrium outcomes under limited arbitrage across pricing rules under the assumption that the arbitrage constraint is binding.

(i) Comparison of p_1:

$$p_1^V - p_1^F = \left[-\left(k_f - w_f\right) + 2w_d\right]/3b$$

Hence, $p_1^V > p_1^F$ iff $w_d > \left(k_f - w_f\right)/2$.

Comparison of p_2:

$$p_2^V - p_2^F = \left[\left(k_f - w_f\right) + w_d\right]/3b > 0.$$

(ii) Since there are (no) incentives to arbitrage under variable (fixed) prices, then $\Delta p^V > 0$ implies $\Delta q_f^V = (k_f - w_f)$; and $\Delta q_f^V = 0$.

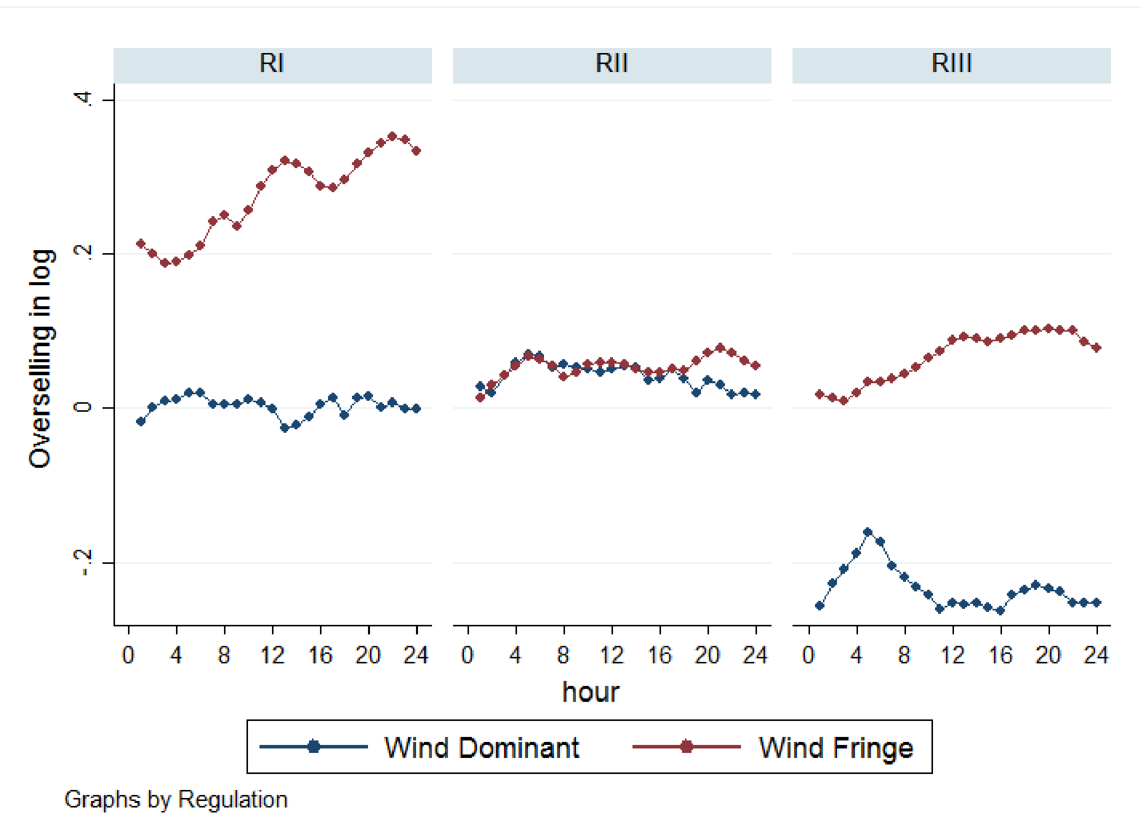
(iii) The price differences are

$$\begin{aligned} \Delta p^V &= (A + w_f - bc - 2k_f)/3b \\ \Delta p^F &= (A - w_d - w_f - bc)/3b \end{aligned}$$

Hence, Δp^V is increasing in w_f while Δp^F is decreasing in w_d and w_f. ■

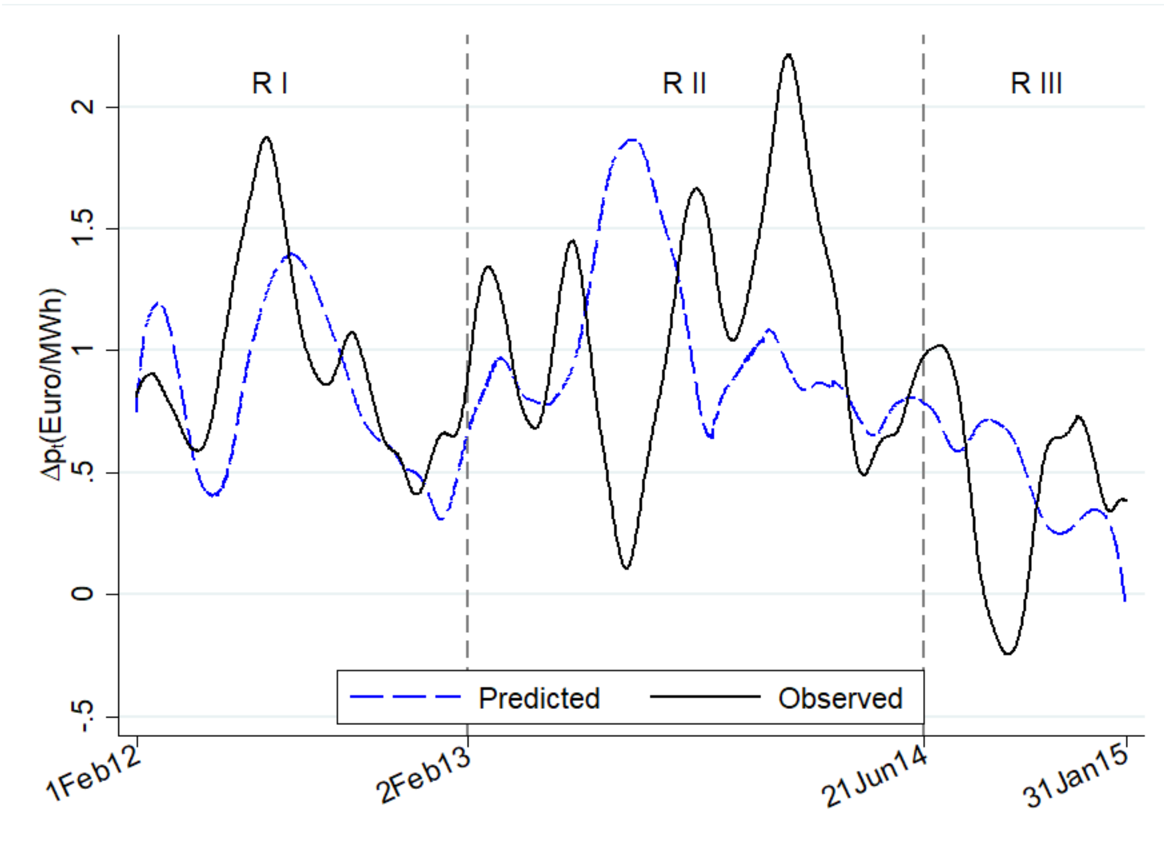
Appendix B: Additional Figures and Tables

Figure 4: Overselling and Withholding by Wind Producers



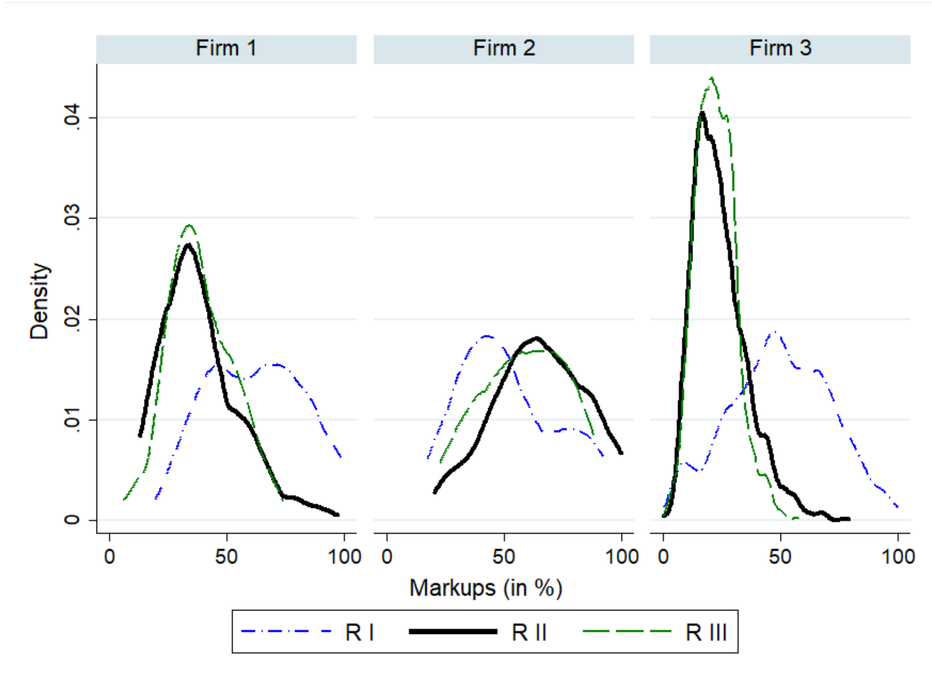
Notes: This figure shows the weekly average of the day-ahead commitments relative to the final commitments of the wind producers, split in three regulatory regimes. Sample is from February 2012 to February 2015. RI is from 1 February 2012 to 31 January 2013; RII is from 1 February 2013 to 21 June 2014;RIII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

Figure 5: Predicted and Observed Price Premium



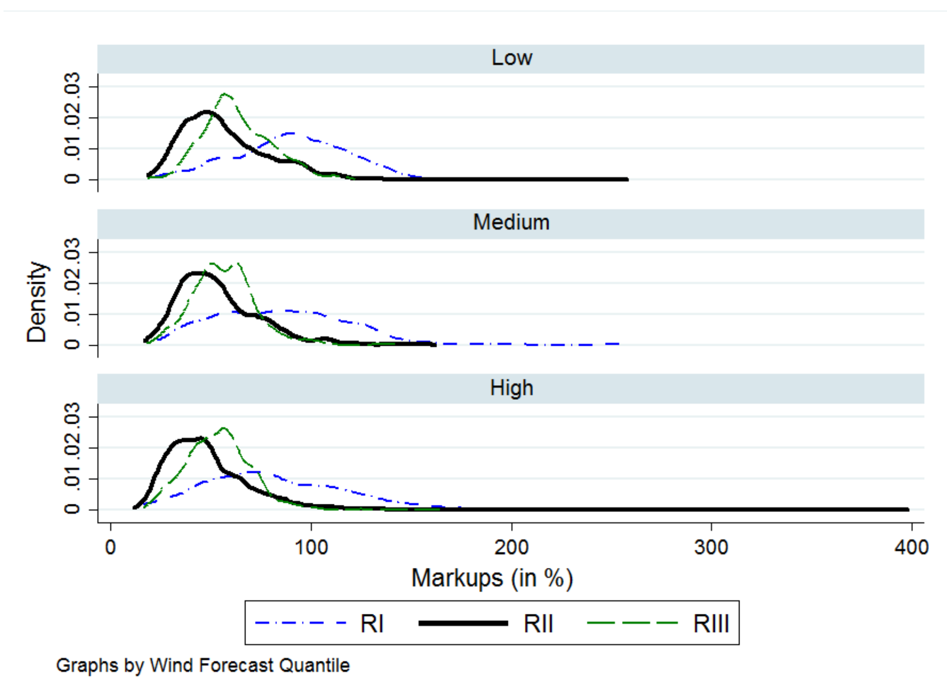
Notes: This figure shows locally weighted linear regressions of $\Delta\hat{p}_t$ (predicted) and Δp_t (observed) from February 2012 to February 2015. The weights are applied using a tricube weighting function (Cleveland, 1979) with a bandwidth of 0.1. The predictions ($\Delta\hat{p}_t$) are done using the estimated coefficients obtained from equation in footnote 44. These $\Delta\hat{p}_t$ are used in equation 11.

Figure 6: Markup Distribution by Firm



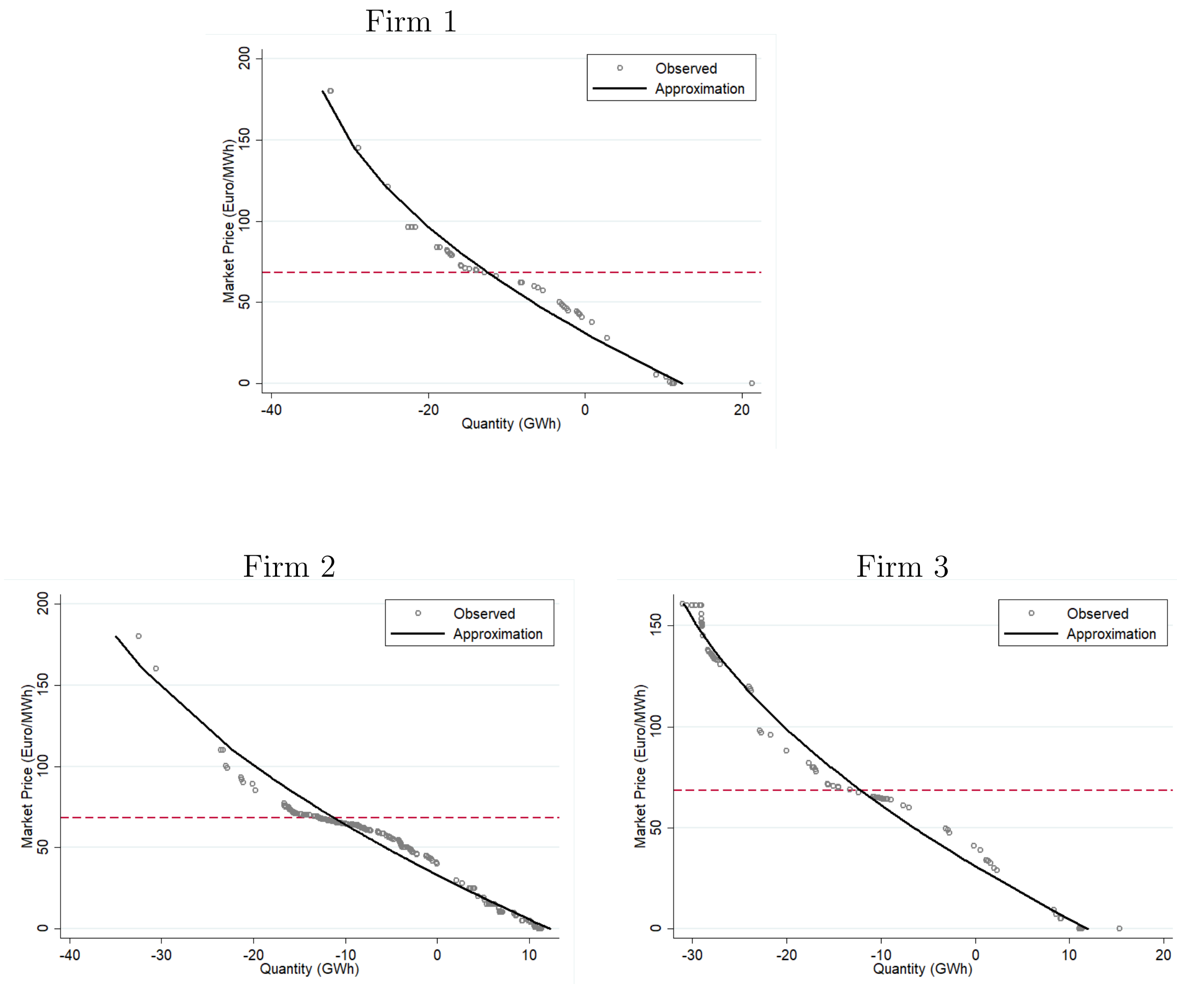
Notes: This figure plots the markup distributions for each of the dominant firms by their pricing regimes for hours with prices above 25 Euro/MWh.

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



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 (9) using 2SLS. All regressions include linear time trends, 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 (11). 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 R I to R II or from R II to R 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 R II, wind and non-wind renewables face the same incentives to oversell – and columns (1)-(3) row 1 or row 3 – under R III, wind, and retailers 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 (12). 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. R I is an indicator for R I periods, R III$_t$ for R III periods, with R 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. R I is from 1 February 2012 to 31 January 2013; R2 is from 1 February 2013 to 21 June 2014; R III is from 22 June 2014 to 31 January 2015.