

Ito, Koichiro; Reguant, Mar

Working Paper

Sequential markets, market power and arbitrage

CSIO Working Paper, No. 0135

Provided in Cooperation with:

Department of Economics - Center for the Study of Industrial Organization (CSIO), Northwestern University

Suggested Citation: Ito, Koichiro; Reguant, Mar (2015) : Sequential markets, market power and arbitrage, CSIO Working Paper, No. 0135, Northwestern University, Center for the Study of Industrial Organization (CSIO), Evanston, IL

This Version is available at:

<https://hdl.handle.net/10419/142009>

Standard-Nutzungsbedingungen:

Die Dokumente auf EconStor dürfen zu eigenen wissenschaftlichen Zwecken und zum Privatgebrauch gespeichert und kopiert werden.

Sie dürfen die Dokumente nicht für öffentliche oder kommerzielle Zwecke vervielfältigen, öffentlich ausstellen, öffentlich zugänglich machen, vertreiben oder anderweitig nutzen.

Sofern die Verfasser die Dokumente unter Open-Content-Lizenzen (insbesondere CC-Lizenzen) zur Verfügung gestellt haben sollten, gelten abweichend von diesen Nutzungsbedingungen die in der dort genannten Lizenz gewährten Nutzungsrechte.

Terms of use:

Documents in EconStor may be saved and copied for your personal and scholarly purposes.

You are not to copy documents for public or commercial purposes, to exhibit the documents publicly, to make them publicly available on the internet, or to distribute or otherwise use the documents in public.

If the documents have been made available under an Open Content Licence (especially Creative Commons Licences), you may exercise further usage rights as specified in the indicated licence.

Sequential Markets, Market Power and Arbitrage*

Koichiro Ito

University of Chicago and NBER

Mar Reguant

Northwestern University and NBER

September 11, 2015

Abstract

We develop a framework to characterize strategic behavior in sequential markets under imperfect competition and restricted entry in arbitrage. Our theory predicts that these two elements can generate a systematic price premium. We test the model predictions using micro-data from the Iberian electricity market. We show that the observed price differences and firm behavior are consistent with the model. Finally, we quantify the welfare effects of arbitrage using a structural model. In the presence of market power, we show that full arbitrage is not necessarily welfare-enhancing, reducing consumer costs but increasing deadweightloss.

*Emails: ito@uchicago.edu, mreguant@stanford.edu. For helpful comments, we thank Simon Board, Severin Borenstein, Thomas Covert, Ali Hortaçsu, Ryan Kellogg, Chris Knittel, Matt Notowidigdo, Nick Ryan, David Salant, Joe Shapiro, and Matt White, as well as seminar participants at the UCEI Energy Camp, 19th POWER Conference on Energy Research and Policy, Universitat Autònoma de Barcelona, IFN Stockholm, SITE Stockholm, University of Gothenburg, UCLA, MIT, TSE, PSE, École Polytechnique, the RIETI, Kellogg, CEMFI, CIRPEE Conference Montreal, Stanford SITE, Carnegie Mellon, Wharton, Calgary, Edmonton, Yale, Chicago, Chicago, Ohio State, Department of Justice, UC Berkeley, VII Taller de Organización Industrial, Pontificia Universidad Católica de Chile, UBC, UPenn, Northwestern, Harvard Kennedy School, and UC Davis. Ito thanks the Stanford Institute for Economic Policy Research for financial support. Reguant gratefully acknowledges the support of the support of NSF grant SES-1455084.

1 Introduction

A variety of economic goods are traded through sequential markets—a set of forward and spot markets for a good such as treasury bonds, stocks, coal, electricity, natural gas, oil, and agricultural products. The rationale behind establishing sequential markets comes from simple economic theory. For a commodity that has uncertainty in its delivery price or quantity, sequential markets can improve the efficiency of the final allocation. Under strong assumptions such as risk neutrality and common information, prices in sequential markets should converge in expectation (Weber, 1981). Empirical evidence is, however, usually inconsistent with this simple economic theory—in practice, prices in sequential markets often do not converge.¹

Previous studies provide several potential channels that explain why prices in sequential markets do not converge, such as risk aversion (Ashenfelter, 1989; McAfee and Vincent, 1993), and asymmetric shocks (Bernhardt and Scoones, 1994; Salant, 2014). We contribute to the literature studying the role of market power in creating such price differences (Saravia, 2003; Borenstein et al., 2008). We present a new theoretical framework to examine how the existence of market power can interact with constraints to arbitrage, and prevent full price convergence. More generally, we show that limited arbitrage can arise endogenously in an oligopolistic setting, when firms are asymmetric in size and entry to arbitrage is restricted. We then analyze the welfare implications of price arbitrage in the presence of market power. Arbitrage almost always improves welfare in a simple model with perfect competition. However, we show that such implications can change once we take into account the existence of market power in sequential markets.

We begin by developing a simple theoretical framework to characterize the behavior of firms in sequential markets in the context of electricity markets. Given that these markets are oligopolistic, we put special emphasis on the behavior of strategic players with market power. In the simplest example, we consider two sequential markets: the forward market and the real-time market.² Both markets trade the same commodity, electricity, to be produced at a particular delivery time. A monopolist decides how much to sell in each market. We assume that demand is inelastic and allocated in full in the forward market. This assumption comes from the fact that market operators in electricity markets typically schedule most or all expected demand in the day-ahead market, and use subsequent markets to allow for modifications in production commitments between producers. The monopolist still faces a downward-sloping demand curve in both markets, due to the presence of fringe suppliers, who offer production at their marginal cost.

¹Examples of empirical evidence include treasury auctions (Coutinho, 2013), wine auctions (Ashenfelter, 1989; McAfee and Vincent, 1993), mutual funds (Zitzewitz, 2003), and wholesale electricity markets (Saravia, 2003; Longstaff and Wang, 2004; Borenstein et al., 2008; Hadsell, 2008; Bowden et al., 2009; Jha and Wolak, 2014; Birge et al., 2014).

²In practice, there can be more than two sequential markets. For example, the Iberian electricity market in our empirical analysis has up to eight sequential markets to allocate hourly electricity production.

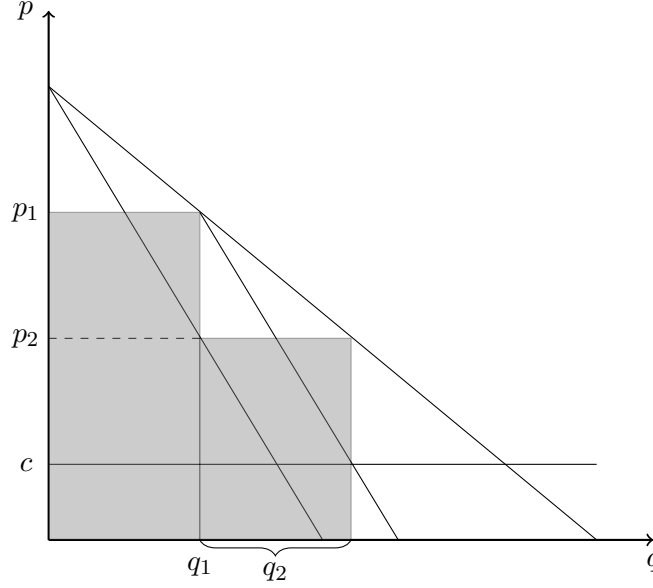


Figure 1: A Price Discriminating Residual Monopolist

This figure shows the intuition behind the declining price result (Result 1). A residual monopolist with marginal cost c has an interest in more expensive power plants setting a high price in the first market (p_1). In the second market, the monopolist can regain some of the withheld quantity by lowering the price (p_2).

Figure 1 provides a graphical illustration of the model. The monopolist participates in two markets. In the first market, it offers q_1 and receives p_1 . In the second market, the monopolist can increase its quantity by q_2 , getting p_2 . The key insight is that, because q_1 has already been committed in the first market, the monopolist's strategic position changes in the second market, creating an incentive to produce more. In this simple example, the monopolist anticipates these effects and splits the quantity equally between the two markets. This equalizes the marginal revenue in the first market to the market price in the second market, which becomes the relevant opportunity cost. In the context of the broader economics literature, the regulation in this market creates something similar to a dynamic price-discriminating monopolist facing naïve consumers, leading to a declining price path analog to a dynamic monopolist facing naïve consumers (Coase, 1972). Indeed, in the presence of infinitely many sequential markets, the monopolist creates a price schedule that mimics first degree price discrimination.

An important assumption in our baseline framework is that fringe producers offer their production at marginal cost. That is, they are not strategic, and are willing to produce as long as the price exceeds their marginal cost. However, given the equilibrium price differences between the two markets, fringe firms could arbitrage by selling more at a high price in the first market, and reducing their output in the second market. We show in the paper that limited arbitrage can arise under more general conditions, even when several firms

are competing in the market. In such environment, large firms have an incentive to withhold quantity in the first market to increase marginal prices, whereas small firms have an incentive to arbitrage some of those price differences away. In equilibrium, the smaller firms reduce price differences in the market by engaging in arbitrage, but not fully.

We test our theoretical predictions by analyzing firm behavior in the Iberian electricity market. The Iberian market provides several key advantages for testing our theoretical predictions. First, the Iberian market allocates hourly electricity production from producers to consumers using a day-ahead auction and seven subsequent intra-day auctions. This market structure allows firms to update their sales and purchase positions multiple times during a day. Second, there is ample publicly available data for the Iberian electricity market, which allow us to analyze firms' strategic behavior in sequential markets at high resolution. Third, the Iberian market consists of a few dominant firms that have 70% of the market share, as well as many competitive fringe firms, making the exercise of market power relevant. Because our data reveals firms' identities, we can investigate how dominant and fringe firms differently respond to the incentives created by the sequential markets.

Consistent with the predictions from our model, we find a systematic day-ahead price premium in the Iberian electricity market. We provide evidence that the day-ahead price premium is driven by the interaction of market power and regulatory restrictions on arbitrage. We show that the day-ahead premium correlates with strategic firms' abilities to exercise market power, such as total forecasted demand and the elasticity of residual demand, in a way that is consistent with the theoretical model. We also find strong empirical evidence that fringe producers systematically oversell electricity in the day-ahead market with a high market clearing price, and update their positions in later markets by purchasing electricity with a lower price, engaging in price arbitrage. Interestingly, we do not find such arbitrage for units operated by dominant firms. Conversely, dominant firms undersell or withhold their total electricity production in the forward markets and update their positions in the opposite way compared to fringe firms, also consistent with our theory.

The results from our empirical analysis reveal that dominant firms exercise market power and competitive fringe firms engage in price arbitrage. Is the price arbitrage welfare-improving and does more arbitrage enhance social welfare? Our theoretical model suggests that, in the presence of market power, price arbitrage may not improve social welfare, whereas it is likely to improve consumer surplus.³ To investigate these welfare implications, we build a structural Cournot model with a forward and real-time market.⁴

The model is useful to analyze the relevance of market power as a channel explaining the price premium.

³As explained below, the intuition parallels the literature on dynamic price discrimination (Lazear, 1986). Arbitrage reduces the scope for price discrimination, which increases consumer surplus but increases the deadweight loss in the market.

⁴The counterfactual model is a dynamic extension to the static Cournot game in Bushnell et al. (2008).

In the context of the Iberian electricity market, we show that this channel appears to be empirically relevant, explaining a good part of the distribution of the day-ahead premium in the data. The structural model is also useful to perform counterfactual analysis on the welfare effects of arbitrage and market power. Paralleling [Allaz and Vila \(1993\)](#), we empirically show the benefits of having sequential markets as a way to reduce market power. Paralleling the literature on dynamic price discrimination, we show that full arbitrage is not necessarily welfare enhancing, even if such arbitrage does not generate transaction costs.

Our findings have important takeaways that can apply to other forms of sequential markets. First, our model suggests that one needs to be cautious at evaluating the benefits of price convergence between forward and spot markets, as full arbitrage does not necessarily lead to more efficient outcomes. Whereas price convergence is in itself a sign of a healthy arbitrage market, it does not always improve the final allocation. We expect this to be more likely in settings in which the second market is less distorted than the first, which in our case is driven by firms lowering markups in the second market. Furthermore, our model emphasizes that, even under full arbitrage, asymmetric firms take different strategic positions as a function of their degree of market power. Therefore, even in well arbitrated markets, one can use sequential markets as a way to learn about the extent of market power.

This finding can be a useful insight into the ongoing policy discussion about whether regulators in electricity markets in the United States and other countries should seek full arbitrage through virtual bidding or speculators as an ultimate goal, given that most electricity markets are believed to have some degree of imperfect competition.⁵ Price convergence in itself is a necessary condition for an efficient market, but not sufficient. Therefore, price convergence in the presence of virtual bidding should not be necessarily interpreted as a sign that the market has become efficient.

Related Literature. Our paper relates to several literatures. First, it relates to the literature examining sequential markets, market power, and arbitrage, starting with the seminal work by [Allaz and Vila \(1993\)](#). Different than the canonical model, in our setting arbitrage is not competitive, giving rise to endogenous systematic price differences. Also, the forwarding market arises from the demand side, which is concentrated in the day-ahead market.⁶ We present a theory in which restrictions to arbitrage combined with market power generate a declining price path, resembling the literature on durable good monopolies when consumers are not sophisticated or impatient ([Coase, 1972](#)), and clearance sales ([Lazear, 1986](#); [Nocke and](#)

⁵Virtual bidding allows bids from purely financial bidders who have neither physical generation capacity nor physical demand for electricity.

⁶In [Allaz and Vila \(1993\)](#), the forward motive arises for strategic reasons, as suppliers compete to obtain market share by lowering their price in the earlier markets. In our setting, the forward market arises from the demand side. In this sense, our baseline setup closely resembles a procurement auction in which demand is allocated among the participants, followed by resale.

Peitz, 2007). This explanation can complement other existing theories explaining the lack of price convergence in sequential markets, such as those related to risk aversion (McAfee and Vincent, 1993) or asymmetric random shocks (Bernhardt and Scoones, 1994; Salant, 2014). The paper is related to Coutinho (2013), who shows that similar strategic effects can arise in markets for re-sale of Treasury bills using a theoretical model of supply function. Our work complements the theoretical literature by quantifying the interaction between market power and arbitrage in sequential markets in a real application, directly testing the predictions from the model using highly disaggregated data.

Second, our theoretical and empirical findings provide key insights into current policy discussions in energy policy. The lack of arbitrage has been documented as a central policy question in many electricity markets in the United States and other countries (Saravia, 2003; Longstaff and Wang, 2004; Borenstein et al., 2008; Hadsell, 2008; Bowden et al., 2009; Jha and Wolak, 2014; Birge et al., 2014; Parsons et al., 2015). Our model predicts that a positive day-ahead premium can arise as a result of market power. We empirically show that this prediction is consistent with the price premium and market power observed in the Iberian electricity market. The model's prediction is also consistent with the price premiums found in the literature for other electricity markets including the California, Midwest, New England, New York, and PJM markets.⁷

Our paper is most closely related to Saravia (2003) and Borenstein et al. (2008). Borenstein et al. (2008) show that the price differences in the forward and spot markets in the California electricity market cannot be fully explained by risk aversion, estimation risks, or transaction costs, finding that market power can be a channel driving price premia in the California electricity market. Saravia (2003) describes that regulatory constraints in the New York electricity market also generate price premia in electricity markets in the presence of congestion. A novel feature of our framework is that we show that limited arbitrage can arise endogenously in the presence of asymmetric firms, i.e., even in the absence of explicit regulatory constraints. Our contribution is to formalize this channel in a model with exogenous and endogenous limited arbitrage, as well as to test and quantify the predictions of the model more explicitly with a structural model estimated with highly disaggregated data.

Finally, our empirical analysis provides a framework to exploit sequential markets to measure market power. We show that fringe and dominant firms behave very differently in sequential markets. Comparing bidding strategies across firms and sequential markets can provide an additional test for competitive

⁷Similar to our empirical findings in the Iberian electricity market, the literature finds *positive* day-ahead price premiums in many electricity markets, including the New York market (Saravia, 2003), the PJM market (Longstaff and Wang, 2004), the New England market (Hadsell, 2008), and the Midwest market (Bowden et al., 2009) for most hours. For the California market, Borenstein et al. (2008) find statistically significant *negative* day-ahead price premiums for part of their sample periods. However, they also document evidence of monopsony power during this period that was exercised by buyers in the market.

behavior, complementing existing methods that are based on markup estimation.⁸

The paper proceeds as follows. In Section 2, we describe a model of sequential markets with market power under alternative forms of arbitrage. In Section 3, we explain the institutional details and data. Section 4 shows how the price differences observed in the data appear to be related to measures of market power, and how fringe and dominant firms behave very differently in the market, in a way that is consistent with the theoretical framework. Section 5 presents a structural model of sequential markets and analyses the effects of arbitrage. Section 6 concludes.

2 Model

In this section, we develop a model of sequential markets. Several aspects of firms' behavior can affect prices in sequential markets, such as information updating or risk aversion, among others. For simplicity, and given that our main focus is on the role of market power, we consider a setting in which there is no private information or common uncertainty.⁹

2.1 Sequential Markets

Consider a simple model in which a residual monopolist is deciding production in two stages. The problem of the monopolist is to decide how much commitment to take at the first market (forward or day-ahead market) at a price p_1 , and how much to adjust its commitment in the second market (real-time market) at a price p_2 . Final production is determined by the sum of commitments in each market.

Residual Demand Residual demand in the first market (day-ahead) is given by,

$$D_1(p_1) = A - b_1 p_1. \quad (1)$$

A represents the total forecasted demand, which is planned for and cleared in the day-ahead market. Whereas demand is inelastically planned for, the monopolist faces a residual demand with slope b_1 . One micro-foundation is that residual demand is the inelastic demand A minus the willingness to produce by fringe suppliers, who are willing to produce with their power plants as long as p_1 is above their marginal cost, $C^{\text{fringe}}(q) = q/b_1$.

⁸There is an extensive literature that estimates market power in electricity markets. For example, see Wolfram (1998, 1999); Borenstein et al. (2002); Kim and Knittel (2006); Puller (2007); Bushnell et al. (2008); McRae and Wolak (2009); Reguant (2014). To estimate market power, most papers estimate power plants' marginal costs using engineering estimates or first-order conditions.

⁹We extend the model to allow for common uncertainty in the counterfactual experiments in Section 5.

In the second market (real-time), commitments to produce can be updated. Therefore, it is a secondary market for reshuffling the agreed production, while the total production remains A . We assume that the residual demand in the second market is given by,

$$D_2(p_1, p_2) = (p_1 - p_2)b_2. \quad (2)$$

This residual demand implies that fringe suppliers produce more than their day-ahead commitment if $p_2 > p_1$, and produce less than their day-ahead commitment if $p_2 < p_1$. Consequently, the monopolist increases its quantity in the second market as long as $p_1 > p_2$. For the special case of $b_1 = b_2$, this residual demand implies that fringe suppliers are willing to move along their original supply curve. In the context of electricity markets, we assume that $b_2 \leq b_1$, as production tends to be less flexible in the real-time market.¹⁰

Monopolist Problem The monopolist maximizes profits by backward induction. At the second market, p_1 and q_1 have already been realized. The monopolist's problem is,

$$\begin{aligned} \max_{p_2} \quad & p_2 q_2 - C(q_1 + q_2), \\ \text{s.t.} \quad & q_2 = D_2(p_1, p_2), \\ & q_1 = D_1(p_1). \end{aligned} \quad (3)$$

The solution to the last stage gives an implicit solution to p_2 and q_2 . In the first stage, the monopolist takes into account both periods. By backward induction, q_2 and p_2 become now a function of p_1 ,

$$\begin{aligned} \max_{p_1} \quad & p_1 q_1 + p_2(p_1) q_2(p_1) - C(q_1 + q_2(p_1)), \\ \text{s.t.} \quad & q_1 = D_1(p_1). \end{aligned} \quad (4)$$

To gain intuition, we consider the results for a simplified example with linear residual demand and constant marginal costs, $C(q) = cq$.¹¹ Result 1 summarizes some useful comparative statics.

Result 1. *Assume that the monopolist is a net seller in this market (i.e., $q_2 > 0$). Then,*

- $p_1 > p_2 > c$;

¹⁰Empirically, we find that b_1 tends to be larger than b_2 by a factor of 5 to 10. [Hortaçsu and Puller \(2008\)](#) find evidence that the supply curve of fringe suppliers is relatively inelastic at the real-time market, which could be explained by a lack of sophistication or adjustment and participation costs.

¹¹We provide a full derivation of equilibrium prices and quantities, as well as proofs of the results, in Appendix A.

- $p_1 - p_2$ is increasing in A , decreasing in b_1 , and increasing in b_2 ;
- if $b_2 = b_1$, $q_1 = q_2$;
- If $b_2 < b_1$, $q_1 > q_2$.

In equilibrium, the monopolist exercises market power in both markets. However, in the second market, its position in the first market is already sunk. Therefore, it has an incentive to produce some more quantity, whereby lowering the price. The monopolist withholds quantity in the first market, and then increases its commitments in the second market, gaining back some more market share.

The results of a day-ahead price premium are analogous to those in the literature considering a monopolist engaging in dynamic price discrimination when facing naïve consumers. In the first stage, the monopolist benefits from selling the good to a set of consumers with high willingness to pay, while in the second stage, it sells the good to consumers with lower valuations. Figure 1 provides the intuition behind this result.

It is important to note that this simplified example has been presented under the assumption that the monopolist is a net seller. Under the alternative assumption that the monopolist is a net buyer (i.e., a monopsonist), the results are reversed: in the absence of arbitrageurs, or in the presence of limits on arbitrage, there would be a real-time premium, i.e., $p_2 > p_1$.¹²

Arbitrage In our example, we have assumed that demand is not elastic and, by construction, is all planned for already in the first market (A). This is motivated by the fact that the electricity day-ahead market is intended to plan for all (or most) forecasted demand. The downward sloping residual demand comes from the presence of fringe suppliers, which are bidding at their marginal cost.

In equilibrium, fringe suppliers sell more in the first market at a better price, and then reduce their commitments in the real-time market at lower prices, making some profit. However, the equilibrium leaves room for further arbitrage. Given that $p_1 > p_2$, competitive fringe suppliers could oversell even more at the first market. In such case, fringe suppliers would need to offer production below marginal cost, and then trade back those commitments. The residual demand would no longer be given by total demand minus the marginal cost curve of fringe producers.

We consider the case in which fringe suppliers compete for these arbitrage opportunities until $p_1 = p_2$.¹³

¹²In the context of the California electricity market, Borenstein et al. (2008) find evidence in support of monopsony power.

¹³An alternative interpretation is that the demand side could arbitrage by waiting until the second period. We emphasize supplier incentives in the theoretical framework because, empirically, it is where we see most of the arbitrage. Demand side arbitrage is not as salient for two main reasons. First, the regulator tends to plan for all forecasted demand in the first market, so total cleared demand tends to be quite constant across markets. This implies that demand, in net, has limited contributions to price arbitrage.

Abstracting from changes in the slope of the residual demands (b_1, b_2), consider an arbitrageur that can shift the residual demand at the forward market, by financially taking a position to sell, and buy back the same quantity at the real-time market.¹⁴ An arbitrageur can sell a quantity s in the first market, and buy it back in the second market.¹⁵ The modified residual demands become,

$$D_1(p_1, p_2, s) = A - b_1 p_1 - s, \quad (5)$$

$$D_2(p_1, p_2, s) = (p_2 - p_1) b_2 + s. \quad (6)$$

Note that this formulation is analogous to demand not clearing in full in the first market. The effective demand in the first market is $A - s$, while s is added to the residual demand in the second market.

If the costs of arbitraging are relatively small and the arbitrageurs market is competitive, s increases until p_1 converges to p_2 . In the equilibrium, therefore, the presence of such arbitrage erases the forward market price premium.

Result 2. *Assume that the monopolist is a net seller and arbitrageurs are competitive so that, in equilibrium, s is such that $p_1 = p_2$. Then,*

- $p_1 = p_2 > c$;
- $p_1(s)$ is decreasing in s and $p_2(s)$ is increasing in s ;
- $q_1(s)$ decreases with s and $q_2(s)$ increases with s ;
- s reduces total output by the monopolist, $q_1^* + q_2^*$.

One important insight that arises from this result is that competitive arbitrage in this market does not lead to competitive prices. The rational for this result is that the monopolist is still required to produce the output after all sequential markets close. The arbitrageurs are only engaging in financial arbitrage, but do not produce s . One can also see that arbitrage reduces *both* the price and the monopoly quantity in the first period, as the monopolist responds to the arbitrage by withholding some more output.

Second, final electricity consumers are very insensitive to prices and retail choice opportunities (Hortaçsu et al., 2015). At the same time, such consumers are served by vertically-integrated generating companies. These companies profit more from increasing generation prices than by lowering rates to consumers, which has very limited impacts on profit. Therefore, even if such arbitrage opportunities exist, the largest companies do not have incentives to exploit them.

¹⁴Virtual bidders in markets such as Midcontinent Independent System Operator (MISO) and California engage in these type of commitments, which, contrary to our empirical application, are allowed in those markets.

¹⁵Because we do not restrict s to be positive, the arbitrageur could be effectively selling at the first market and buying back at the second market. In equilibrium, however, $s > 0$.

Exogenous Limited Arbitrage In practice, s might not be chosen to equalize prices, e.g., due to some institutional constraints or transaction costs. In electricity markets, it is common to limit participation to agents that have production assets. An arbitrageur cannot take a purely financial position in the market unless it is “backed up” by an actual power plant.

We introduce arbitrage constraints on fringe suppliers, by introducing an exogenous limit K on s .

Result 3. *Assume that arbitrageurs are limited in their amount of arbitrage, i.e. $s \leq K$. Then,*

- *whenever the arbitrage capacity is binding, i.e. $s = K$, then $p_1 > p_2$;*
- *price differences are more likely to arise when K is lower, all else equal;*
- *price differences are more likely to arise when A and b_2 are large, and when b_1 is small, all else equal;*
- *$p_1 - p_2$ is increasing in A , decreasing in b_1 , and increasing in b_2 .*

The result shows that a price premia arises whenever arbitrageurs are capacity constrained. In such case, the comparative statics are similar to the case without arbitrage, and the price premia is larger when market conditions are more extreme, e.g., when demand is large or the fringe supply is less elastic.

Endogenous Limited Arbitrage Limited arbitrage can arise endogenously due to limited competition on the arbitrageur side. For example, in electricity markets, participation by purely financial companies is often not allowed. We consider the presence of a single arbitrageur, who has an incentive to arbitrage price differences, but not to close the gap completely. In our setting, and given the limitations to arbitrage in the market, we interpret this special case as representing a scenario in which a limited set of players can engage in price arbitrage. The profits of the arbitrageur are given by $(p_1 - p_2)s$.

We calculate the sequential Cournot equilibrium between the monopolist producer (q_1, q_2) and the strategic arbitrageur (s) . In the first stage, they choose q_1 and s simultaneously, in the second stage, the monopolist can adjust to q_2 .

Result 4. *Assume that there is a single firm which has the ability to arbitrage, and maximizes profits. Then,*

- *$p_1 > p_2 > c$;*
- *$p_1 - p_2$ is increasing in A , decreasing in b_1 , and increasing in b_2 ;*
- *$p_1 - p_2$ is smaller than in the absence of strategic arbitrage, i.e., $s > 0$.*

In the presence of a strategic arbitrageur, the main predictions of the model hold. The price premium is larger when demand is large, fringe suppliers submit inelastic supplies, and when the real-time market is more elastic.

2.2 Relative Size and Incentives to Arbitrage

In our empirical setting, arbitrage is performed by firms that also produce in the market. Could this be explained as an equilibrium? We consider a situation in which there are two firms, one of which is large and sells substantial amounts of output, and one of which is small. Both of them have the ability to engage in strategic withholding or arbitrage. For the purposes of the empirical exercise, it is useful to think about the large firm as one with several types of production (e.g., coal, gas, nuclear, wind), and the small producer as one with wind farms.¹⁶

We model the large firm as the monopolist in the above cases, with constant marginal cost c . We assume that the marginal cost of the monopolist is low enough that it becomes a large player in equilibrium. For the small firm, we assume that it behaves as the strategic arbitrageur in the previous example, with the main difference that, on top of getting profits from arbitrage, it also gets profits from wind output. The profit function becomes $p_1 q^w + (p_1 - p_2)s$, where q^w is the farm's wind output, which is exogenously given by weather patterns, e.g. wind speed and direction.¹⁷

The presence of wind output attenuates the incentives of the arbitrageur to bring p_1 down. If the wind farm is small enough, it still has a net incentive to arbitrage and increase its profits by overselling in the first markets, i.e., setting $s > 0$. However, if the quantity produced by the wind farm is large enough, the arbitrageur does no longer have an incentive to arbitrage, and behaves in line with the monopolist, driving a price premium. Result 5 summarizes the comparative statics.

Result 5. *Assume that there is a single firm which has the ability to arbitrage, who also owns wind farms, and maximizes profits. Then,*

- $p_1 > p_2$;
- $p_1 - p_2$ is increasing in A and q^w , decreasing in b_1 , and increasing in b_2 as long as $q^w < \tilde{q}^w$;
- $s > 0$ as long as $q^w < \underline{q}^w$, otherwise $s \leq 0$;

¹⁶We will show that, empirically, these results also hold for other technologies, but wind makes the comparison cleaner as actual final production is mostly exogenous.

¹⁷Similar insights arise with the second firm choosing quantity endogenously, but just being smaller in size due to other factors, e.g. due to capacity constraints or higher marginal costs.

- $q_2 > 0$ as long as $q^w < \bar{q}^w$.¹⁸

Under this scenario, a price premium still arises. If the wind farm is small, it has an incentive to arbitrage price differences, i.e., $s > 0$. However, if the wind farm is large enough, then it has no incentive to arbitrage. In fact, it may have an incentive to undersell in the first market, i.e., $s < 0$. The monopolist, on the contrary, does not arbitrage the price differences away as long as it is large relative to the other player. If the monopolist became small enough relative to the wind producer, the roles could eventually revert. The monopolist would behave as an arbitrageur ($q_2 \leq 0$), while the wind farm would create the price premium. For an intermediate range of wind output $q^w \in [\underline{q}^w, \bar{q}^w]$, both strategic players have aligned incentives to increase the premium, i.e., $s < 0$ and $q_2 > 0$. In all cases, $p_1 > p_2$.

Result 5 is important, as it highlights that asymmetric behavior in arbitrage can arise endogenously as the result of firms with asymmetric sizes. The larger firms will have an incentive to behave as a “monopolist” in our model, withholding in the day-ahead market to increase the marginal price of electricity. On the contrary, the smaller firms will have an incentive to arbitrage some of the price differences.

2.3 Summary

Results 1-5 describe the behavior of a strategic firm under alternative assumptions regarding the extent and nature of arbitrage. Table 1 shows common predictions across alternative models of arbitrage (no arbitrage, full arbitrage, exogenous limited arbitrage, and endogenous limited arbitrage). One can see that a price premium arises as long as arbitrage is not full, and in such cases it is increasing with demand, decreasing with the slope of the residual demand in the first period, and increasing with the slope of the residual demand in the second period. Furthermore, in all equilibria the largest firm has an incentive to withhold output in the first market, and increase its production commitments in the second one.

[Table 1]

We explore these testable implications in the empirical section. Before we proceed to our empirical analysis, we give some more institutional details on how sequential markets are organized in our particular application, the Iberian electricity market.

¹⁸In particular, $\tilde{q}^w \equiv \frac{(5b_1^2 + 2b_1b_2 + b_2^2)(A - b_1c)}{17b_1^2 - 6b_1b_2 + b_2^2}$, $\underline{q}^w \equiv b_1 \frac{A - b_1c}{5b_1 - b_2}$, and $\bar{q}^w \equiv \frac{(3b_1 + b_2)(A - b_1c)}{7b_1 - b_2}$, with $\underline{q}^w \leq \tilde{q}^w \leq \bar{q}^w$, see Appendix A for details.

3 Institutions and Data

A deregulated electricity market usually consists of a day-ahead forward market and a real-time spot market. Most energy production is first allocated in the day-ahead market. The real-time market is used to ensure the balance between scheduled demand and supply. In this paper, we leverage the unique market structure of the Iberian electricity market, which consists of several sequential markets during a day, to study strategic behavior in these markets.¹⁹ We begin by providing institutional details on how the sequential markets are organized. We then explain what features of a typical deregulated electricity market restrict full arbitrage between the forward market and the spot market. Finally, we describe the data used for our empirical analysis.

3.1 Sequential Markets in the Iberian Electricity Market

The Iberian electricity market is organized in a centralized fashion, with a day-ahead market and up to seven intra-day (real-time) markets. Figure 2 shows how the sequential markets are structured. In the day-ahead market (day $t - 1$), producers and consumers submit their supply and demand bids for each of the 24 hours of delivery day t , and production for each hour is auctioned simultaneously using a uniform rule, setting a marginal price of electricity for each hour of the day.²⁰ The day-ahead plans for roughly all expected electricity, whereas sequential markets allow for re-trading.²¹ After the clearance of the day-ahead market, the system operator checks congestion in the electricity grid. In the presence of congestion, the system operator may require some changes in the initial commitments, re-adjusting the position of several units based on their willingness to re-adjust.

After the congestion market, the first intra-day market opens, still on day $t - 1$. In the first intra-day market, producers and consumers can bid for each of the 24 hours of day t to change their scheduled production from the day-ahead market. For example, if suppliers want to reduce their commitments to produce, they can purchase electricity in the intra-day market. Likewise, if firms want to produce more than the assigned quantity, they can sell more electricity in the intra-day market. This means that an electricity supplier can become a net seller or buyer in the intra-day market. After the first intra-day market, firms have additional opportunities to update their positions through subsequent intra-day markets as shown in the figure. In each of the intra-day markets, the market clearing price is determined by a set of simultaneous uniform price auctions for each delivery hour.

¹⁹The Iberian electricity market encompasses both the Spanish and Portuguese electricity markets, and was created in July 2007.

²⁰In reality, the auction takes the form of a modified uniform auction, as explained in Reguant (2014).

²¹In terms of volume, roughly 80 percent of the electricity that is traded in the centralized market is sold through this day-ahead market. Firms can also have bilateral contracts in addition to their transactions in the centralized market.

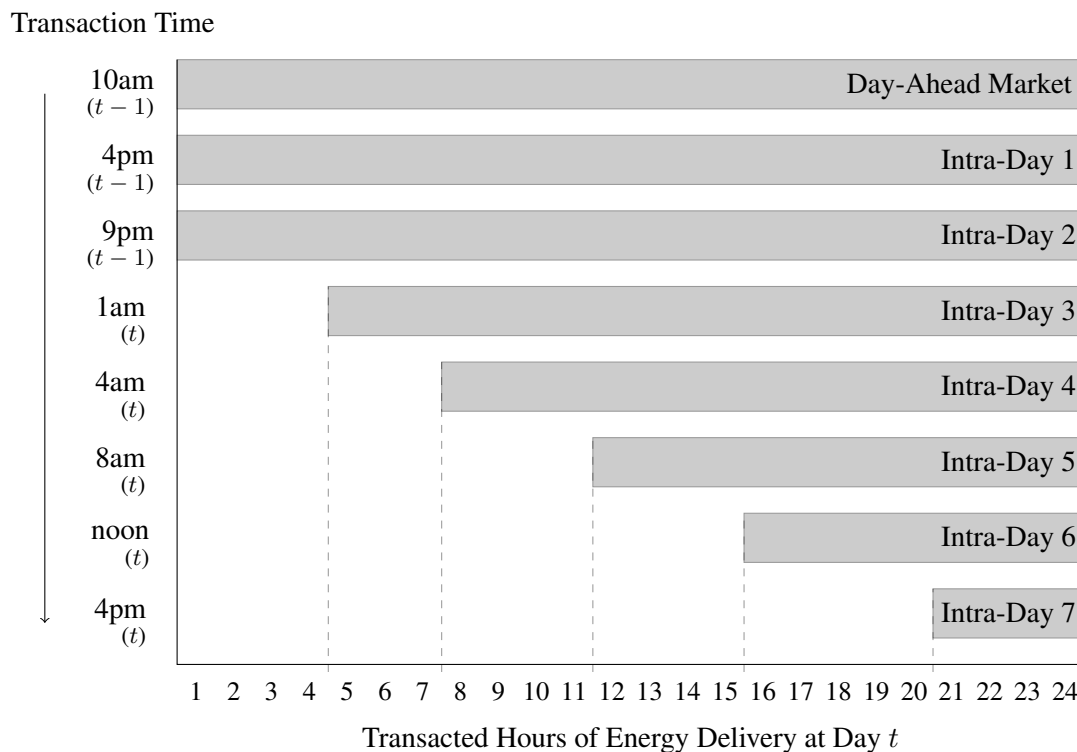


Figure 2: Sequential Markets in the Iberian Electricity Market

This figure describes the timeline of sequential markets in the Iberian Electricity Market during our sample period. For a given hour of their production, firms can bid in the day-ahead market and multiple intra-day markets. The position in the last market for a given hour represents their final physical commitment to produce electricity. For example, at noon firms can change their commitments until the 5th intra-day market. Their position at the 5th intra-day market determines the amount of electricity that they are expected to produce.

Sequential markets allow firms to adjust their scheduled production multiple times. For example, consider a firm that wants to deliver electricity for 9 pm on day t . The firm first participates in the day-ahead market at 10 am on the day before production (day $t - 1$). After realizing the auction outcome of the day-ahead market, the firm can update their position by purchasing or selling electricity in the subsequent seven intra-day markets. The final intra-day market—the 7th intra-day market—closes at 4 pm on day t . Note that the number of sequential markets available for the firm is different depending on the hour of energy delivery. For example, the firm has only three markets for their production hours from 1 am to 4 am, while the firm has four markets for hours from 5 am to 7 am.

Firms have no more opportunities to change their scheduled quantity after the final market. If their actual production deviates from the final commitment, they have to pay a price for the deviation. The market operator determines the deviation price as a function of the imbalance between the market-level demand and supply for the hour, and the willingness to adjust by other participants. We find that firms in general minimize their final deviations in response to deviation prices. We therefore do not focus on this aspect and assume that firms have appropriate incentives to minimize the deviation between the scheduled and actual production in the final market.

3.2 Restrictions to Arbitrage

In the theoretical framework, we highlight that the potential lack of arbitrage is a key institutional feature in electricity markets.²² There are a few features that restrict arbitrage in the Iberian market. First, virtual bidding is not allowed. This restriction implies that a supply bid has to be tied to a specific generation unit, and a demand bid has to be tied to a specific location for demand.²³

Second, generation firms are not allowed to sell a quantity higher than their generation capacity. This rule limits their ability to sell electricity short. In particular, if firms intend to use most of their full generation capacity to produce electricity, this rule implies that such firms have a very limited ability to sell electricity short. Similarly, generation firms cannot purchase electricity in intra-day markets if their net production reaches zero. This rule limits their ability to purchase electricity in a market with lower expected price.

Finally, the system operator clears roughly all forecasted demand in the day-ahead market, to plan for how the electricity will flow through the grid and prepare for potential contingencies. This rule limits the

²²See [Borenstein et al. \(2008\)](#) for a description of similar issues in the context of California.

²³While some electricity markets recently started to allow virtual bidding, it is still prohibited in many electricity markets, including the Iberian electricity market. For example, the New York electricity market started to allow virtual bidding in November 7, 2001 ([Saravia, 2003](#)) and the California electricity market recently started to allow virtual bidding ([Jha and Wolak, 2014](#)). Although economists are usually in favor of introducing virtual bidding, system operators in many electricity markets are often hesitant about its implementation. They are often concerned that virtual bidding may create large uncertainty in the final deliveries of electricity, which affects the system reliability.

arbitrage ability for the demand side. Whereas some demand agents arbitrage, large distribution companies do not appear engage in such behavior. Indeed, we find that distribution companies often compensate for the arbitrage by other agents, to better match forecasted demand.²⁴

3.3 Ability and Incentives to Arbitrage

What about the ability and incentive to arbitrage? Given explicit and implicit restrictions on arbitrage, some technologies might be better suited than others. For example, it is relatively difficult to arbitrage at the margin with thermal plants, because, whenever they produce, they tend to use their full capacity (e.g., see Cullen (2015)). Therefore, it would be difficult to oversell in the day-ahead market, as firms cannot bid more than their plant capacity. They also have some minimum production requirements to operate safely. Therefore, if they want to offer some output to arbitrage when they are not operating, they need to offer a substantial amount of their capacity (typically 40% of their capacity). Thermal power plants also tend to be, for the most part, in the hands of large producers.

As we will show in the data, we find that wind is one of the most active technologies arbitraging in the market. Wind farms have some technological advantages that make them quite attractive to arbitrage. First, wind farms almost never use their maximum capacity because wind does not blow all the time. On average, they use about one third of their installed capacity. This means that they have greater abilities to sell electricity short in a lower-priced market. Second, wind generation faces substantial uncertainty in their expected wind. Therefore, these units have limited control on their final output, requiring them to update their reports. This means that participation costs in arbitrage might be smaller. Finally, a substantial part of wind farms are not owned by dominant firms. Therefore, from a market structure point of view, a share of wind farms has not only the ability, but also the incentive, to arbitrage.²⁵

3.4 Data

We construct a dataset using publicly available data from the market operator, Operador del Mercado Ibérico de Energía (OMIE), and the system operator, Red Eléctrica de España (REE), of the Iberian electricity market. Our dataset comes from three main sources.

The first dataset is the bidding data from the day-ahead and intra-day markets. On a daily basis, elec-

²⁴As explained above, large retail companies also have limited incentives to look for low electricity prices, as they are vertically integrated and final consumers are very price insensitive. High day-ahead prices, on the contrary, benefit their generation profits.

²⁵During our main sample period, production from wind farms received the market price and a flat subsidy. The subsidy was based on final production, so over-stating production in forward markets does not increase revenues from the subsidy. This structure was changed in 2013, one year after our main sample period. We exploit this policy change in section 4.2.

electricity producers submit 24 hourly supply functions specifying the minimum price at which they are willing to produce a given amount of electricity at a given hour of the following day. Similarly, retailers and large electricity consumers submit 24 hourly demand functions specifying the price-quantity pairs at which they are willing to purchase electricity. The market operator orders the individual bids to construct the aggregate supply and demand functions for every hour, and the intersection of these two curves determines the market clearing price and quantities allocated to each bidder. Sellers (buyers) receive (pay) the market clearing price times their sales (purchases). Accordingly, for each of the 24 hours of the days in the sample, we observe the price-quantity pairs submitted by each firm for each of their power plants. We also observe all the price-quantity pairs submitted by the buyers. Importantly, we observe each bidding unit's curves both at the day-ahead and the intra-day markets. For each of the bidding units, we know whether their identity and type (buyers, traditional power producers (thermal, hydro) or "special regime" producers, such as renewable production, biomass, cogeneration).

The second dataset includes planning and production outcomes from the system operator. These system operator data include market clearing prices, aggregate demand and supply from each type of generation, demand forecast, wind forecast, and weather forecasts. The dataset also includes production commitments at each sequential market at the unit level. One advantage of the system operator data is that we can separate production commitments from wind, solar and other renewable technologies, whereas in the bidding data these units are often aggregated into a single bidding entity, due to their smaller size. One limitation of the system operator data, however, is that it comes from the Spanish system operator, and therefore it does not include Portuguese production units. Our results are very similar whether we focus on the Spanish electricity market (using these more detailed operational data), or the Iberian electricity market as a whole (using only bidding data).

The third dataset, which is particularly important for our welfare counterfactual analysis, includes plant characteristics, such as generation capacity, type of fuel, thermal rates, age, and location, for conventional power plants (nuclear, coal and gas). Combining these data with fuel cost data, we can obtain reasonable estimates of the marginal cost of production at the unit level. We also obtain CO₂ emissions prices and emissions rates at the plant level. As shown in [Fabra and Reguant \(2014\)](#), firms in the Spanish electricity markets fully internalize emissions costs. Therefore, we add them to the unit level marginal costs.

We use data from January 2010 until December 2012. During this period, the four largest generating firms were Iberdrola, Endesa, EDP, and Gas Natural. Their generation market share was on average 68 percent during this period (22%, 19%, 13%, and ,11% respectively).²⁶ These firms own a variety of power

²⁶Figure D.1 in Appendix D shows the evolution of their market shares over the sample.

plants from thermal plants to wind farms. In the empirical analysis, we define these four largest firms as *dominant firms*. The market also includes many new entrants that own wind farms or new combined cycle plants. We define them as *fringe firms*.

Table 2 shows the summary statistics of the bidding data and market outcomes, where each variable is associated to its closest analogue in the theoretical model. There are 26,304 hour-day observations in the sample, with an average market price of 44.7€/MWh in the day-ahead forward market and 43.8€/MWh in the spot market. On average, there is a day-ahead market premium of 0.9€/MWh. Whereas the premium is not large on average, there is substantial heterogeneity across days and hours, as discussed below. The table also reports the slopes of the residual demand curves that are used in the following sections. The slope is systematically larger for the day-ahead market, as the day-ahead market tends to have more participants. Finally, the average forecasted wind production is 5.0 GWh, being on average approximately 17 percent of total demand.

[Table 2 about here]

4 Evidence of Market Power and Arbitrage

In the theory section, we developed a model that characterizes how market power, arbitrage, and constraints for arbitrageurs influence market equilibrium prices in sequential markets. In this section, we provide empirical evidence for the theoretical predictions by analyzing firm behavior in the Iberian wholesale electricity market.

4.1 Forward-Market Price Premium and Market Power

We begin by documenting systematic forward market price premiums in the Iberian wholesale electricity market. Our theory predicts that a forward-market price premium could emerge if a net-seller firm has market power and market participants have limited arbitrage abilities. This prediction is consistent with the forward price premium observed in the Iberian wholesale electricity market.²⁷ Figure 3 shows average market prices (Euro/MWh) for each of the eight sequential markets (the day-ahead market and seven intra-day markets), in which the horizontal axis shows hours for electricity delivery. The figure indicates that there

²⁷Our theory is also consistent with empirical evidence of price premiums in the U.S. electricity markets documented by previous studies. For example, Saravia (2003) documents a forward-market price premium in the New York electricity market, which is similar to our finding in the Iberian electricity market. Borenstein et al. (2008) and Jha and Wolak (2014) find a spot-market price premium in the California electricity market, which is still consistent with our theoretical prediction because monopsony power is likely to be an important factor for the price premium in the California market, as documented by Borenstein et al. (2008).

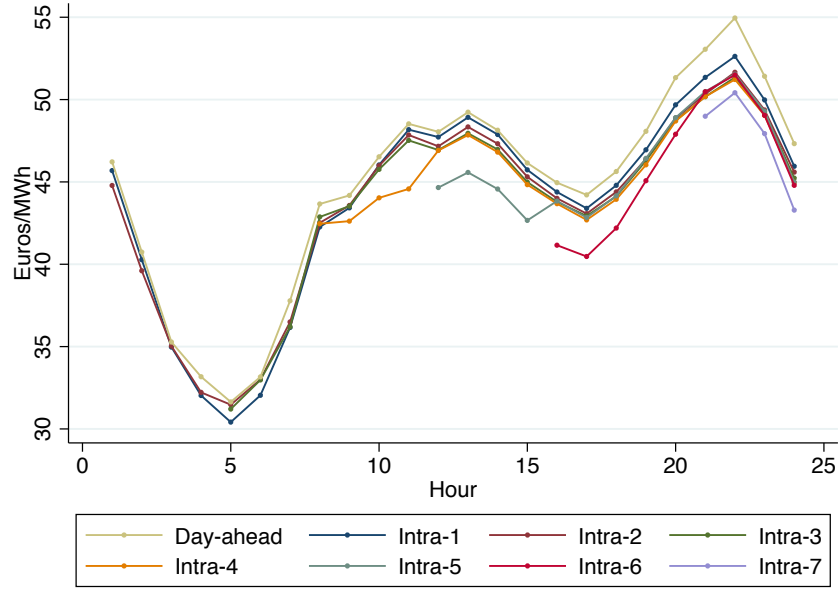


Figure 3: Market Clearing Price in the Day-ahead and Intra-day Markets

This figure shows the average market clearing price (Euro per MWh) in the day-ahead and intra-day markets, in which the horizontal axis shows hours for electricity delivery. Day-ahead market tends to exhibit prices that are on average higher than in the subsequent sequential markets.

is a systematic positive day-ahead price premium—the day-ahead prices are higher than intra-day market prices. The prices also appear to be declining in time. This is particularly true for the last intra-day market. For example, see prices for hours 12 to 15. The fifth intra-day market has a particularly lower price than the prices in the other markets for the same hours.

In addition to the average market prices presented in this figure, we provide the 25th, 50th, and 75th percentiles of the day-ahead price premium in Table 3. The table suggests that the positive average day-ahead price premium in the figure is not an artifact of some price outliers. The evidence is particularly strong for the afternoon and evening hours, in which the median day-ahead price premium is above 1 Euro/MWh across the sequential markets. For hours after the midnight, the median day-ahead premium is zero, but the distribution of the price premium is systematically shifted to the right, still giving a positive day-ahead premium on average. Table 3 also suggests that the day-ahead price premium has substantial variation across days and hours. The median of the price premium differs substantially across hours, and there is large dispersion between the 25th and 75th percentiles for a given hour and market.

[Table 3 about here]

Our theory indicates that several key factors can influence the price premium. The results summarized in Table 1 predict that the day-ahead price premium should be increasing in demand A , decreasing in the slope of the residual demand in the day-ahead market b_1 , and increasing in the slope of the residual demand in the intra-day market b_2 . An important advantage of our micro-level bidding data is that we can directly calculate the slopes of residual demand (b_1 and b_2) from the bidding data because we observe plant-level supply and demand bids for every hour in every market. For hour h , day t , and market k , we calculate a residual demand curve for the four dominant firms, Iberdrola (IBEG), Endesa (ENDG), Gas Natural Fenosa (GASN), and EDP/HC (HCENE). We then calculate the slopes of the residual demand at the market clearing price.²⁸ We then test our theoretical predictions by estimating an OLS regression:

$$\Delta p_{ht} = \alpha + \beta A_{ht} + \gamma_1 b_{1ht} + \gamma_2 b_{2ht} + \phi X_{ht} + u_{ht} \quad (7)$$

where Δp_{ht} is the day-ahead price premium (Euro/MWh) for hour h and day t , A_{ht} is the day-ahead demand forecast (GWh), b_{1ht} and b_{2ht} are the slopes of residual demand for the day-ahead market and for the first intra-day market. The parameters of interest, β , γ_1 , and γ_2 , describe how the demand forecast and the slopes of the residual demand are associated with the day-ahead price premium. For the control variables in X_{ht} , we include week of sample fixed effects and hour fixed effects.²⁹ We cluster the standard errors at the week of sample.

[Table 4 about here]

Table 4 shows our regression results for equation (7). We begin by including only the demand forecast as the independent variable. Column 1 shows that an increase in the demand forecast is associated with an increase in the price premium. In column 2 and 3, we include the slopes of residual demand at the day-ahead market and the first intra-day market. Consistent with our theoretical predictions in Result 3, we find that 1) more elastic residual demand in the day-ahead market are associated with a decrease in the price premium and 2) more elastic residual demand in the intra-day market are associated with an increase in the price premium. In column 4, we include wind forecast. Large wind forecast implies that wind farms operate at closer to their generation capacities. This means that, if wind farms are major arbitrageurs, their arbitrage capacity is lower when there is more wind forecast. In addition, Result 5 suggests that

²⁸We use two methods to calculate the slope at the market clearing price. The first approach is to fit a quadratic function to the residual demand curve and obtain a local slope at the market clearing price. The second approach is to fit linear splines with knots at $\{0, 10, 20, 30, 40, 50, 60, 70, 90\}$ Euro/MWh to the residual demand curve. We use the first approach for our main results. Because the two approaches produce similar local slopes, our regression results change very little if we use the second approach.

²⁹Including alternative dimensions of time fixed effects (e.g. day-of-sample fixed effects or month-of-sample fixed effects) does not significantly change the results.

the presence of wind output may attenuate the incentives to arbitrage, as wind farms become larger. For these two reasons, we expect a positive sign for the effect of the wind forecast on the day-ahead price premium. The result in column 4 indicates that we find empirical evidence consistent with the theoretical prediction. Finally, a potential concern for the OLS regression is that the slopes of residual demand can be endogenous, which is likely to produce attenuation bias for the relationship between the price premium and the slopes.³⁰ To address this concern, we instrument the slopes of residual demand with hourly weather variables (temperature, dew point, and humidity) in column 5. The estimates from the IV regression provide evidence consistent with our theoretical predictions.

4.2 Arbitrage by Fringe and Dominant Firms

The findings in the previous section imply that 1) there are systematic day-ahead price premiums in the Iberian sequential electricity market, and that 2) market power plays an important role in creating the price premiums. With such arbitrage opportunities, our theory predicts that fringe firms should engage in arbitrage, but dominant firms that exercise market power may not arbitrage, and more generally, have an incentive to withhold output in the forward markets. In this section, we examine how fringe firms and dominant firms respond to the price arbitrage opportunities in sequential markets.

The first part of this section investigates graphical evidence of arbitrage. We focus on arbitrage by wind farms and arbitrage by all technologies as a whole. As explained in Section 3.3, wind farms have technological advantages that make them quite attractive to arbitrage. Importantly, these advantages are common to wind farms owned by dominant firms and those owned by fringe firms. Therefore, wind provides empirical advantages for us to test if dominant and fringe firms respond to arbitrage opportunities differently. The second part of this section leverages our micro data at the plant level to provide statistical evidence on heterogeneity across production technologies. Players in electricity markets are heterogeneous in their technologies such as wind, cogeneration, demand, thermal, hydroelectric, and solar. We examine how firms use these technologies differently to arbitrage in sequential markets.

Aggregate Patterns. We begin by showing graphical evidence from the raw data. We examine how fringe and dominant firms update their positions (i.e. commitment to produce or purchase a certain amount of electricity for a given hour) through the sequential markets. Consider electricity production from wind farms (q^w). We aggregate plant-level production to the total production for two groups: 1) fringe firms and

³⁰Note that the demand forecast is exogenous and predetermined because it is publicly available to firms before the day-ahead market.

2) dominant firms. The dominant firms include the four largest firms in the market—IBEG, ENDG, GASN, and HCENE.³¹ Recall that firms have up to seven markets to update their positions before their final position is determined. We use subscript k to denote each market—the day-ahead market ($k = 0$), the first intra-day market ($k = 1$), ..., and the seventh intra-day market ($k = 7$). For each of the two groups, we define the position at a given market relative to the final position by:

$$\Delta q_{ghk}^w = q_{ghk}^w - q_{ghk, \text{final}}^w, \quad \text{with } g = \{\text{fringe, dominant}\}, \quad (8)$$

where q_{ghk}^w is group g 's position at market k for electricity production for hour h on day t , and $q_{ghk, \text{final}}^w$ is its final position. Therefore, Δq_{ghk}^w shows the extent to which group g oversells in market k relative to the final position. Similarly, we study how firms update their positions for Q , which is their total production from all types of power plants, including wind, thermal, hydroelectric, and others. $\Delta Q_{ghk} = Q_{ghk} - Q_{ghk, \text{final}}$ shows the extent to which group g oversells its total production in market k relative to its final position. We calculate the means of Δq_{ghk}^w and ΔQ_{ghk} for group g , hour h , and market k , during our sample period, which is from January 2010 to December 2012.

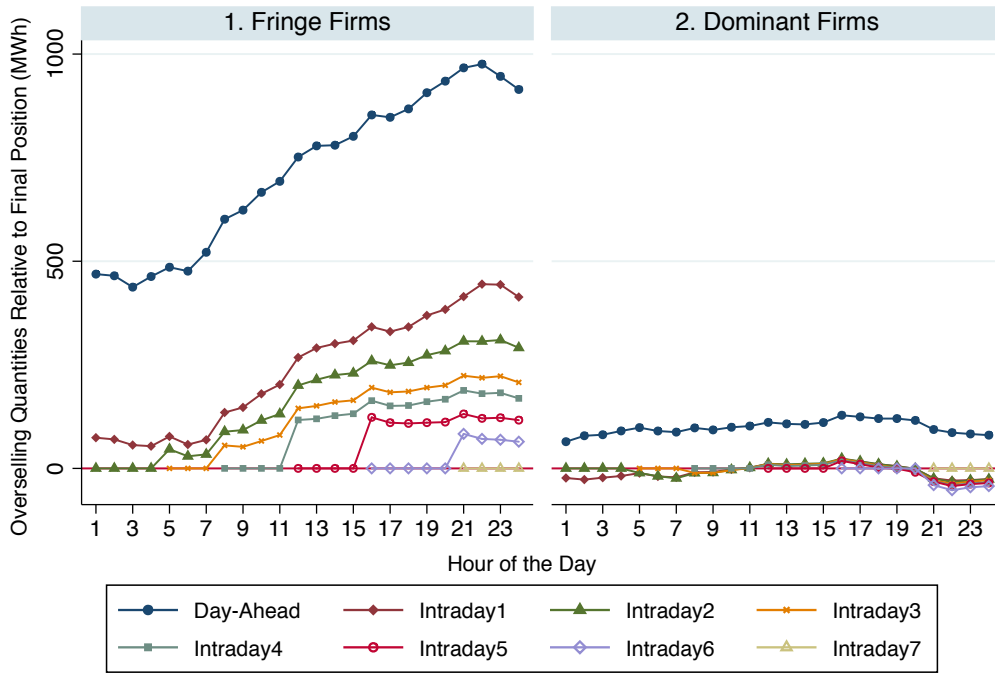
Figure 4 shows the mean of Δq_{ghk}^w in Panel A and the mean of ΔQ_{ghk} in Panel B. For fringe wind farms, we find substantial overselling in the forward markets. They oversell in forward markets and gradually adjust their positions toward their final positions. This gradual adjustment reflects the option values to adjust positions in the sequential markets. This evidence is not an artifact of their portfolio composition because Panel B shows the same evidence for fringe firms' aggregate production, which include production from all technologies. On aggregate across production technologies, fringe firms commit to produce more energy at the forward markets than what they actually deliver.

The evidence is particularly compelling at the discontinuous differences in Δq_{ghk}^w between the sequential markets for hour 5, 8, 12, 16, and 21. These discontinuities are consistent with the market structure. For example, at hour 12, firms have five intra-day markets to update their positions. The overselling is largest at the first market and decreases over time. In particular, there is a discontinuous drop between the fourth and fifth intra-day markets. This is because firms have no more opportunity to correct their positions after the last market. In the last market, they set their positions nearly equal to their actual final production.³² In contrast, the overselling behavior is very different for hour 11. First, firms do not oversell in the fourth intra-day market. This is because the fourth intra-day market is the last market for hour 11. Second, they

³¹During our sample period, about 30 percent of wind generation came from the wind farms owned by the four dominant firms.

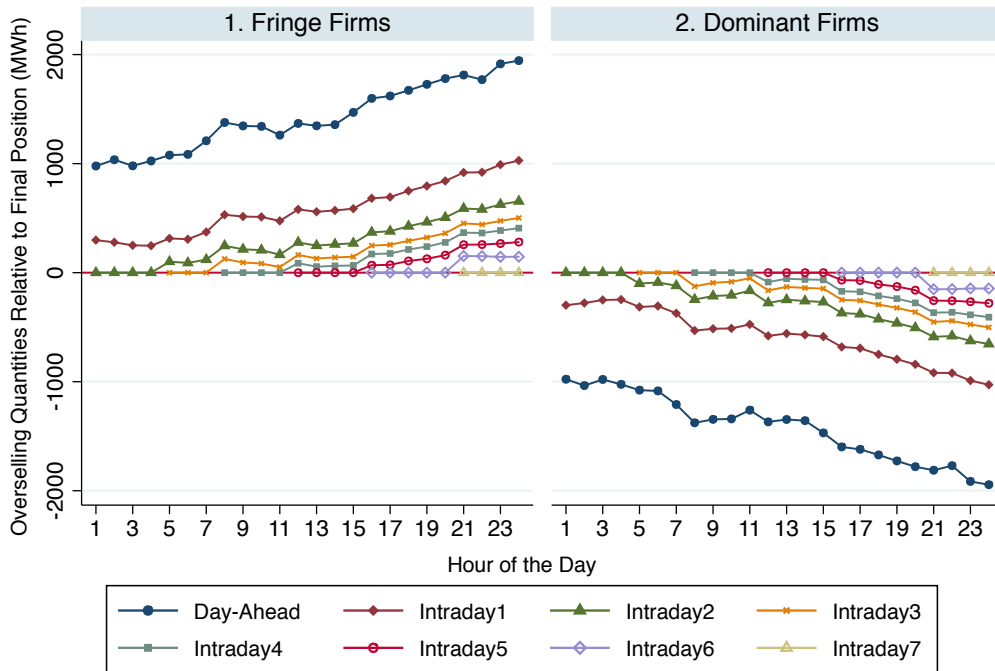
³²Note that wind farms in this market have incentives to minimize the deviation between their final commitment quantities and actual production because there are "deviation prices" for the deviation. Although we do not focus on their responses to the deviation prices in this paper, we find evidence that wind farms generally respond to the incentive and minimize the deviations.

Panel A: Wind Farms



Graphs by Fringe

Panel B: All Power Plants



Graphs by Fringe

Figure 4: Systematic Overselling and Underselling in Forward-Markets Relative to Final Positions

This figure shows average changes in fringe and dominant positions between a given market and their final commitment. Positive values imply that a group is promising more production than it actually delivers after all markets close.

oversell less in the first, second, and third markets for hour 11 relative to the amount of overselling for hour 12. This is because hour 11 has a smaller number of available markets, which creates different option values compared to option values in hour 12.

The data show notably different evidence for dominant firms. Panel A shows that there is almost no significant amount of overselling with wind by these large firms. The difference between their positions in the forward markets and the final production is much smaller than that for fringe wind farms. Furthermore, Panel B shows that dominant firms *undersell* in the forward markets with their overall portfolio. They withhold sales in the forward markets and sell more in the later markets, as suggested by our theory. This evidence is consistent with our theoretical prediction (Result 5)—dominant firms that exercise market power have an incentive to withhold output in the forward markets.³³

One potential concern is that there is slight overselling by dominant wind farms for the day-ahead market. However, the nature of overbidding appears to be quite different, as it is flat across hours, while overselling by fringe wind farms appears to correspond to the price arbitrage opportunities. The most likely reason for this behavior is the congestion market, which happens between the day-ahead and the first intra-day market. Dominant firms appear overstate wind production in the day-ahead market to reshuffle their production after the congestion market, even though in net they are withholding output, as shown in Panel B.³⁴ In fact, we see no overselling by dominant wind farms in all of the intra-day markets, which open after the congestion market. In Appendix D, we present additional graphs, in which we show the position of each of the four biggest firms, both for wind farms and their overall portfolio. The graphs confirm that congestion induces substantial reshuffling across the dominant firms.³⁵ After congestion is controlled for, behavior in the intra-day markets is very consistent across firms, and in line with the predictions of our model.

Further Evidence from a Policy Change in 2013. Starting from January 2013, the electricity price for wind farms became a rate that was not linked to prices in the sequential markets. This new policy made wind farms have no incentive to arbitrage in the sequential markets. We exploit this quasi-experiment to test if

³³When we compare the overselling quantities by fringe firms and those by dominant firms, a potential concern is that the levels of production are different. To examine this point, we contract the figures based on the natural log of production quantities in Appendix D, in which we find consistent evidence.

³⁴Importantly, the congestion market does not typically ration wind generation in itself, as it is given priority in the grid. The Spanish wind association reports “In 2012, curtailment on wind power generation reached 0.25% of total possible generation, above the 0.18% of the previous year” (Spanish Wind Energy Association, Wind Power '13).

³⁵Congestion is particularly relevant for GASN and ENDG. ENDG appears to be overselling with its portfolio, but this is because some of its power plants are in constrained regions. GASN, on the other hand, appears to massively undersell in the day-ahead market, which is again driven by congestion in the opposite direction. Unfortunately, these congestion patterns are very persistent, and therefore it is difficult to find a period with no congestion during our sample. Most of the flows in the congestion market are traded among these two firms, although IBEG and HCENE also experience some congestion events during the sample, which involve smaller amount of energy.

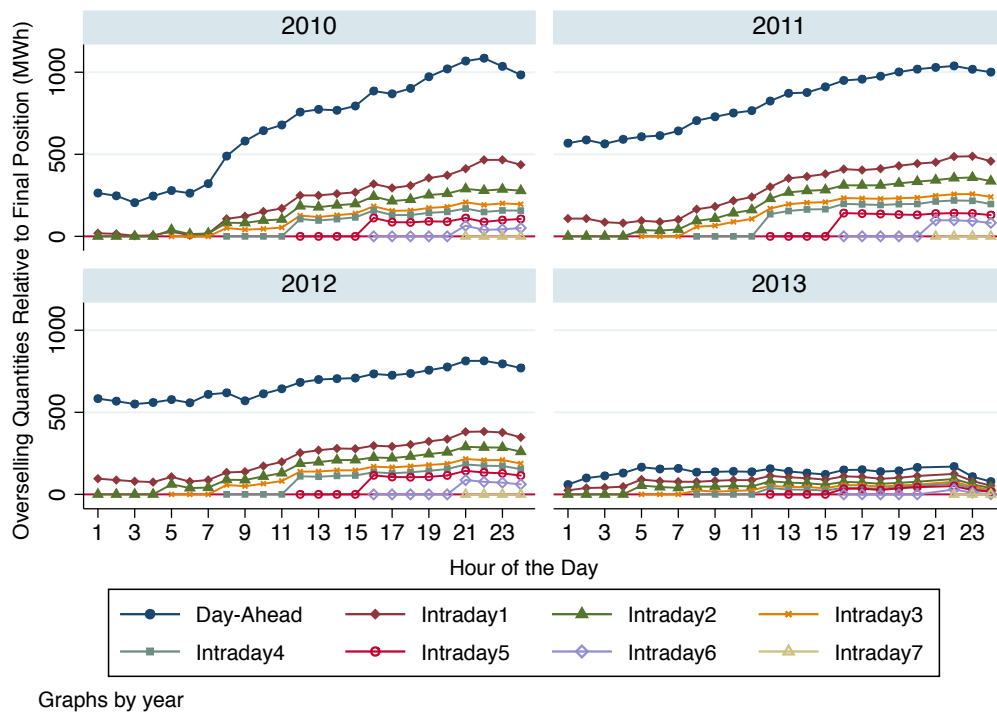


Figure 5: Effect of Policy Change in 2013 on Forward-Market Overselling by Fringe Wind Farms

This figure shows the forward-market overselling quantities for fringe wind farms by calendar year. Also see notes in Figure 4.

fringe wind farms stopped engaging in arbitrage in 2013, which is the year after our main data period. Figure 5 shows the overselling quantities of fringe wind farms by calendar year. There is systematic forward-market overselling in 2010, 2011, and 2012. However, there is no more significant overselling in 2013. Note that the amount of wind production by fringe wind farms is similar between 2012 and 2013. Therefore, this result is not driven by a change in wind production. To explore this point further, we also provide the same figure using the changes in the log of wind production in Appendix D. We find consistent evidence that the fringe wind farms stopped engaging in arbitrage in response to the policy change in 2013. Furthermore, we find that the price premiums in 2013 are slightly larger than those in the previous years, which is consistent with our theory because less arbitrage should produce larger price premiums.

Arbitrage by Sophisticated and Non-Sophisticated Bidders. Hortaçsu and Puller (2008) find differences in bidding behavior between “sophisticated” bidders and others in the Texas electricity market. In our context, we find that fringe wind farms engage in arbitrage most, but a potentially interesting possibility is that, even among fringe wind farms, there can be sophisticated and non-sophisticated bidders who exploit

arbitrage opportunities differently.³⁶ To examine this question, we exploit our bidding data at the firm-level, in which we observe hourly bids by each bidder. We find that a few bidders manage bids for large capacity of fringe wind farms, whereas others manage bids for relatively smaller capacity of fringe wind farms.³⁷ We test if the large bidders, who are likely to be more sophisticated bidders, arbitrage differently than the small bidders. In appendix Table D.2, we show three findings. First, both small and large bidders show systematic overselling in 2010, 2011, and 2012. Second, both types of bidders do not show systematic overselling in 2013, which is because of the policy change discussed in the previous section. Third, the large bidders oversell more strongly than small bidders. These findings suggest that sophistication in bidding is a key factor to explain heterogeneity in arbitrage among fringe wind farms.

Heterogeneity in Arbitrage by Production Technologies. The aggregate patterns provide strong evidence that fringe and dominant firms respond to the incentives in the sequential markets in a way that is consistent with our theoretical predictions. Our theory also suggests that the amount of arbitrage should be positively associated with price premiums that are forecastable from market fundamentals such as demand forecasts. In addition, arbitrage can differ by production technologies because the ability to arbitrage depends on power plant types.

To test these predictions, we leverage our micro data at the firm level by production technologies—wind, cogeneration, demand, thermal, hydroelectric, solar, and all technology as a whole. Because the level of production is very different by firms and production technologies, we examine log deviations. For firm j , production technology s , hour h , and day t , we define the change in the firm's position from the day-ahead market to the final commitment by $\Delta \ln q_{jht,DA}^s = \ln q_{jht,DA}^s - \ln q_{jht,FI}^s$ and the day-ahead price premium by $\Delta p_{ht,DA} = p_{ht,DA} - p_{ht,FI}$. Similarly, we define the same variables for the change in the firms' positions and the price premium between the first intra-day market and the final market: $\Delta \ln q_{jht,I1}^s = \ln q_{jht,I1}^s - \ln q_{jht,FI}^s$ and $\Delta p_{ht,I1} = p_{ht,I1} - p_{ht,FI}$. Given that we want to test how firms change their positions in response to price premiums that are forecastable at the time of bidding, we need to construct forecastable price premiums $\Delta \hat{p}_{htk}$.

To obtain a purely predetermined forecastable relationship between the price premiums and the demand forecast, we use hourly data in 2009 (the year before our main data period) to regress Δp_{htk} on the demand forecast, which is a key explanatory variable for the variation of price premiums and publicly available at the time of bidding. We then use the regression coefficients to obtain forecastable price premiums $\Delta \hat{p}_{htk}$.

³⁶We thank a referee who suggested this analysis.

³⁷Some bidders act as an aggregator for multiple wind farms. Therefore, the owner of a wind farm is not necessarily the one who manages bids in the market. Our bidding data allow us to identify the bidders, which enables us to do the analysis in this section.

for the 2010-12 period. The idea behind this approach is that firms can forecast the price premiums by knowing the relationship between the price premiums and the demand forecast from the past.³⁸ We estimate the following equation by OLS, separately for each technology s and each market k ,

$$\Delta \ln q_{jhtk}^s = \alpha + \beta \Delta \hat{p}_{htk} + u_{htk}, \quad \text{with } k = \{\text{DA}, \text{I1}\}, \quad (9)$$

where β shows the percentage change in the arbitrage with respect to a change in the forecastable price premium by one Euro/MWh. We include firm fixed effects and month of sample fixed effects to regression (9).³⁹ We cluster the standard errors at the month of sample.⁴⁰

[Table 5 about here]

Table 5 presents the regression results for the day-ahead market in Panel A and the first intra-day market in Panel B. Each cell in the table shows the point estimate and standard error of β from a separate regression of (9) for particular technology type and firm type (fringe or dominant). For example, the estimate in the top-left cell implies that one Euro/MWh increase in the forecastable forward-market price premium is associated with an increase in the log arbitrage by a 0.067 percentage point for fringe wind farms.⁴¹ The results across technology types indicate that fringe firms engage in arbitrage by using a variety of technologies, including wind, cogeneration, demand, and hydroelectric. Among them, wind shows the largest response to the price arbitrage opportunities. This is consistent with our theoretical prediction about the ability to arbitrage—wind has the most flexibility to arbitrage because their capacity constraints tend to be less binding.

A useful comparison is solar. Similar to wind, electricity production from solar is volatile and often does not reach its capacity, which provides an advantage for arbitrage. An important difference to wind is that most solar plants do not participate in the intra-day markets and receive a flat tariff. Therefore, solar

³⁸If firms can forecast the price premiums better than our approach, our approach attenuates β . That is, the estimates from our approach provide a lower bound (in absolute values) for the responses to the forecastable price premiums. We explore alternative forecasting models (e.g. including nonlinear terms and interaction terms with hour dummy variables or week dummy variables), but we find that these alternative methods produce very similar estimates to our main results.

³⁹Including these fixed effects has almost no effects on the point estimate of β . We also run the regression with different dimensions of fixed effects such as hour fixed effects and find that our results are robust to different dimensions of time fixed effects.

⁴⁰We also estimate the standard errors for different levels of clusters. Clustering at the day of sample and at the week of sample produce very similar standard errors to our main results. A potential concern for clustering at the month of sample is that it may not adjust for potential serial correlation between observations within a firm. To examine this point, we estimate the standard errors using the two-way clustering at the month of sample level and at the firm level. We find that the two-way clustering makes little difference in the standard errors for our data.

⁴¹To interpret the magnitude of our estimates, it is useful to report the distribution of the right hand side variables. For $\Delta p_{ht, \text{DA}}$, we have -2.7 (p10), -0.42 (p25), 0.05 (p50), 2.56 (p75), and 5 (p90). For $\Delta p_{ht, \text{I1}}$, we have -3.3 (p10), -1.14 (p25), 0 (p50), 1.55 (p75), and 3.95 (p90), all in euro/MWh. Therefore, considering “one euro/MWh increase” is reasonable given the variation in the price premium from the data.

plants do not have an incentive to arbitrage in the sequential markets. This is consistent with our finding that fringe solar plants show statistically insignificant responses to the arbitrage opportunities. Another useful comparison is wind in 2013. As explained in the previous section, wind plants lost their incentive to arbitrage after the policy change in 2013. In the last column of the table, we find statistically insignificant responses by fringe wind farms in 2013, which is consistent with the fact that the new policy made them have no incentive to arbitrage.

In contrast to the results for fringe firms, we find little evidence of arbitrage for dominant firms. For most technology types, we find insignificant estimates, which indicate that dominant firms do not change their positions in the sequential markets in response to the forecastable arbitrage opportunities. Importantly, we find a statistically significant *negative* coefficient for demand, hydroelectric, and thermal plants, and all technology as a whole. It implies that dominant firms respond to the price premiums in the opposite direction, as compared to the responses by fringe firms that engage in price arbitrage. This finding is consistent with our theory, which suggests that dominant firms that exercise market power withhold sales in the forward markets and sell more in the later markets.⁴²

Summary. To summarize, we find that fringe firms engage in profitable arbitrage, whereas dominant firms do not. It is important to note, however, that we do not show that the amount of arbitrage is optimal, and certainly not enough to fully close the price differences. This fact could be explained by several reasons: transaction costs, institutional constraints on the amount of arbitrage (most likely of regulatory nature, as capacity constraints are usually not binding for wind, even with such levels of arbitrage), and strategic arbitrage. We explore these hypotheses in the counterfactual experiments in the next section, by comparing the observed amount of arbitrage to the equilibrium levels under full arbitrage and strategic arbitrage.

5 Counterfactual Experiments

We find evidence that there is a systematic day-ahead premium in the Iberian electricity market, and that fringe wind farmers appear to arbitrage some of these differences away. How much does this behavior contribute to closing the price gap? What are the welfare implications?

Consider the simple example in Section 2 under two polar cases, one with no arbitrage (Result 1) and

⁴²Note that the negative relationship between the forecastable price premiums and the deviation does not necessarily imply that dominant firms reduce the deviation *because* they expect lower price premiums. The findings from the previous sections indicate that it is likely to be the opposite. When the demand forecast is high, dominant firms withhold their sales in the forward markets, which increases the price premiums. Our regression (9) examines the relationship between the forecastable price premiums and the deviation, which does not necessarily imply the causal relationship.

one with full arbitrage (Results 2). From the equilibrium analysis, it follows that the total quantity produced by the monopolist is lower when there is full arbitrage, as p_1 decreases, but p_2 increases. Given that p_2 determines the final allocation, the quantity produced by the monopolist is further away from the first best under full arbitrage. The intuition is that full arbitrage removes the ability of the monopolist to dynamically exercise market power across sequential markets. Under full arbitrage, the monopolist exercises relatively less market power in the first market, but more market power in the last market. These results suggest that introducing full arbitrage in this market is not necessarily welfare enhancing, as it reduces consumer costs at the expense of lower productive efficiency.

In this section, we quantify this trade-off between consumer surplus and productive efficiency. To do so, we construct a counterfactual model that allows us to empirically assess the interaction between market power and arbitrage. To make the counterfactual experiments empirically relevant, we extend the theoretical model to accommodate for several strategic firms, a flexible marginal cost function, and demand uncertainty.

5.1 Model for Counterfactual Simulations

We construct an empirical model to simulate the effects of alternative arbitrage policies in this market. The model extends the simple framework in several ways. We consider a model with two markets and N strategic firms that are playing a Cournot Nash equilibrium. Firms have capacity constraints. Each firm has a marginal cost curve that is piece-wise linear and continuous. The residual demand that the strategic firms face is also piece-wise linear. Demand in the second period is uncertain, with a commonly known distribution.

We solve the model by backward induction. In the real-time market, firms choose their optimal output levels given their previous commitments, which are the state variable of the game. We solve the last stage as a complementary problem, as in [Bushnell et al. \(2008\)](#), for a given quantity sold in the day-ahead market. For the cases in which there is arbitrage, firms take the amount of arbitrage as given. See Appendix B.1 for the equation details.

In the first stage, firms decide how much energy to sell in the day-ahead market, taking into account the strategic impacts to second-stage payoffs. We solve the optimal quantity in the first market with an iterated best-response algorithm in which firms are maximizing their joint profits between the first and the second market. See Appendix B.2 for the pseudo-code of the iteration.

We consider four different regimes for our simulations:⁴³

⁴³Appendix B details how these counterfactuals mathematically affect the simulation procedure.

- **No Arbitrage:** We consider the case in which the oligopolists participate in sequential markets, and arbitrage is not allowed. Fringe firms passively offer their production at marginal cost.
- **Wind Arbitrage:** We consider the case in which wind farms are arbitraging price differences by, on aggregate, overbidding 20% of their actual expected production. We do not take a stand on whether such 20% is optimal.
- **Strategic Arbitrage:** We consider the case in which there is an arbitrageur who is strategic. It maximizes its profit by extracting rents from arbitrage without fully closing the price gap. Limited arbitrage arises as an equilibrium outcome.
- **Full Arbitrage:** We consider the case in which there is full arbitrage. The arbitrageurs engage in arbitrage so that the price in the first market equals the expected price in the second market.

We use data from the Iberian electricity market to validate the baseline model and assess the welfare implications of these various counterfactuals. To set the different parameters, it is important to emphasize that we exploit the richness of our data and avoid using the model to fit the parameters. Instead, we use direct empirical analogues in the data. Given that our model is admittedly stylized, this provides an extra check on the validity of the framework.⁴⁴

Dominant Firms. We can obtain a reasonable estimate of the marginal cost of production at the generation unit level. We collect unit-level technology parameters, such as heat rates, from the regulatory report by the market operator. We also obtain daily fuel cost data for gas-, coal-, and oil-fired plants and nuclear power plants from the Bloomberg database. Using engineering cost functions for each type of units, we calculate the constant marginal cost for each unit for each day. Based on this procedure, we can construct an increasing step function of the marginal cost curve for each firm that includes their thermal and nuclear power plants.

There are a few important factors to be considered when constructing the marginal cost curve. First, we focus on the marginal cost curve of thermal and nuclear plants owned by dominant firms. The units included in our cost curve produce on average around 40% of all electricity generation in the market. Second, not all power plants are available for a given day. For example, a plant is unavailable when it has a scheduled maintenance. We exclude these units to create the marginal cost curves based on available units for a given day. Third, power plants often have bilateral contracts in addition to their production through the

⁴⁴Here we provide an overview of the steps that we follow to estimate the different parameters. The interested reader can find more details in Appendix C.

centralized markets. Our data include bilateral contracts, which we take into account when building firms' net position.⁴⁵

Finally, we make a simplifying assumption on congestion. As explained above, between the day-ahead and the intra-day markets, the system operator adjusts for the congestion by asking firms to change their production, which can give rise to local market power. Modeling the strategic incentives that arise from congestion, by endogenizing network flows in this market, is beyond the scope of this paper.

Residual Demand. We approximate the residual demand curve faced by dominant firms from the data. Using the bidding data from fringe firms and the approach used in Section 4, we obtain the residual demand curve for the largest four dominant firms. We then calculate b_1 and b_2 , the slopes of the residual demand curves at the market clearing prices for the day-ahead market and the first intra-day market, respectively. It is important to note that our residual demand slopes also take into account any elasticity coming from demand bids. They are also specific to each day and hour, so the slopes capture varying conditions in the competitive environment.

We take the residual demand slopes around the observed equilibrium price, and approximate residual demand linearly. In order to estimate the demand intercept, A , we use day-ahead clearing prices and quantities. For a given day-ahead price p_{1t} , dominant production q_{1t} , and residual demand slope b_{1t} , we calculate $A_t = q_{1t} + b_{1t}p_{1t}$.⁴⁶ The resulting estimates of the term A cannot be directly interpreted. Rather, the term A is an auxiliary construct that allows us to fit the residual demand around equilibrium prices in a parsimonious way. In our approach, this approximation approach is valid as long as our counterfactuals are of local nature, so that the slope estimate for the residual demand is still meaningful.⁴⁷

The empirical evidence from the previous sections shows that wind farms oversell in the day-ahead market. For our counterfactual analysis, we consider arbitrage as a shift in the residual demand curve. We assume that in the data, firms are overstating their wind output by 20 percent in the day-ahead market. Therefore, we set arbitrage to be 20% of the public wind forecast. In other counterfactuals, we investigate alternative market outcomes that endogenize the amount and nature of the arbitrage.

Finally, to model changes in forecasted net demand between the day-ahead market and the real-time market, we use the distribution of changes in scheduled demand minus scheduled wind production. We compute the standard deviation of these changes, on top of other forecastable differences, using a prediction

⁴⁵We treat bilateral contracts as a financial position, but we obtain similar results if we impose that firms always produce at least enough electricity to cover their bilateral contracts, as the constraint is almost never binding in equilibrium.

⁴⁶A similar approach is used in [Bushnell et al. \(2008\)](#).

⁴⁷We have decided to keep the residual demand as locally linear so that our computational model closely matches the theoretical framework. A linear demand also makes the computational simulations less demanding.

model. We find that the residual uncertainty is approximated very well by a normal distribution, and thus use a normal distribution with mean zero and standard deviation equal to 350.⁴⁸ In the simulations, and in order to reduce computation time, we approximate such a distribution with 15 representative draws, which are weighted according to their densities.

5.2 Baseline Results

We present results from the counterfactual model for the period between January 2010 and December 2011. For our baseline results, we simulate the Cournot equilibrium for the case in which wind farms are overbidding, which is the closest to the actual observed behavior.

Figure 6 presents the day-ahead price distribution and day-ahead premium against the actual data over different hours. One can see that the model does a fairly good job at capturing the main patterns in the data. The price distribution is comparable to that observed in our data, in spite of missing some price spikes.⁴⁹ The model also predicts a distribution of price premium that resembles the one in the data. The distribution shows that, in the presence of market power and limited arbitrage, a positive price premium can arise in equilibrium. Table 6 below also shows that the baseline case (wind arbitrage with $b_2 < b_1$) fits well the observed market quantities in the data.

We can also use our simulations to compare predicted arbitrage under alternative assumptions. Our model computes arbitrage outcomes under several alternative hypothesis: 20% of wind production, strategic arbitrage and full arbitrage. Because a price premium is present in the market, we know that wind arbitrage is not full. Yet, how far is it from full arbitrage? How does it compare to the amount of arbitrage that a strategic arbitrageur would do?

Figure 7 presents the distribution of arbitrage amounts under the different counterfactuals considered for the more realistic case in which $b_2 < b_1$. We observe that the observed amount of arbitrage in this market is larger than what a single strategic arbitrageur would do, consistent with firms competing, to some extent, for these arbitrage opportunities. However, the arbitrage amount is less than what would be needed for prices to converge. There are several potential explanations. First, there could be some costs to arbitrage, such as having a person in charge of preparing optimal strategies. Second, such large amounts of arbitrage may be discouraged by the regulator. Finally, whereas fringe firms engage in arbitrage, only a few sophisticated ones exploit the most profitable arbitrage strategies. As shown in the theoretical model, if only few firms

⁴⁸The estimated distribution has little skewness and a kurtosis near 3. See Appendix C for details.

⁴⁹Our simplified model does not have startup costs. It is well known that abstracting from startup costs will limit the ability to generate price spikes (Bushnell et al., 2008; Reguant, 2014). Consistent with the literature, our model overpredicts production at hours of high demand, and thus underpredicts prices.

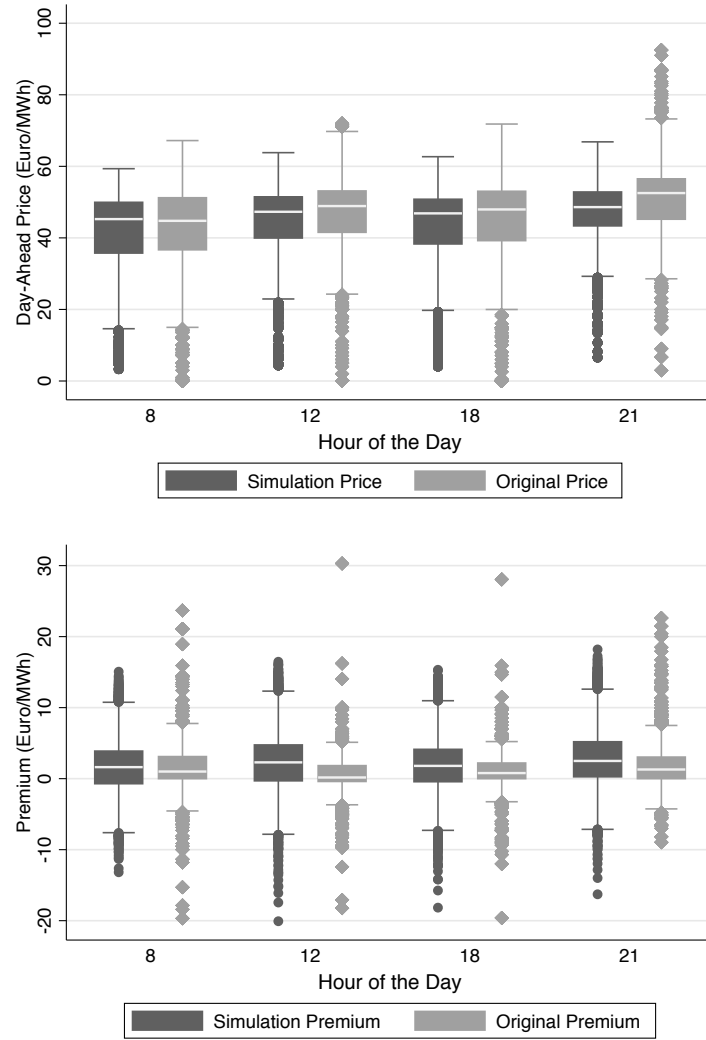


Figure 6: Baseline Simulation Results for $b_2 < b_1$

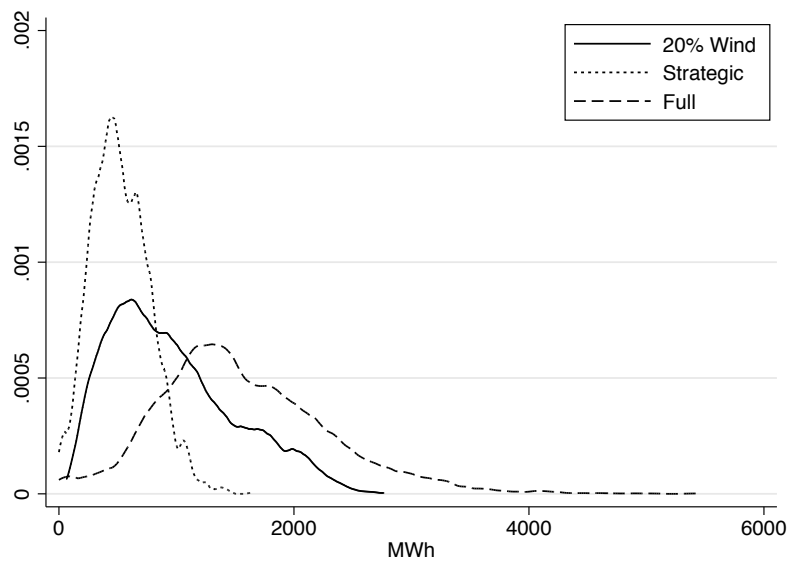


Figure 7: Strategic vs. Full Arbitrage for $b_1 > b_2$

The figures show the distribution of arbitrage under alternative assumptions regarding arbitrage behavior. One can see that the amount of arbitrage set as 20% of wind production appears to be between the amount of arbitrage a single arbitrageur would do, and that under perfect competition.

participate in the market, they may have little incentives to fully close the price gap. In this sense, whereas arbitrage is not monopolistic, it becomes limited endogenously.

5.3 The Role of Arbitrage

We compare the performance in terms of welfare under five different arbitrage regimes (baseline, full arbitrage, no arbitrage, and strategic arbitrage), together with a spot-only and a first-best counterfactual. For each of the counterfactuals, we consider two cases: one in which the residual demand has the same slope in the second market ($b_2 = b_1$), and one in which the residual demand in the second market becomes less responsive ($b_2 < b_1$). As explained above, empirically, the residual demand tends to be less responsive in the second market. For each of the counterfactuals, we compute the price in the day-ahead and the real-time markets (in Euro/MWh), the implied premium (in Euro/MWh), the quantity scheduled by the dominant firms in at each market (in GWh), dominant firm profits (in 000 Euro per hour), as well as the difference in efficiency between the counterfactual and the first-best benchmark (in 000 Euro per hour).

[Table 6 about here]

Table 6 presents hourly averages of the counterfactual results. We also show the results for each hour in appendix tables D.3-D.6. Several findings come out from the counterfactual simulations. First, it is important to note that sequential markets, independent from the form of arbitrage, perform better than a single market. Prices tend to be lower in the presence of two markets, and the deadweight-loss is also lower. This difference in performance is isolating the role of sequential markets in reducing firms' market power, as pointed out by Allaz and Vila (1993).⁵⁰ One can see that market power and its associated inefficiencies go down very substantially, by more than 50%. In the spot only case, the inefficiency is about 17,200 Euros per hour, but it goes down to 7,100 or less in the presence of sequential markets. Whereas these hourly welfare measures might appear to be small, such inefficiencies can add up to annual amounts of roughly 140M and 60M Euro, which are economically significant. The last column of the table shows that the reduction in market power also translates into significant reductions of consumer payments.

Case $b_2 = b_1$. Conditional on having sequential markets, what is the role for arbitrage? For the case in which $b_1 = b_2$, one confirms the intuition from the simple framework. Full arbitrage closes the gap between p_1 and p_2 , and results in the lowest p_1 among the four regimes. Even though the hourly price reduction might seem small in levels, it represents savings of 5 to 6%. As seen in Table 6, such price differences represent substantial hourly consumer savings, which can add up to thousands of Euro per hour. At the same time, however, arbitrage increases total production costs because the quantity produced by the strategic firms inefficiently goes down, due to increased withholding. We find that full arbitrage *increases* market inefficiencies by more than double. This result highlights a key implication of arbitrage in the existence of market power. In a simple model with perfect competition, arbitrage almost always *lowers* market inefficiencies. However, our result shows that such implications can change once we take into account the existence of market power in sequential markets.

Whereas sequential markets improve the final allocation, firms are still able to substantially extract rents, as the discriminating monopolist in the model.⁵¹ These findings relate to the role of price discrimination on welfare, a topic that is relevant beyond sequential markets. It is a well-known result that price discrimination may hurt consumers (as consumer rents are extracted more effectively), but that it might increase overall welfare. In our setting, we find that full arbitrage (no discrimination) reduces efficiency, but to the benefit of consumers (consumer payments go down substantially). These quantifications help highlight the trade-

⁵⁰In our model, we allow the single market to clear under best conditions, after uncertainty has been revealed and with slope equal to b_1 . Therefore, the differences are driven by attenuation of market power.

⁵¹Strategic firms are better off in the case of no arbitrage, as compared to the one with full arbitrage, as seen in Table 6. Interestingly, in the absence of arbitrage, firms make almost as much profit as in the case with a single market, highlighting their ability to extract rents.

off between market efficiency and consumer surplus that is common in other settings when assessing the welfare effects of banning price discrimination (in our case, allowing arbitrage).

Case $b_2 < b_1$. Once we incorporate stickiness into the adjustments that can occur in the real-time market, we find that sequential markets do not contribute as much at approaching the first best, due to the limits on reshuffling in the second market. We also find that the benefits to consumers are smaller. Strategic firms anticipate limited reshuffling in the real-time market and withhold more output in the first market. Because reshuffling is limited, strategic firms are better off by withholding output in a way that avoids a price drop in the first market. Given these anticipation effects, an important implication is that the reductions in consumer costs from full arbitrage are greatly attenuated. In our simulations, consumers see a reduction in prices of less than 50c/MWh even under full arbitrage, which translates into more modest consumer savings.

When assessing the role of arbitrage on efficiency, we find similar results than in the previous case. The case with full arbitrage is the least efficient, due to its interaction with market power. We find that the inefficiency is on average 7,100 Euro per hour under full arbitrage, while it is 5,800 under no arbitrage. These average results mask important heterogeneity across hours. In electricity markets, the degree of market power varies by hours and days, as firms can exercise more market power in hours of high demand. To examine the relationship between the degree of market power and the magnitude of the welfare change, we compare the inefficiencies from arbitrage (inefficiencies under full arbitrage versus inefficiencies under no arbitrage) across hours in Figure 8. Inefficiency from arbitrage tends to be largest at 9 pm, which is the hour of peak demand in the Iberian market. In addition, the skewness of the distribution highlights that the inefficiency from arbitrage is particularly large in hours of extremely high demand, in which firms can exercise substantial market power. No arbitrage is particularly beneficial for these hours because it allows firms to extract rents without sacrificing the efficiency of the final allocation.

Arbitrage and Market Liquidity. Our results are also useful to think about the role of having a responsive secondary market (large b_2). Comparing the case in which $b_2 = b_1$ versus the case in which $b_2 < b_1$, one can see that sequential markets are most efficient at reducing market power when both markets are well participated. First, all arbitrage counterfactuals showcase less inefficiency than in the case in which the second market is less responsive. One can also see that the amount of inefficiency is very low for the case in which the secondary market is responsive and there is no arbitrage, being only 1,300 Euro per hour on average. Additionally, the price effects are substantial, specially when full arbitrage is implemented. This suggests that arbitrage, as a measure to reduce consumer costs, will be most effective when fringe firms

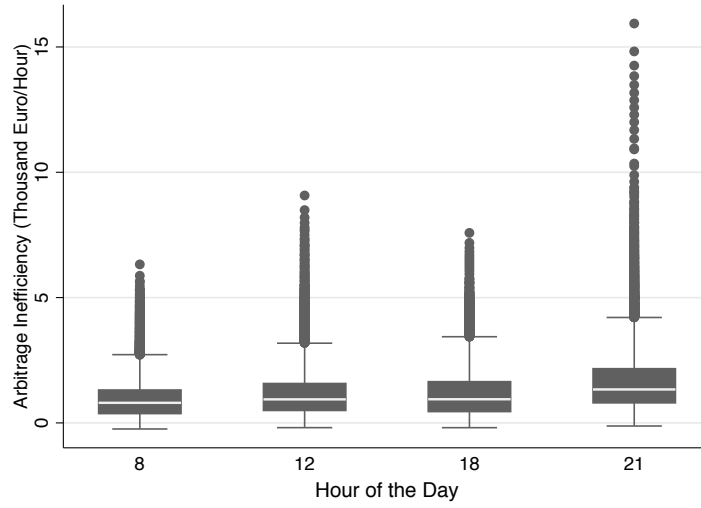


Figure 8: Inefficiencies from Arbitrage (Full vs. No Arbitrage)

actively participate in both the day-ahead and the real-time markets. On the contrary, when the second market is not responsive, the scope for reducing consumer costs through arbitrage is much more limited.

Discussion. Finally, it is important to discuss our assumptions on the costs and benefits of arbitrage in itself, which we assume to be zero. On the benefits side, we assume that arbitrage is not productive in itself. One could argue that arbitrage provides additional benefits, e.g. if arbitrageurs have better information, which could improve the counterfactual outcomes under full arbitrage. Arbitrage could also encourage market participation and potentially make secondary markets more liquid. On the cost side, we assume that arbitrage comes at no additional cost, i.e., arbitrage is frictionless and entails no transaction costs. To the extent that arbitrage entails some real costs, the counterfactual welfare outcomes of full arbitrage would be worsened.⁵² Whereas modeling these elements is not the focus of our paper, it is important to keep in mind that they might increase or reduce the attractiveness of arbitrage in practice.

⁵²For example, whether wind farms or financial agents perform the arbitrage can have real consequences (Jha and Wolak, 2014). In our setting, arbitrage by wind farms could generate dynamic inefficiencies if the system operator is not planning for the right amount of wind production when scheduling reserves. In practice, system operators can circumvent some of these issues by using centralized forecasts. Arbitrage can interact with reliability planning more generally. Parsons et al. (2015) discuss other potential ways in which virtual bidding might be counter-productive when interacting with reliability and ramping constraints.

6 Conclusions

We study price differences in sequential markets. In the context of electricity markets, we find that a declining price path can arise in equilibrium under imperfect competition and limited arbitrage, even in the absence of other potential explanations playing a role, such as information updating or risk aversion. Empirically, we show that the price differences across sequential markets are correlated with traditional measures of market power, and can be interpreted as a lower bound on markups.

In the presence of these price differences, producers appear to engage in profitable arbitrage, specially with their wind farms. We show that the behavior observed at the firm-level is consistent with the hypothesis of market power. Wind farms that do not have substantial levels of market power exploit price differences in these market. On the contrary, dominant firms that have market power underschedule production in the day-ahead market.

Finally, we analyze the interaction of arbitrage and market power with a counterfactual model. We find that market power and arbitrage are empirically relevant factors explaining the price premium. In our baseline counterfactual, we find a day-ahead premium distribution that is comparable to the one in the actual data. We also find that, holding the degree of market power unchanged, arbitrage does not necessarily have positive welfare effects in this market. For the case in which production can be easily adjusted, full arbitrage substantially reduces day-ahead prices, but at the expense of reduced productive efficiency.

References

- Allaz, B. and Vila, J.-L. (1993). Cournot competition, forward markets and efficiency. *Journal of Economic Theory*, 59(1):1–16.
- Ashenfelter, O. (1989). How auctions work for wine and art. *Journal of Economic Perspectives*, 3(3):23–36.
- Bernhardt, D. and Scoones, D. (1994). A Note on Sequential Auctions. *American Economic Review*, 84(3):653–57.
- Birge, J., Hortaçsu, A., Mercadal, I., and Pavlin, M. (2014). The Role of Financial Players in Electricity Markets: An Empirical Analysis of MISO. Technical report, The University of Chicago.
- Borenstein, S., Bushnell, J., Knittel, C. R., and Wolfram, C. (2008). Inefficiencies and Market Power in Financial Arbitrage: A Study of California’s Electricity Markets. *Journal of Industrial Economics*, 56(2):347–378.

- Borenstein, S., Bushnell, J., and Wolak, F. (2002). Measuring Market Inefficiencies in California's Restructured Wholesale Electricity Market. *American Economic Review*, 92(5):1376–1405.
- Bowden, N., Hu, S., and Payne, J. (2009). Day-ahead premiums on the midwest ISO. *The Electricity Journal*, 22(2):64–73.
- Bushnell, J., Mansur, E., and Saravia, C. (2008). Vertical Arrangements, Market Structure, and Competition: An Analysis of Restructured US Electricity Markets. *American Economic Review*, 98(1):237–66.
- Coase, R. H. (1972). Durability and Monopoly. *Journal of Law and Economics*, 15(1):pp. 143–149.
- Coutinho, P. B. (2013). *When-Issued Markets and Treasury Auctions*. PhD thesis, UCLA.
- Cullen, J. (2015). Dynamic Response to Environmental Regulation in Electricity Markets. Technical report, Washington U.
- Fabra, N. and Reguant, M. (2014). Pass-through of emissions costs in electricity markets. *American Economic Review*, 104(9):2872–99.
- Hadsell, L. (2008). Day-ahead premiums on the new england ISO. *The Electricity Journal*, 21(4):51–57.
- Hortaçsu, A., Madanizadeh, S. A., and Puller, S. L. (2015). Power to Choose? An Analysis of Consumer Inertia in the Residential Electricity Market. Technical report, NBER.
- Hortaçsu, A. and Puller, S. L. (2008). Understanding Strategic Bidding in Multi-unit Auctions: A Case Study of the Texas Electricity Spot Market. *RAND Journal of Economics*, 39(1):86–114.
- Jha, A. and Wolak, F. A. (2014). Testing for Market Efficiency with Transactions Costs: An Application to Convergence Bidding in Wholesale Electricity Markets. Technical report, Stanford University.
- Kim, D. and Knittel, C. R. (2006). Biases in static oligopoly models? evidence from the california electricity market. *The Journal of Industrial Economics*, 54(4):451–470.
- Lazear, E. P. (1986). Retail Pricing and Clearance Sales. *American Economic Review*, 76(1):14–32.
- Longstaff, F. A. and Wang, A. W. (2004). Electricity forward prices: A high-frequency empirical analysis. *The Journal of Finance*, 59(4):1877–1900.
- McAfee, R. P. and Vincent, D. (1993). The Declining Price Anomaly. *Journal of Economic Theory*, 60(1):191–212.
- McRae, S. D. and Wolak, F. A. (2009). How do firms exercise unilateral market power? evidence from a bid-based wholesale electricity market. Working paper.
- Nocke, V. and Peitz, M. (2007). A theory of clearance sales. *The Economic Journal*, 117(522):964–990.

- Parsons, J. E., Colbert, C., Larrieu, J., Martin, T., and Mastrangelo, E. (2015). Financial Arbitrage and Efficient Dispatch in Wholesale Electricity Markets. Technical report, MIT Center for Energy and Environmental Policy Research.
- Puller, S. L. (2007). Pricing and firm conduct in california's deregulated electricity market. *Review of Economics and Statistics*, 89(1):75–87.
- Reguant, M. (2014). Complementary Bidding Mechanisms and Startup Costs in Electricity Markets. *The Review of Economic Studies*. Forthcoming.
- Salant, D. J. (2014). Sequential Auctions and Auction Design. Technical report, Toulouse School of Economics.
- Saravia, C. (2003). Speculative Trading and Market Performance: The Effect of Arbitrageurs on Efficiency and Market Power in the New York Electricity Market. CSEM WP 121, University of California Berkeley.
- Weber, R. J. (1981). Multiple-Object Auctions. In Englebrecht-Wiggans, R., Shubik, M., and Stark, R. M., editors, *Auctions, Bidding, and Contracting: Uses and Theory*, pages 165–191. New York: New York University Press.
- Wolfram, C. D. (1998). Strategic Bidding in a Multiunit Auction: An Empirical Analysis of Bids to Supply Electricity in England and Wales. *The RAND Journal of Economics*, 29(4):703–725.
- Wolfram, C. D. (1999). Measuring Duopoly Power in the British Electricity Spot Market. *American Economic Review*, 89(4):805–826.
- Zitzewitz, E. (2003). Who cares about shareholders? Arbitrage-proofing mutual funds. *Journal of Law, Economics, and Organization*, 19(2):245–280.

Table 1: Summary of Predictions

	No Arbitrage (Result 1)	Full Arbitrage (Result 2)	Limited (Result 3)	Strategic (Result 4)	Strategic Wind (Result 5)
Positive Premium	✓	-	✓	✓	✓
Increasing with A	✓	-	✓	✓	✓
Decreasing with b_1	✓	-	✓	✓	✓
Increasing with b_2	✓	-	✓	✓	✓*
Undercomm. by Dominant	✓	✓	✓	✓	✓
Overcomm. by Fringe	-	✓	✓	✓	✓*

Notes: Premium refers to $p_1 > p_2$. Undercommitment by Dominant refers to additional quantity in the second period being positive, $q_2 > 0$. Overcommitment by Fringe refers to additional quantity supplied by the arbitrageur/smaller firm being positive in the first period, $s > 0$. See Table A.1 in the Appendix for numerical expressions under the assumption that $b_1 = b_2$.

*As long as second strategic firm is small enough.

Table 2: Summary Statistics of Main Variables

	Mean	SD	P25	P50	P75
Price Day-ahead (p_1)	44.7	14.1	38.6	48.0	53.5
Price Intra-day 1 (p_2)	43.8	13.9	38.0	46.2	52.5
Day-ahead premium ($p_1 - p_2$)	0.9	4.0	-0.4	0.5	2.6
Average Slope of DA Res. Demand (b_1)	343.2	102.9	281.9	316.4	369.9
Average Slope of I1 Res. Demand (b_2)	69.9	24.6	54.5	66.2	80.7
Demand Forecast (A)	29.3	5.2	24.8	29.4	33.3
Wind Forecast (q^w)	5.0	2.8	2.8	4.5	6.7

Note: Prices in Euro/MWh. Slopes in MWh/Euro. Demand and wind forecasts in GWh. Slope of residual demand computed for the four biggest firms in the market. Number of observations: 26,304.

Table 3: Systematic Day-Ahead Price Premium

	pDA vs. pI1	pDA vs. pI2	pDA vs. pI3	pDA vs. pI4	pDA vs. pI5	pDA vs. pI6	pDA vs. pI7
Hour 1	0.00 [-1.01,2.21]	0.00 [-1.99,4.33]					
Hour 2	0.00 [-1.19,2.62]	0.02 [-2.05,4.49]					
Hour 3	0.00 [-1.44,2.51]	0.00 [-3.40,3.77]					
Hour 4	0.00 [-0.53,3.39]	0.00 [-3.00,4.65]					
Hour 5	0.10 [-0.11,3.23]	0.00 [-2.60,3.00]	0.00 [-3.52,4.11]				
Hour 6	0.00 [-0.52,3.10]	0.00 [-2.56,3.00]	0.00 [-3.64,3.51]				
Hour 7	0.50 [-0.01,3.18]	0.00 [-1.10,3.03]	0.00 [-2.00,3.95]				
Hour 8	0.55 [0.00,3.00]	0.00 [-0.90,2.92]	0.00 [-1.37,2.64]	0.00 [-2.70,4.17]			
Hour 9	0.00 [-0.48,2.05]	0.00 [-1.27,2.42]	0.00 [-1.30,2.56]	0.00 [-2.38,4.54]			
Hour 10	0.00 [-0.54,1.82]	0.00 [-1.08,2.27]	0.00 [-1.12,2.63]	0.03 [-2.00,5.37]			
Hour 11	0.00 [-0.76,1.73]	0.00 [-1.00,2.32]	0.00 [-1.00,2.81]	0.80 [-1.88,7.47]			
Hour 12	0.00 [-0.61,1.66]	0.01 [-0.76,2.28]	0.00 [-0.85,2.64]	0.03 [-1.00,3.44]	0.50 [-1.75,6.82]		
Hour 13	0.00 [-0.68,1.78]	0.04 [-0.82,2.48]	0.10 [-0.68,2.89]	0.24 [-0.97,3.53]	0.83 [-1.82,7.00]		
Hour 14	0.00 [-0.70,1.72]	0.10 [-0.62,2.34]	0.10 [-0.72,2.65]	0.45 [-0.97,3.64]	1.00 [-1.57,6.62]		
Hour 15	0.08 [-0.72,1.72]	0.10 [-0.59,2.29]	0.12 [-0.73,2.71]	0.44 [-0.73,3.56]	1.00 [-1.21,6.75]		
Hour 16	0.10 [-0.50,1.82]	0.31 [-0.46,2.37]	0.07 [-0.44,2.51]	0.51 [-0.55,3.34]	0.15 [-0.93,3.05]	1.05 [-1.70,7.29]	
Hour 17	0.47 [-0.15,2.00]	0.50 [-0.13,2.68]	0.29 [-0.21,2.82]	0.90 [-0.49,3.75]	0.33 [-0.60,3.41]	1.12 [-1.41,7.05]	
Hour 18	0.53 [-0.10,2.00]	0.65 [-0.19,2.68]	0.45 [-0.26,3.00]	1.00 [-0.34,3.96]	0.50 [-0.69,3.66]	0.86 [-1.67,6.50]	
Hour 19	0.75 [-0.01,2.35]	1.00 [-0.07,3.08]	0.74 [-0.09,3.11]	1.00 [-0.20,4.13]	0.50 [-0.75,3.72]	0.45 [-2.00,6.01]	
Hour 20	1.00 [0.00,2.90]	1.08 [0.00,3.85]	1.10 [-0.05,4.15]	1.18 [-0.20,4.86]	0.76 [-0.78,5.00]	0.40 [-2.12,6.78]	
Hour 21	1.06 [0.00,3.00]	1.43 [0.00,4.18]	1.39 [0.00,4.70]	1.50 [-0.01,5.40]	1.12 [-0.33,5.00]	0.52 [-0.85,5.40]	0.54 [-1.83,8.13]
Hour 22	1.55 [0.00,3.71]	1.64 [0.00,5.00]	1.80 [0.00,5.35]	2.04 [0.00,6.12]	1.62 [-0.10,5.43]	1.00 [-0.51,6.34]	1.13 [-1.62,8.64]
Hour 23	1.00 [0.00,2.65]	1.22 [0.00,3.53]	1.13 [0.00,4.00]	1.56 [0.00,4.98]	1.00 [-0.27,4.23]	0.56 [-0.59,4.99]	0.21 [-1.57,6.71]
Hour 24	1.09 [0.00,2.50]	1.31 [0.00,3.26]	1.40 [0.00,3.76]	1.79 [0.00,4.79]	1.69 [0.00,4.23]	1.25 [0.00,5.00]	1.45 [-0.40,7.01]

Note: This table shows the 25th, 50th, and 75th percentiles of the day-ahead price premium for each market by hours. pDA is the day-ahead price and pI1,...,pI7 are the prices in the first,...,seventh intra-day markets. We show the 25th and 75th percentiles in brackets below the 50th percentile. The distributions show that the day-ahead price tends to be larger than the prices in other markets, particularly during later hours of the day.

Table 4: Day-ahead Price Premium, Demand Forecast, and Slope of Residual Demand

Dependent Variable: Day-Ahead Price Premium (EUR/MWh)					
	(1)	(2)	(3)	(4)	(5)
Demand Forecast (GWh)	0.132 (0.025)	0.135 (0.025)	0.103 (0.025)	0.098 (0.024)	-0.002 (0.039)
Slope of Residual Demand in Day-Ahead Market		-0.019 (0.003)	-0.024 (0.003)	-0.040 (0.003)	-0.090 (0.014)
Slope of Residual Demand in Intra-Day Market			0.050 (0.008)	0.065 (0.009)	0.241 (0.050)
Wind Forecast (GWh)				0.365 (0.039)	0.786 (0.121)
Observations	26145	26145	26145	26145	26093
IV	No	No	No	No	Yes

Note: This table shows the estimation results of equation (7). The dependent variable is the day-ahead price premium in EUR/MWh. All regressions include hour of the day fixed effects and week fixed effects. The standard errors are clustered at the week of sample. For the IV regression, we use average daily temperature, maximum daily temperature, minimum daily temperature, hourly temperature, dew points, and humidity interacted with the hour of the day dummy variables to instrument the slopes of the residual demand for the day-ahead market and the intra-day market.

Table 5: Heterogeneity in Arbitrage by Fringe and Dominant Firms Across Production Technologies

Panel A: Day-Ahead Market								
	Wind	Cogen	Demand	Thermal	Hydro	Solar	All Tech	Wind 2013
Fringe Firms	0.067 (0.005)	0.029 (0.003)	0.007 (0.001)	-0.002 (0.005)	0.025 (0.004)	0.005 (0.003)	0.040 (0.003)	0.004 (0.008)
Dominant Firms	0.014 (0.005)	0.002 (0.001)	-0.004 (0.001)	-0.017 (0.014)	-0.005 (0.002)	0.006 (0.004)	-0.063 (0.010)	0.001 (0.005)

Panel B: First Intra-Day Market								
	Wind	Cogen	Demand	Thermal	Hydro	Solar	All Tech	Wind 2013
Fringe Firms	0.098 (0.006)	0.027 (0.003)	0.026 (0.002)	-0.006 (0.003)	0.034 (0.009)	0.007 (0.007)	0.057 (0.003)	0.025 (0.022)
Dominant Firms	0.006 (0.005)	-0.000 (0.003)	0.000 (0.001)	-0.024 (0.004)	-0.003 (0.003)	0.006 (0.005)	-0.131 (0.010)	0.000 (0.011)

Note: This table shows the estimation results of equation (9). The dependent variable is the log deviation between the forward market position and the final position (Panel A) and the log deviation between the first intra-day market position and the final position (Panel B). The independent variable is the forecastable price premium defined in the text. All regressions include firm fixed effects and month of sample fixed effects. The standard errors are clustered at the month of sample. All regressions use data from 2010-12 except that the last column uses wind data in 2013 to test the effect of the policy change. With four decimal points, the estimate for dominant cogeneration plants in Panel A is 0.0015 (0.0012), and the estimate for fringe thermal plants in Panel B is -0.0060 (0.0033).

Table 6: Hourly Welfare Comparison Across Counterfactuals

	p_1 (E/MWh)	p_2 (E/MWh)	Premium (E/MWh)	Q_1 (GWh)	$Q_1 + Q_2$ (GWh)	Dominant Profit (000 E/h)	Δ Ineff. from FB (000 E/h)	Δ Cons. Cost from FB (000 E/h)
First best (b_1)	-	38.2	-	-	15.3	60.5	-	-
Spot only (b_1)	-	46.5	-	-	12.8	123.2	17.2	265.5
Case $b_2 = b_1$								
No arbitrage	45.1	39.5	5.6	13.2	14.9	122.0	1.3	221.8
Str. arbitrage	44.6	40.2	4.4	12.0	14.7	119.0	1.7	204.3
Wind 20%	44.7	39.9	4.9	12.4	14.8	116.4	1.5	210.3
Full Arbitrage	42.5	42.5	0.0	7.7	14.0	100.7	4.8	138.0
Case $b_2 < b_1$								
No arbitrage	44.0	38.7	5.3	13.6	13.9	112.3	5.8	186.1
Str. arbitrage	43.8	40.3	3.5	13.1	13.8	111.4	6.2	180.8
Wind 20%	43.7	41.5	2.2	12.7	13.8	110.0	6.4	178.4
Full Arbitrage	43.5	43.5	0.0	12.2	13.7	108.3	7.1	170.3
Original Data	46.0	44.8	1.3	12.1	13.8	-	-	-

Note: Welfare comparisons use sample of hours (8am, noon, 6pm and 9pm) during January 2010 to December 2011. Profits and costs represent average *hourly* costs. Profits are the sum of net profits across the four dominant firms. The inefficiency measures compares production costs between a given scenario and the first best. Changes in consumer costs are also with respect to the first best, and are assumed to be equal to the market price in the first market multiplied by total demand. The outcomes in the original data are taken from the day-ahead market and the first intra-day.

Appendix

A Derivation of Equilibrium Strategies

A.1 Equilibrium without Arbitrage

Consider the case in which there is no arbitrage. At the second stage, the monopolist sets

$$p_2(p_1) = \frac{p_1 + c}{2}, \quad (\text{A.1})$$

$$q_2(p_1) = b_2 \frac{p_1 - c}{2}. \quad (\text{A.2})$$

From these expressions one can already see that, if the monopolist is a net seller in the first stage and $p_1 \geq c$, then p_2 will be at most p_1 .

At the first stage, optimal strategies imply,

$$p_1^* = \frac{2A + 2b_1c - b_2c}{4b_1 - b_2}, \quad (\text{A.3})$$

$$q_1^* = \frac{(2b_1 - b_2)(A - b_1c)}{4b_1 - b_2}, \quad (\text{A.4})$$

$$p_2^* = \frac{A + 3b_1c - b_2c}{4b_1 - b_2}, \quad (\text{A.5})$$

$$q_2^* = b_2 \frac{A - b_1c}{4b_1 - b_2}. \quad (\text{A.6})$$

Link to Result 1. We can use these expressions to show the results in Result 1. From the above expressions, one can see that the monopolist will be adjusting its quantity upwards in the second market as long as $A > b_1c$, which is a necessary condition for q_1^* to be positive. Under the assumption that the monopolist is a net seller, it also implies that $p_1^* > p_2^*$, as $2A - 2b_1c > A + 3b_1c$. The forward premium is given by, $p_1^* - p_2^* = \frac{A - b_1c}{4b_1 - b_2}$. The premium is increasing in A , decreasing in b_1 and increasing in b_2 , showing the first and second part of Result 1. Looking at the special case of $b_1 = b_2$, the expressions of q_1^* and q_2^* simplify, and $q_1^* = q_2^*$. This implies that, if the forward and real-time market have the same elasticity, then the monopolist will sell the same amount of quantity in both markets. If $b_1 > b_2$ and the monopolist is a net seller (i.e., $A - b_1c > 0$), $q_1^* - q_2^* = \frac{2(b_1 - b_2)(A - b_1c)}{4b_1 - b_2} > 0$. This shows the third and fourth part of Result 1.

A.2 Equilibrium with Arbitrage

Now consider the case in which there is a competitive arbitrageur that can choose a quantity s to arbitrage between markets. We consider a Nash equilibrium in which the arbitrageur takes the actions of the monopolist as given, and the monopolist takes the actions of the arbitrageur as given.

Under the modified demands presented in (5) and (6), optimal strategies at the second stage imply,

$$p_2(p_1, s) = \frac{p_1 + c}{2} + \frac{s}{2b_2}, \quad (\text{A.7})$$

$$q_2(p_1, s) = b_2 \frac{p_1 - c}{2} + \frac{s}{2}. \quad (\text{A.8})$$

At the first stage, optimal strategies imply, for a given level of arbitrage s ,

$$p_1(s) = \frac{2A + 2b_1c - b_2c - s}{4b_1 - b_2}, \quad (\text{A.9})$$

$$q_1(s) = \frac{(2b_1 - b_2)(A - b_1c) - (3b_1 - b_2)s}{4b_1 - b_2}, \quad (\text{A.10})$$

$$p_2(s) = \frac{A + 3b_1c - b_2c + \frac{2b_1 - b_2}{b_2}s}{4b_1 - b_2}, \quad (\text{A.11})$$

$$q_2(s) = \frac{Ab_2 - b_1b_2c + (2b_1 - b_2)s}{4b_1 - b_2}. \quad (\text{A.12})$$

The arbitrage level is given by the non-arbitrage condition $p_2(p_1, s) = p_1$. Setting p_2 equal to p_1 in equation (A.7), we obtain

$$s(p_1) = (p_1 - c)b_2. \quad (\text{A.13})$$

Using this equilibrium condition in expressions (A.9)-(A.12), we obtain

$$p_1^{**} = \frac{A + b_1c}{2b_1}, \quad (\text{A.14})$$

$$q_1^{**} = (b_1 - b_2) \frac{A - b_1c}{2b_1}, \quad (\text{A.15})$$

$$p_2^{**} = \frac{A + b_1c}{2b_1}, \quad (\text{A.16})$$

$$q_2^{**} = b_2 \frac{A - b_1c}{2b_1}, \quad (\text{A.17})$$

$$s^{**} = \frac{b_2(A - b_1c)}{2b_1}. \quad (\text{A.18})$$

Link to Result 2. From $q_1(s)$ and $q_2(s)$ it is clear that quantities in the first market are decreasing in s and quantities in the second market are increasing in s . Comparing p_1^{**} to p_1^* and p_2^* , one can check that p_1^{**} is smaller than p_1^* as long as $A - b_1c > 0$, whereas p_2^* is lower than $p_1^{**} = p_2^{**}$. In particular, $p_1^{**} - p_1^* = -b_2 \frac{A - b_1c}{8b_1^2 - 2b_1b_2} < 0$, and $p_2^{**} - p_2^* = \frac{(2b_1 - b_2)(A - b_1c)}{2b_1(4b_1 - b_2)} > 0$. The monopolist reacts to the arbitrage by lowering total quantity, and $q_1^{**} + q_2^{**} > q_1^* + q_2^*$. In particular, $(q_1^{**} + q_2^{**}) - (q_1^* + q_2^*) = -b_2 \frac{A - b_1c}{8b_1 - 2b_2} > 0$, which completes the results.

A.3 Equilibrium with Limited Arbitrage

Now we include the restriction that $s \leq K$, i.e., there are some institutional constraints that limit the amount of arbitrage. As explained in the main text, the justification for such restrictions can be physical (power

plants cannot arbitrage more than their total capacity), or regulatory. Taking the equilibrium value of s^{**} in the case with unlimited arbitrage, this implies that the constraint will be binding as long as,

$$K < \frac{(A - b_1 c)b_2}{2b_1}, \quad (\text{A.19})$$

in which case $s = K$. Otherwise, the equilibrium features full arbitrage and $s = s^{**}$. Whenever the constraint is binding, the equilibrium becomes,

$$\bar{p}_1^{**} = \frac{2 + bc - K}{3b}, \quad (\text{A.20})$$

$$\bar{q}_1^{**} = A - K, \quad (\text{A.21})$$

$$\bar{p}_2^{**} = \frac{b_2(3b_1 - b_2)c + (2b_1 - b_2)K - A(b_1 - b_2) - b_1^2 c}{b_2(3b_1 - b_2)}, \quad (\text{A.22})$$

$$\bar{q}_2^{**} = \frac{(2b_1 - b_2)K - A(b_1 - b_2) - b_1^2 c}{3b_1 - b_2}, \quad (\text{A.23})$$

$$\bar{s}^{**} = K. \quad (\text{A.24})$$

Link to Result 3. From the equations describing the capacity constrained equilibrium, one can see that, if K is binding, $\bar{p}_1^{**} > \bar{p}_2^{**}$, as $\bar{p}_1^{**} - \bar{p}_2^{**} = \frac{Ab_2 - b_1 b_2 c - 2b_1 K}{4b_1 b_2 - b_2^2} > 0$, whenever the constraint is binding. Trivially, the tighter the constraint K , the more often this will happen. From the constraint itself expressed in expression (A.19), we can also see that it is more likely to bind when A is larger. Taking derivatives with respect to b_1 and b_2 , it is easy to check that the constraint is more likely to bind when b_1 is smaller and b_2 is larger.

A.4 Equilibrium with Strategic Arbitrage

We consider the case in which there is a single arbitrageur. Therefore, it is not optimal for the arbitrageur to close price differences, but rather to close them in an optimal way that maximizes its profits. We calculate the Cournot equilibrium between the monopolist producer (q_1, q_2) and the monopolist arbitrageur (s). The profit of the arbitrageur is given by,

$$\Pi^a = (p_1(q_1, s) - p_2(q_1, s))s,$$

where q_1 is taken as given and p_2 is implicitly defined by the equilibrium price in the second stage as a function of the first stage choices.

In the presence of strategic arbitrage (monopolist), the equilibrium becomes,

$$p_1^a = \frac{4Ab_1 + 2Ab_2 + 4b_1^2c + b_1b_2c - b_2^2c}{8b_1^2 + 3b_1b_2 - b_2^2}, \quad (\text{A.25})$$

$$q_1^a = \frac{(4b_1^2 - b_1b_2 - b_2^2)(A - b_1c)}{8b_1^2 + 3b_1b_2 - b_2^2}, \quad (\text{A.26})$$

$$p_2^a = \frac{3Ab_1 + Ab_2 + 5b_1^2c + 2b_1b_2c - b_2^2c}{8b_1^2 + 3b_1b_2 - b_2^2}, \quad (\text{A.27})$$

$$q_2^a = \frac{b_2(3b_1 + b_2)(A - b_1c)}{8b_1^2 + 3b_1b_2 - b_2^2}, \quad (\text{A.28})$$

$$s^a = \frac{2b_1b_2(A - b_1c)}{8b_1^2 + 3b_1b_2 - b_2^2}. \quad (\text{A.29})$$

Link to Result 4. The price difference is given by $p_1^a - p_2^a = \frac{(b_1+b_2)(A-b_1c)}{8b_1^2+3b_1b_2-b_2^2} > 0$. Therefore, as in Result 1, the price premium is increasing in A and b_2 , and decreasing in b_1 . One can also see that price differences are smaller than in the case where no arbitrage is present, i.e., $p_1^a - p_2^a < p_1^* - p_2^*$.

A.5 Equilibrium with Wind Farms

Assume now that the strategic arbitrageur is producing q^w units of wind, which are exogenously given. The profit of the arbitrageur becomes,

$$\Pi^w = (p_1(q_1, q^w, s) - p_2(q_1, q^w, s))s + p_1(q_1, q^w, s)q^w,$$

where prices are now also affected by wind production.

The wind farmer has now a smaller interest to arbitrage, as arbitraging reduces the price received by wind production. Note that this formulation still allows the arbitrageur to set $s < 0$, in which case the wind farmer would be withholding output from the first market. In equilibrium,

$$p_1^w = \frac{4Ab_1 + 2Ab_2 + 4b_1^2c + b_1b_2c - b_2^2c - 4b_1q^w}{8b_1^2 + 3b_1b_2 - b_2^2}, \quad (\text{A.30})$$

$$q_1^w = \frac{(4b_1^2 - b_1b_2 - b_2^2)(A - b_1c) + 2(2b_1^2 + 5b_1b_2 - b_2^2)q^w}{8b_1^2 + 3b_1b_2 - b_2^2}, \quad (\text{A.31})$$

$$p_2^w = \frac{3Ab_1 + Ab_2 + 5b_1^2c + 2b_1b_2c - b_2^2c - 7b_1q^w + b_2q^w}{8b_1^2 + 3b_1b_2 - b_2^2}, \quad (\text{A.32})$$

$$q_2^w = \frac{b_2(3b_1 + b_2)(A - b_1c) + b_2q^w(b_2 - 7b_1)}{8b_1^2 + 3b_1b_2 - b_2^2}, \quad (\text{A.33})$$

$$s^w = \frac{2b_2(Ab_1 - b_1^2c - 5b_1q^w + b_2q^w)}{8b_1^2 + 3b_1b_2 - b_2^2}. \quad (\text{A.34})$$

Link to Result 5. The price premium is still positive, as $p_1^w - p_2^w = \frac{(b_1+b_2)(A-b_1c)+(3b_1-b_2)q^w}{8b_1^2+3b_1b_2-b_2^2} > 0$. The price premium increases with A and q^w , and decreases with b_1 . The premium increases with b_2 as long

Table A.1: Comparison Across Equilibria when $b_1 = b_2 = b$

	No Arbitrage	Full Arbitrage	Limited	Strategic	Strategic Wind
p_1	$\frac{2A+bc}{3b}$	$\frac{A+bc}{2b}$	$\frac{2A-K+bc}{3b}$	$\frac{3A+2bc}{5b}$	$\frac{3A+2bc-2q^w}{5b}$
p_2	$\frac{A+2bc}{3b}$	$\frac{A+bc}{2b}$	$\frac{A-2K+bc}{3b}$	$\frac{2A+3bc}{5b}$	$\frac{2A+3bc-3q^w}{5b}$
$p_1 - p_2$	$\frac{A-bc}{3b}$	0	$\frac{A-bc-2K}{3b}$	$\frac{A-bc}{5b}$	$\frac{A-bc+q^w}{5b}$
q_1	$\frac{1}{3}(A-bc)$	0	$\frac{1}{3}(A-bc-2K)$	$\frac{1}{5}(A-bc)$	$\frac{1}{5}(A-bc+q^w)$
q_2	$\frac{1}{3}(A-bc)$	$\frac{1}{2}(A-bc)$	$\frac{1}{3}(A-bc+K)$	$\frac{2}{5}(A-bc)$	$\frac{2}{5}(A-bc-\frac{3}{2}q^w)$
$q_1 + q_2$	$\frac{2}{3}(A-bc)$	$\frac{1}{2}(A-bc)$	$\frac{2}{3}(A-bc-\frac{K}{2})$	$\frac{3}{5}(A-bc)$	$\frac{3}{5}(A-bc-\frac{2}{3}q^w)$
s	-	$\frac{1}{2}(A-bc)$	$\frac{1}{2}(3K-2A-bc)$	$\frac{1}{5}(A-bc)$	$\frac{1}{5}(A-bc-4q^w)$

Notes: Limited arbitrage case for the case in which the arbitrage capacity is binding, i.e., $K < \frac{1}{2}(A-bc)$.

as wind production is small enough, i.e., $q^w < \bar{q}^w \equiv \frac{(5b_1^2+2b_1b_2+b_2^2)(A-b_1c)}{17b_1^2-6b_1b_2+b_2^2}$. Wind farm arbitrages price differences as long as it is small enough, i.e., as long as $s^w > 0$, which implies $q^w < \underline{q}^w \equiv \frac{b_1A-b_1c}{5b_1-b_2}$. Otherwise, the farm will no longer arbitrage price differences, and behave as an oligopolistic producer instead, with an incentives to drive the premium up. The monopolist will contribute to the price premium as long as $q_2^w > 0$, which implies $q^w < \bar{q}^w \equiv \frac{(3b_1+b_2)(A-b_1c)}{7b_1-b_2}$. One can check that $\bar{q}^w - \underline{q}^w = \frac{(8b_1^2+3b_1b_2-b_2^2)(A-b_1c)}{35b_1^2-12b_1b_2+b_2^2} > 0$. One can also check that $\bar{q}^w - \tilde{q}^w = \frac{2(b_1-b_2)(8b_1^2+3b_1b_2-b_2^2)(A-b_1c)}{(7b_1-b_2)(17b_1^2-6b_1b_2+b_2^2)} > 0$, and $\tilde{q}^w - \underline{q}^w = \frac{(b_1+b_2)(8b_1^2+3b_1b_2-b_2^2)(A-b_1c)}{(5b_1-b_2)(17b_1^2-6b_1b_2+b_2^2)} > 0$.

A.6 Comparison for special case, $b_1 = b_2$

To gain some intuition on the comparative statics between regimes, it is useful to consider the simplified expressions for the case in which $b_1 = b_2 = b$. Table A.1 presents equilibrium prices and quantities for each of the cases considered. The table is useful to confirm some of the basic predictions of the model. First, one confirms that $p_1 > p_2$ for all equilibria considered, except for the case of full arbitrage, in which case $p_1 = p_2$. One can also see that, whenever positive, the premium is increasing in A , decreasing in b and increasing in q^w .

From the table, the price premium is largest in the absence of arbitrage, as long as q^w is sufficiently small. One can also see that the strategic arbitrageur reduces the price premium compared to the case of no arbitrage, but also that a strategic arbitrageur with wind production will have a lesser incentive to arbitrage. In this simplified example, the wind arbitrageur will have an incentive to arbitrage as long as $q^w < \frac{1}{4}(A-bc)$, i.e., as long as the wind farm is sufficiently small. As a point of comparison, the monopolist total production is $\frac{2}{3}(A-bc)$ in the case of no arbitrage and $\frac{1}{2}(A-bc)$ in the case of full arbitrage.

B Computational details

B.1 Last stage: Capacity-constrained Cournot

We use a mixed integer solver to find the solution to the capacity-constrained Cournot equilibrium. The first order conditions can be expressed as a complementarity problem (Bushnell et al., 2008). We use an equivalent mixed-integer representation, and represent the first-order conditions as a set of constraints.

Assume market demand is $Q = A - bp$ in the day-ahead market. We observe Q , b and p in the data, and back out A to infer the intercept.⁵³ As in Bushnell et al. (2008), we model the marginal cost curve in piece-wise linear segments. For a given firm $i = 1, \dots, N$, segment $j = 1, \dots, J$, and quantity q $c_{ij}(q) = \alpha_{ij} + \beta_{ij}q$. Each segment has a maximum capacity \bar{q}_{ij} . Marginal costs are constructed so that the cost curve is continuous across segments, i.e. $\alpha_{ij} + \beta_{ij}\bar{q}_{ij} = \alpha_{i,j+1}$. The model can also accommodate non-continuous, weakly increasing steps.

Define \underline{u} and \bar{u} a vector of dummies of length $N \times J$ that specifies whether a given step in the marginal cost curve is used at all ($q_{ij} > 0$), and whether it is used at full capacity ($q_{ij} = \bar{q}_{ij}$), respectively. Define $\psi_{ij} \geq 0$ as the shadow value when \bar{u}_{ij} is binding. The equilibrium solves for the optimal vectors \underline{u} , \bar{u} , ψ , and \mathbf{q} . In addition to the range conditions, the equilibrium conditions using a mixed integer formulation are as follows:

$$\text{[FOC 1]} \quad P - \sum_J q_{ij}/b - \alpha_{ij} - \beta_{ij}q_{ij} - \psi_{ij} \leq 0 \quad \forall i, j, \quad (\text{B.1})$$

$$\text{[FOC 2]} \quad P - \sum_J q_{ij}/b - \alpha_{ij} - \beta_{ij}q_{ij} - \psi_{ij} \geq M\underline{u}_{ij} - M \quad \forall i, j, \quad (\text{B.2})$$

$$\text{[Complementarity]} \quad \psi_{ij} - M\bar{u}_{ij} \leq 0 \quad \forall i, j, \quad (\text{B.3})$$

$$\text{[Definition } \underline{u}] \quad q_{ij} - \bar{q}_i \underline{u}_{ij} \leq 0 \quad \forall i, j, \quad (\text{B.4})$$

$$\text{[Definition } \bar{u}] \quad \bar{q}_i \bar{u}_{ij} - q_{ij} \leq 0 \quad \forall i, j, \quad (\text{B.5})$$

$$\text{[Sorting 1]} \quad \bar{u}_{ij} - \underline{u}_{ij} \leq 0 \quad \forall i, j, \quad (\text{B.6})$$

$$\text{[Sorting 2]} \quad \underline{u}_{i,j-1} - \underline{u}_{ij} \leq 0 \quad \forall i, j = 2 \dots J, \quad (\text{B.7})$$

$$\text{[Sorting 3]} \quad \bar{u}_{ij} - \bar{u}_{i,j-1} \leq 0 \quad \forall i, j = 2 \dots J, \quad (\text{B.8})$$

where P is implicitly defined as $P \equiv A/b - \sum_{N,J} q_{ij}/b$, and M is a large value, e.g., $M = 10^6$.

The first condition establishes that marginal revenue is below or equal marginal cost. The second condition establishes that the marginal revenue equals marginal cost whenever a given step is used to produce. The third condition (Complementarity) establishes that the shadow value will only be positive if the step is binding, as it is the shadow value for capacity. This ensures that if a step is used to produce at an interior range, the FOC will be satisfied with equality and the shadow value will be equal to zero. The rest of the equations are used to define the auxiliary integer variables \underline{u} and \bar{u} , as well as to establish the merit order in the supply curve.

⁵³The intercept is not directly interpretable. It is a way to ensure that our local approximation to demand is in the right range. Alternatively, the model can be adapted to have a full representation of the demand curve using a piece-wise linear approximation.

We use a mixed-integer solver (CPLEX) to find a solution to the first-order conditions.

Link to the dynamic model The equations here are defined broadly for a capacity-constrained equilibrium. However, in our setting, the capacity-constrained equilibrium is the second stage of a dynamic game. Two key variables play a role: \mathbf{Q}_1 and s . \mathbf{Q}_1 represents the vector of committed quantities by each firm in the first stage. s determines the amount of arbitrage in the first stage. All these variables are pre-determined at this stage. \mathbf{Q}_1 affects the first order conditions as follows:

$$\text{[FOC 1 Dynamic]} \quad P - \sum_J q_{ij}/b + Q_{i1}/b - \alpha_{ij} - \beta_{ij}q_{ij} - \psi_{ij} \leq 0 \quad \forall i, j, \quad (\text{B.9})$$

$$\text{[FOC 2 Dynamic]} \quad P - \sum_J q_{ij}/b + Q_{i1}/b - \alpha_{ij} - \beta_{ij}q_{ij} - \psi_{ij} \geq M\underline{u}_{ij} - M \quad \forall i, j, \quad (\text{B.10})$$

i.e., it reduces the incentives of the firm to put markups, for $Q_{i1} > 0$.

The amount of arbitrage affects the equilibrium price, which is now defined as $P \equiv (A + s)/b - \sum_{N,J} q_{ij}/b$, as the arbitrageurs buy back their commitments in the second stage, increasing the effective demand. In the simulations, we also allow for exogenous cost shocks to demand, so that $P \equiv (A + s + \epsilon)/b - \sum_{N,J} q_{ij}/b$.

Finally, it is important to clarify how we accommodate for a different b in the second market. We calibrate the residual demand in the second market to go through the same point as the residual demand at the equilibrium price from the first market, absent any arbitrage. Therefore, we set A_2 such that $A_2 - b_2 p_1 = Q_1$. As explained above, A_2 is not directly interpretable, but it provides a convenient computational formulation to model local changes around the residual demand curve.

From the equilibrium price and quantities, we can compute the profit of each firm,

$$\Pi_{i2} = P \cdot \left(\sum_J q_{ij} - Q_{i1} \right) - \sum_J \left(\alpha_{ij} + \beta_{ij} \frac{q_{ij}}{2} \right) q_{ij}$$

Impact of counterfactuals on last stage The main effect of the different counterfactuals is on the amount of arbitrage s . In the no arbitrage case, $s = 0$. In the wind arbitrage (baseline case), $s^w = 0.20q^w$. In the strategic arbitrage case, $s = s^m$, where s is given by the solution in the first stage where the arbitrageur maximizes profits. Finally, the full arbitrage case sets $s = s^{**}$, such that $p_1 = E[p_2]$, and is also determined in the first stage. Importantly, for the purposes of the last stage, s is sunk and given by the first stage.

B.2 First stage: Gauss-Seidel iteration

The pseudo-code in Algorithm 1 describes the iteration procedure, which is a standard Gauss-Seidel procedure that iteratively calculates the best response of each firm until no firm finds a profitable deviation. To define the profit of the firm when computing a best-response, we consider the case in which there is uncertainty being realized between the forward and the real-time market. Therefore, it is an expected profit over several realizations of uncertainty.

Algorithm 1 First stage iteration

```
procedure COURNOTDYNAMIC
  guess  $\leftarrow$  zeros(N,1)
  crit  $\leftarrow$  1000.0
  iter  $\leftarrow$  1
  while iter < maxiter & crit > tol do
    oldguess  $\leftarrow$  guess
    for n = 1 : N do
      guess(i)  $\leftarrow$   $\operatorname{argmax}_{q_i} \sum_{\epsilon} \Pi_i(q_i, \textit{guess}_{-i}, s, \epsilon)$ 
    end for
    crit  $\leftarrow$   $\| \textit{guess} - \textit{oldguess} \|$ 
    iter  $\leftarrow$  iter + 1
  end while
end procedure
```

Define a firm's profit as,

$$\Pi_i(q_i, q_{-i}, s, \epsilon) = p_1(q_i, q_{-i}, s) + \Pi_{2i}^*(q_i, q_{-i}, s, \epsilon),$$

where $\Pi_{2i}^*(q_i, q_{-i}, s)$ is the equilibrium profit in the second stage when q_i, q_{-i} , and s are played in the first stage. The differences across counterfactuals come from the amount of arbitrage. As explained above, $s = 0$ in the case of no arbitrage, and $s = 0.20q^w$ for the case of wind arbitrage. The strategic arbitrage case and the full arbitrage case need to solve endogenously for the amount of arbitrage. In those cases, the algorithm is expanded to also compute the best response for the arbitrageur (who maximizes profits in the strategic case, and equalizes prices in the full arbitrage case). This is implemented adding a fifth firm to the iteration procedure, who is either maximizing arbitrage profits or equalizing prices, taking the actions of the other players as given. The vector *guess* in the algorithm is modified to be of size $N + 1$. The algorithm stops when both firm quantities and arbitrage have converged.⁵⁴

C Estimation details

In this section, we detail how we estimate the different parameters that are part of the model.

C.1 Dominant Firms

Unit-level characteristics, such as generation capacity, type of fuel, thermal rates, age, and location are publicly available for power plant units in the Iberian electricity market.⁵⁵ In addition to the unit-level characteristics, we collect daily fuel cost data such as the price of natural gas, oil, and coal from Bloomberg.⁵⁶

⁵⁴We have examined the properties of the algorithm, and we have found that the algorithm converges smoothly in few iterations (typically less than 10). We have also examined the possibility of multiple equilibria both at the second stage and the first stage using some new tools that we are concurrently developing (Reguant, 2015), and we have not found evidence of multiple equilibria.

⁵⁵Thermal parameters for the Spanish power are obtained from the Ministry of Industry. Parameters for newly constructed combined-cycle plants are based on industry standards.

⁵⁶For coal units, we use the MCIS Index, for fuel units we use the F.O.1% CIF NWE prices, and for gas units we use EEX prices.

For each unit, we calculate the marginal cost of production using the unit-level characteristics, daily fuel costs, and 3) parameters from an engineering model that provides the relationship between the marginal cost, plant characteristics, and fuel costs. Finally, we obtain CO₂ emissions prices and emissions rates at the unit level.⁵⁷ We add emissions costs to the unit level marginal costs, following [Fabra and Reguant \(2014\)](#). This calculation provides daily unit-level marginal costs. We use this information to obtain daily firm-level marginal cost curves for the dominant firms—Iberdrola, Endesa, EDP, and Gas Natural.

This marginal cost curve can deviate from the actual cost curve relevant for our structural estimation for a few reasons. First, marginal costs are likely to be observed with error due to a variety of factors (measurement error in the thermal rates, the presence of transportation or other transaction costs due to long term contracts, etc.).⁵⁸ Therefore, our measures of marginal cost should be interpreted as an estimate that reflects average marginal costs for these technologies, but not necessarily an exact precise measurement of marginal cost for a given unit and/or date. To the extent that marginal costs are not systematically off, this enables us to capture firm-behavior reasonably in our simulations. Second, firms may not use some plants because of maintenance and other reasons. We identify units that are not available at a given date, and exclude these plants from that daily marginal cost curve. Together with these adjustments, we can obtain a daily firm-level marginal cost curve that characterizes the firm's actual marginal cost curve given the assumptions in our calculation.

To finalize the data construction for dominant firms, we also gather data on bilateral contracts. We observe all bilateral contracts tied to units of operation. Firms are required to report their bilateral contracts to the market operator. In the auction, they act as zero-price bids that shift the supply (or price-cap bids that shift the demand). By construction, supply and demand bilateral contracts cancel each other. Bilateral contracts are not given priority in the congestion market, and therefore cannot be used strategically to ensure access to the network. Absent congestion, firms typically produce the amount of power specified by their bilateral contracts. In the simulations, we treat bilateral contracts as a financial position, but we obtain similar results if we impose that firms always produce at least enough electricity to cover their bilateral contracts. In our simulations, we find that the constraint is binding less than 1% of the times.

In the simulations, we simulate firms' choices for their portfolio of nuclear and thermal plants. We take into account the bilateral contracts associated with these plants only. We have also experimented with alternative definitions of forward positions. In particular, we considered including observed production minus bilateral contracts from other units owned by those plants. We found similar qualitative results using this alternative bilateral definition, although it appeared to overstate the degree of market power, leading to larger welfare losses from market power and arbitrage. We believe there are two why such definition of bilateral contracts might overstate market power. First, we do not have financial contracts which can become more of an issue as we add more and more production, and second, such infra marginal quantity assumes that output from other technologies is sunk, but in practice firm choose it endogenously at the market. In any case, qualitative results are similar, although the estimates of market power and inefficiencies from arbitrage are larger, and the predicted price premia larger than in the actual data due to the increased market power.

⁵⁷We obtained EU-ETS permit prices from <http://www.eea.europa.eu/data-and-maps/figures/eua-future-prices-200520132011>: Last accessed on September 7, 2015.

⁵⁸See [Fabra and Reguant \(2014\)](#) for evidence on measurement error for these cost estimates.

C.2 Residual Demand

Our bidding data provide unit-level demand and supply bids for each market and for each hour of production. We aggregate unit-level bids to obtain firm-level bids. We then identify fringe firms' supply bids that are accepted in the market. To obtain residual demand, we subtract fringe firms' accepted supply bids from aggregate demand. Note that we do not need to "estimate" residual demand in this process because we observe firm-level demand and supply bids. The obtained residual demand is usually a downward step function because bidding prices are discontinuous. In addition, the residual demand curve is often nonlinear, which makes the slope of residual demand vary by the price. We use two methods to calculate the slope of residual demand around the market clearing price. The first approach is to fit a quadratic function to the residual demand curve and obtain a local slope at the market clearing price. The second approach is to fit linear splines with knots at 0, 10, 20, 30, 40, 50, 60, 70, 90 Euro/MWh to the residual demand curve.

We use the first approach for our main regression results and simulations. In terms of regression results, the two approaches produce very similar results, as the local slopes that we obtain using the two methods are highly correlated. In terms of simulation results, we find the quadratic approximation to produce simulation results that better fit the actual data. The reason is that the linear spline approximation does not perform as well is that the slopes, even at 10 Euro intervals, can be quite local in nature and often rely only on a limited number of bids to be estimated. Because we use a linear approximation around the equilibrium price, we find that such slopes can produce quite volatile prices and poor fit.⁵⁹ The quadratic fit, on the contrary, provides a smoother fit that can be extrapolated with a linear approximation in a more stable manner.

To approximate the uncertainty in the demand intercept (A), we obtain data from total scheduled demand and renewable power from the market operator from 2007 to 2012. We prefer to use data from the market operator, because the goal is to capture the uncertainty faced by the firms between the day-ahead and the real-time market. To estimate the residual uncertainty faced by the firms, we estimate a predictive model of changes in demand and renewable power between the day-ahead and the intra-day market, as some of the shifts in demand are endogenous to the model, e.g., renewable power has predictable changes in their offered quantity as shown in this paper. The dependent variable is the change in demand between the day-ahead and intra-day market, net of renewable power changes. In the model, we include controls for the hour interacted with day of the week, hour interacted with month, day of the week interacted with month, hour interacted with publicly available demand and wind forecasts, and day of the week interacted with demand and wind forecasts. In some specifications, we also include lagged changes in the scheduled net demand from the same hour on previous days.

The residual uncertainty that results from the above procedure, appears to be normally distributed, but suffers from serious outliers due to the nature of demand and renewable forecasting.⁶⁰ By removing the top and bottom 1% of predictions, we find that the normal approximation used in the simulations fits very well the data.⁶¹ The fact that the residual error is normal looking is reassuring, as it should resemble white

⁵⁹For example, if the local slope at low prices happens to be very inelastic, the model might predict extremely high or extremely low negative prices. However, in reality the inverse residual demand tends to zero as quantity grows, as the price is capped. The quadratic fit will capture such flattening of the inverse residual demand curve more parsimoniously.

⁶⁰Whereas the histogram appears to be bell-shaped, severe outliers bring the skewness to 26 and the kurtosis to 950.

⁶¹After removing outliers, we find low levels of skewness, and kurtosis that are only slightly above 3.

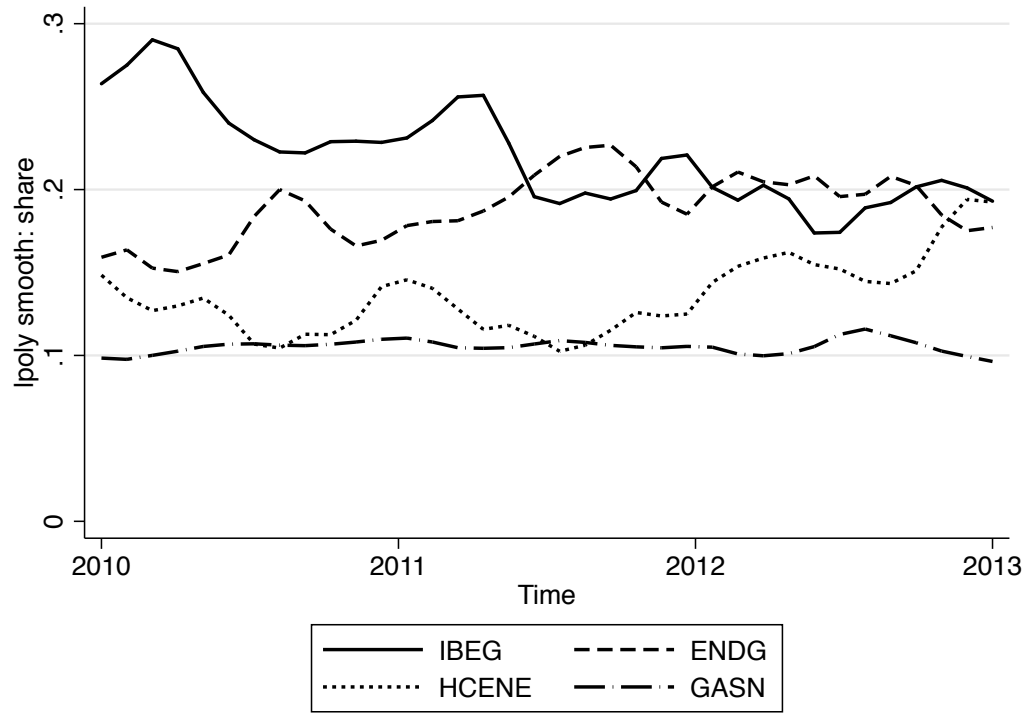


Figure D.1: Market Share of the Four Biggest Producers Over Time

Note: This figure shows the evolution of market share by the four biggest producers. As one can see, there are some fluctuations over time, which are driven by seasonality in electricity demand and hydro power, as well as changes in input costs, given that each firm has a different composition of power plants.

noise if it is unpredictable to the firms. We find that such procedure leads to residual uncertainty with a standard deviation between 300 and 500 MWh, depending on the specification and hour considered. We set the standard deviation in the simulations to 350 MWh, but our results are similar for alternative values of the standard deviation.⁶²

D Additional Figures and Tables

⁶² Alternative standard deviations will affect the dispersion of prices and premiums, but we have not found the simulations to be extremely sensitive to such dispersion. The main quantitative and qualitative results are similar to those reported in the paper.

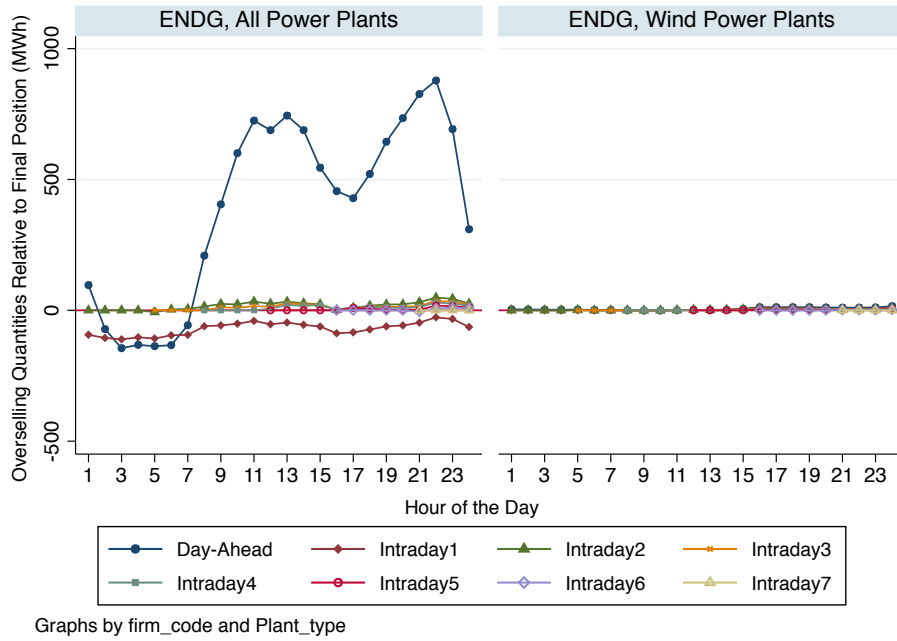
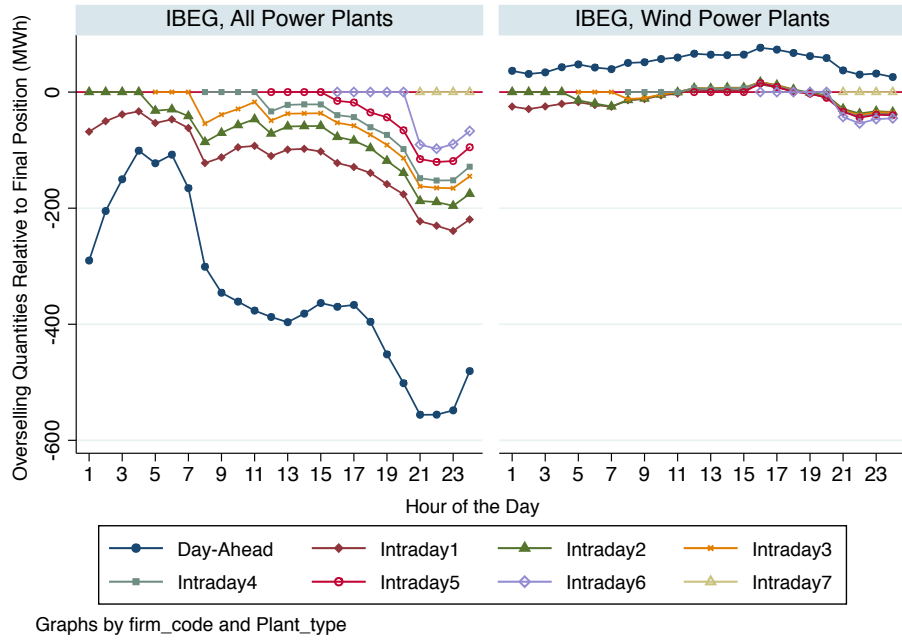


Figure D.2: Overselling and Underselling Relative to Final Positions (in MWh) by Each Dominant Firm
Note: This figure shows average changes in a firm position between a given market and a firm's final commitment. Positive values imply that a firm is promising more production than it actually delivers after all markets close.

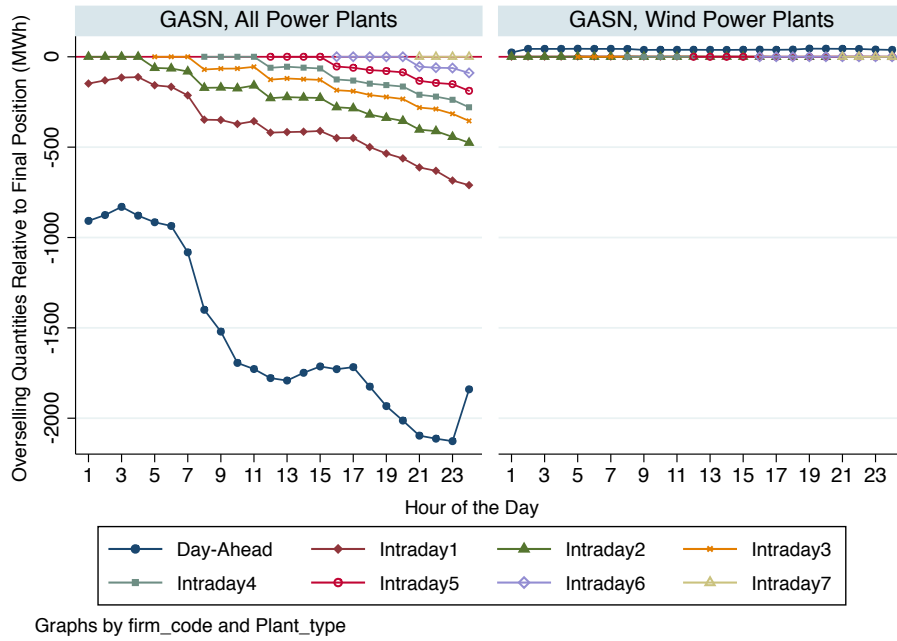
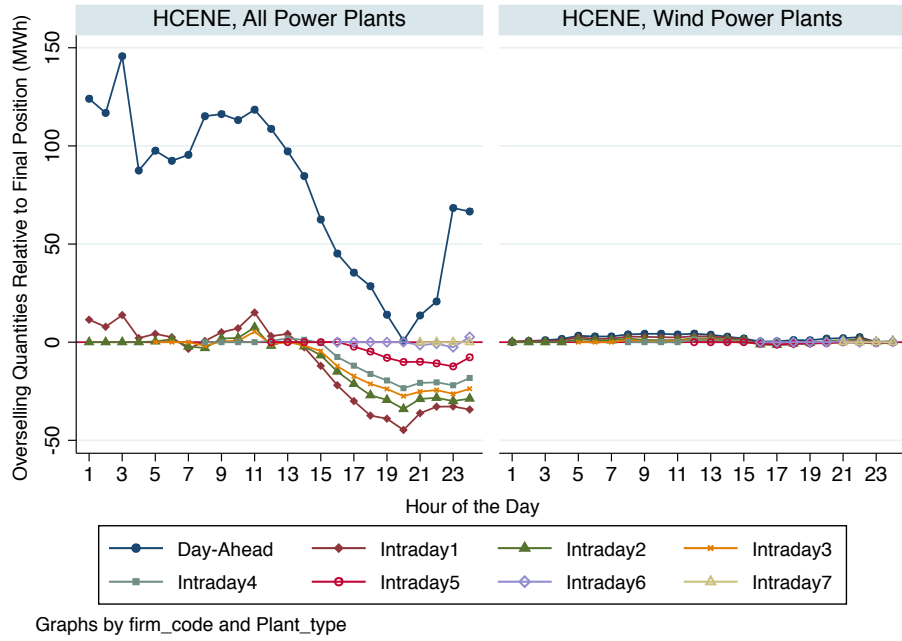
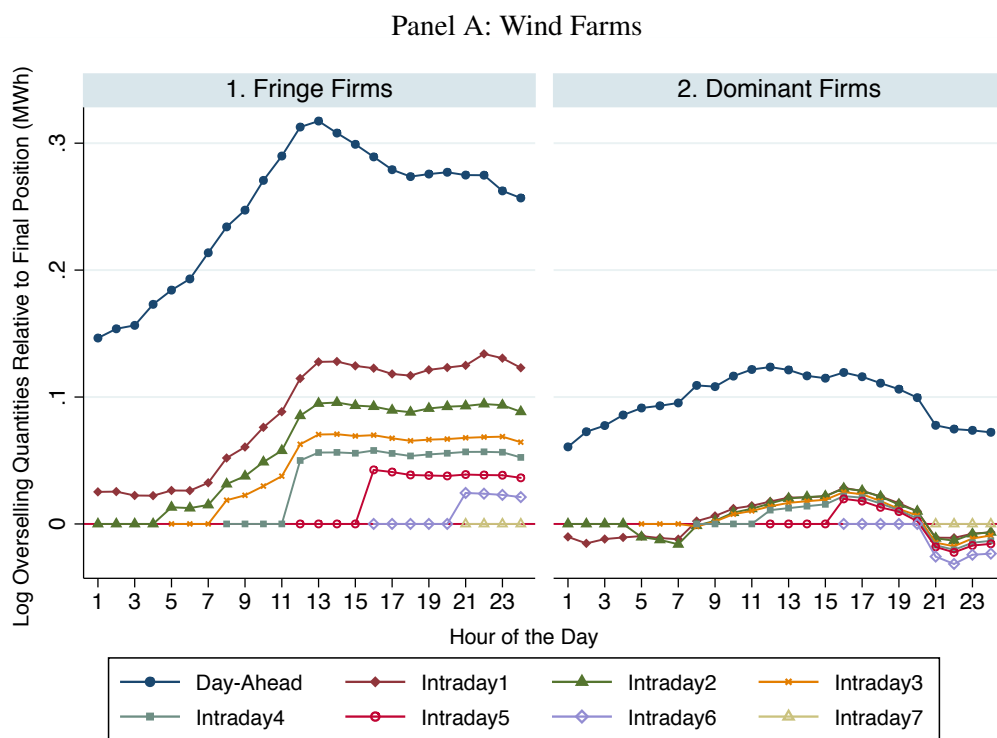
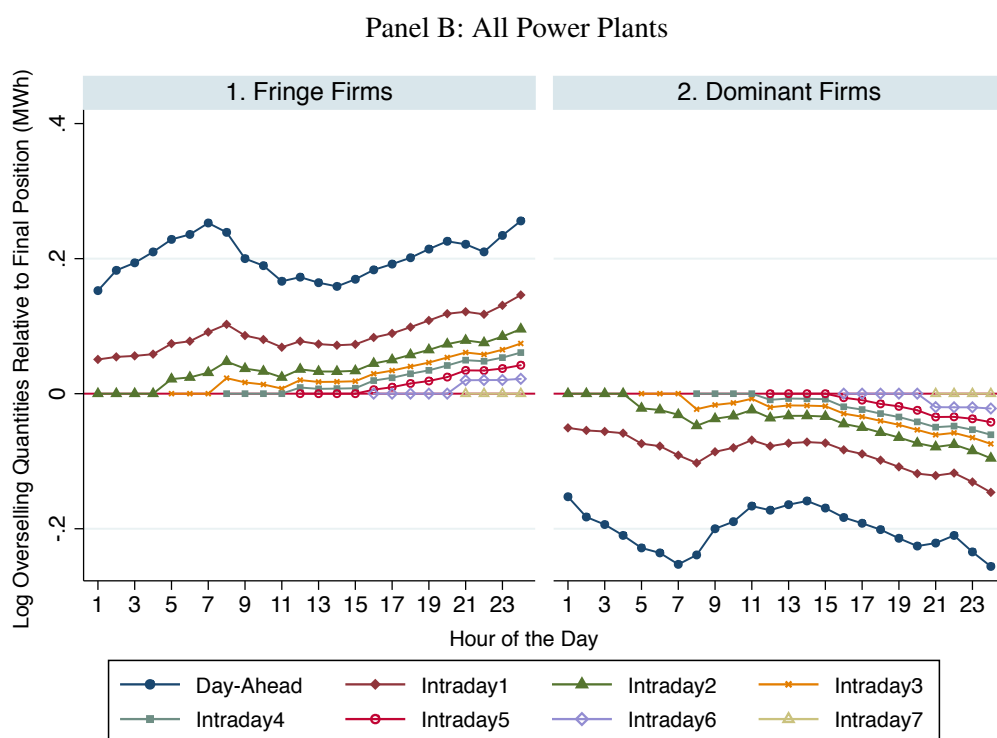


Figure D.3: Overselling and Underselling Relative to Final Positions (in MWh) by Each Dominant Firm

Note: This figure shows average changes in a firm position between a given market and a firm's final commitment. Positive values imply that a firm is promising more production than it actually delivers after all markets close.



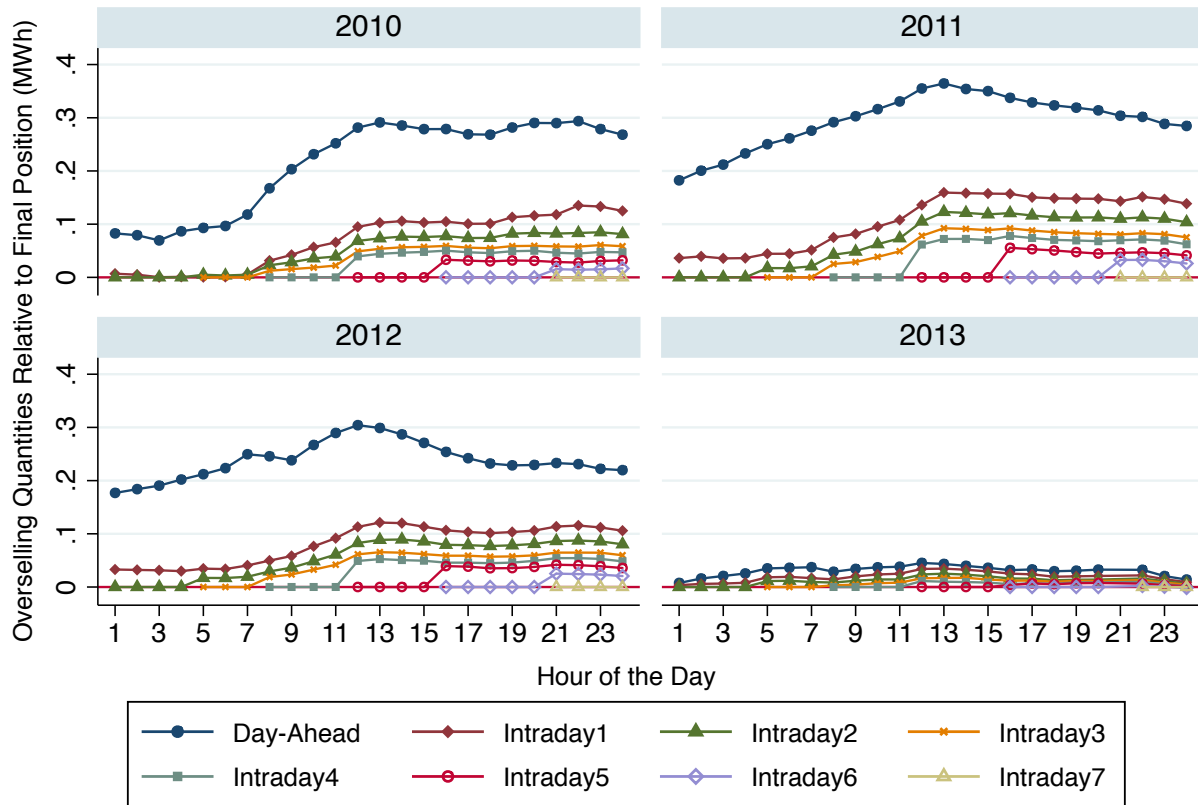
Graphs by Fringe



Graphs by Fringe

Figure D.4: Systematic Overselling and Underselling in Forward-Markets Relative to Final Positions (in Log)

Note: This figure shows average changes in fringe and dominant positions between a given market and their final commitment. Positive values imply that a group is promising more production than it actually delivers after all markets close.



Graphs by year

Figure D.5: By Calendar Year: Overselling in Forward-Markets by Fringe Wind Farms (in Log)

Table D.1: Day-ahead Price Premium, Demand Forecast, and Slope of Residual Demand

Dependent Variable: Day-Ahead Price Premium (EUR/MWh)					
	(1)	(2)	(3)	(4)	(5)
Demand Forecast (Log)	3.50 (0.73)	3.68 (0.76)	2.64 (0.74)	2.56 (0.73)	0.72 (0.99)
Slope of Residual Demand in Day-Ahead Market (Log)		-4.19 (0.58)	-5.13 (0.61)	-7.82 (0.66)	-14.09 (2.15)
Slope of Residual Demand in Intra-Day Market (Log)			1.86 (0.24)	2.35 (0.25)	6.27 (1.28)
Wind Forecast (Log)				1.42 (0.15)	2.52 (0.38)
Observations	26145	26143	26142	26142	26090
IV	No	No	No	No	Yes

Note: This table shows the estimation results of equation (7). The dependent variable is the day-ahead price premium in EUR/MWh. The standard errors are clustered at the week of sample. For the IV regression, we use average daily temperature, maximum daily temperature, minimum daily temperature, hourly temperature, dew points, and humidity interacted with the hour of the day to instrument the slopes of the residual demand for the day-ahead market and the intra-day market.

Table D.2: Heterogeneity in Arbitrage Among Fringe Wind Farms: Large v.s. Small Bidders

Panel A: Fringe wind bidders with capacity less than 300 MWh				
Year	Mean	25th percentile	50th percentile	75th percentile
2010	0.032	-0.002	0.009	0.047
2011	0.026	-0.002	0.010	0.055
2012	0.037	-0.002	0.046	0.072
2013	0.015	-0.006	0.004	0.027

Panel B: Fringe wind bidders with capacity more than 300 MWh				
Year	Mean	25th percentile	50th percentile	75th percentile
2010	0.066	0.005	0.057	0.118
2011	0.095	0.020	0.080	0.160
2012	0.073	0.008	0.059	0.129
2013	0.002	-0.041	0.002	0.048

Note: For each bidder, we calculate the log deviation between day-ahead sales and final output by: $\Delta \ln q_{jht,DA} = \ln q_{jht,DA} - \ln q_{jht,FI}$ for firm j , hour h , day t . Then, we calculate the mean, 25th, 50th, and 75th percentiles of $\Delta \ln q_{jht,DA}$ for each firm by year. There are 46 bidders that manage bids for fringe wind farms, 7 of which have total wind capacity more than 300 MWh. We define these bidders as “large bidders” and other bidders as “small bidders.” For the large bidders and the small bidders, we calculate the average of each statistic by year. For example, the top-left cell in Panel A shows that the average of the mean of $\Delta \ln q_{jht,DA}$ for the small bidders in 2010 is 0.032. The table shows three findings. First, both small and large bidders show systematic overselling in 2010, 2011, and 2012. Second, both types of bidders do not show systematic overselling in 2013, which is the effect of the policy change discussed in the paper. Third, the large bidders oversell more strongly than small sellers.

Table D.3: Welfare Comparison for 8am

	p_1 (E/MWh)	p_2 (E/MWh)	Premium (E/MWh)	Q_1 (GWh)	$Q_1 + Q_2$ (GWh)	Dominant Profit (000 E/h)	Δ Ineff. from FB (000 E/h)	Δ Cons. Cost from FB (000 E/h)
First best (b_1)	-	36.4	-	-	13.6	51.8	-	-
Spot only (b_1)	-	43.5	-	-	11.5	97.5	13.4	200.1
Case $b_2 = b_1$								
No arbitrage	42.3	37.5	4.9	11.8	13.2	97.0	1.1	166.9
Str. arbitrage	41.9	38.0	3.9	10.9	13.1	94.8	1.4	153.7
Wind 20%	42.0	37.8	4.2	11.0	13.1	92.6	1.2	156.8
Full Arbitrage	40.0	40.0	0.0	7.2	12.5	81.0	3.7	102.0
Case $b_2 < b_1$								
No arbitrage	41.2	36.6	4.6	12.2	12.4	89.4	4.4	137.1
Str. arbitrage	41.1	38.0	3.1	11.8	12.4	88.8	4.7	133.3
Wind 20%	41.0	39.4	1.6	11.3	12.3	87.9	4.9	130.8
Full Arbitrage	40.8	40.8	0.0	10.9	12.3	86.5	5.4	125.4
Original Data	41.7	40.2	1.5	11.3	13.4	-	-	-

Note: Welfare comparisons at 8am during January 2010 to December 2011. Profits and costs represent average *hourly* costs. Profits are the sum of net profits across the four dominant firms. Total costs include both dominant firms production costs and fringe production costs.

Table D.4: Welfare Comparison for noon

	p_1 (E/MWh)	p_2 (E/MWh)	Premium (E/MWh)	Q_1 (GWh)	$Q_1 + Q_2$ (GWh)	Dominant Profit (000 E/h)	Δ Ineff. from FB (000 E/h)	Δ Cons. Cost from FB (000 E/h)
First best (b_1)	-	38.6	-	-	15.6	61.5	-	-
Spot only (b_1)	-	46.7	-	-	13.1	124.1	17.3	272.7
Case $b_2 = b_1$								
No arbitrage	45.4	39.9	5.5	13.4	15.2	122.9	1.3	228.2
Str. arbitrage	44.9	40.5	4.4	12.2	15.0	119.9	1.7	210.3
Wind 20%	45.1	40.2	4.9	12.7	15.1	118.2	1.4	217.8
Full Arbitrage	42.8	42.8	0.0	7.8	14.3	101.6	4.8	141.9
Case $b_2 < b_1$								
No arbitrage	44.3	39.1	5.2	13.8	14.1	113.0	5.9	190.1
Str. arbitrage	44.1	40.7	3.4	13.4	14.1	112.1	6.3	185.0
Wind 20%	44.1	41.8	2.3	13.0	14.0	111.2	6.4	183.5
Full Arbitrage	43.8	43.8	0.0	12.5	14.0	109.3	7.1	175.5
Original Data	46.2	45.7	0.5	12.4	13.9	-	-	-

Note: Welfare comparisons at noon during January 2010 to December 2011. Profits and costs represent average *hourly* costs. Profits are the sum of net profits across the four dominant firms. Total costs include both dominant firms production costs and fringe production costs.

Table D.5: Welfare Comparison for 6pm

	p_1 (E/MWh)	p_2 (E/MWh)	Premium (E/MWh)	Q_1 (GWh)	$Q_1 + Q_2$ (GWh)	Dominant Profit (000 E/h)	Δ Ineff. from FB (000 E/h)	Δ Cons. Cost from FB (000 E/h)
First best (b_1)	-	37.9	-	-	15.1	57.7	-	-
Spot only (b_1)	-	45.5	-	-	12.7	115.0	16.0	244.2
Case $b_2 = b_1$								
No arbitrage	44.2	39.0	5.2	13.1	14.8	114.1	1.1	204.3
Str. arbitrage	43.7	39.6	4.1	11.9	14.6	111.3	1.5	188.1
Wind 20%	43.9	39.4	4.5	12.2	14.6	108.8	1.4	192.9
Full Arbitrage	41.8	41.8	0.0	7.7	13.9	94.4	4.4	125.9
Case $b_2 < b_1$								
No arbitrage	43.1	38.3	4.9	13.5	13.8	105.0	5.3	169.9
Str. arbitrage	43.0	39.8	3.2	13.0	13.7	104.1	5.7	165.0
Wind 20%	42.9	41.0	1.9	12.6	13.7	102.9	5.8	162.4
Full Arbitrage	42.7	42.7	0.0	12.1	13.6	101.2	6.5	155.2
Original Data	44.5	43.5	1.0	12.2	13.8	-	-	-

Note: Welfare comparisons at 6pm during January 2010 to December 2011. Profits and costs represent average *hourly* costs. Profits are the sum of net profits across the four dominant firms. Total costs include both dominant firms production costs and fringe production costs.

Table D.6: Welfare Comparison for 9pm

	p_1 (E/MWh)	p_2 (E/MWh)	Premium (E/MWh)	Q_1 (GWh)	$Q_1 + Q_2$ (GWh)	Dominant Profit (000 E/h)	Δ Ineff. from FB (000 E/h)	Δ Cons. Cost from FB (000 E/h)
First best (b_1)	-	40.0	-	-	16.9	70.8	-	-
Spot only (b_1)	-	50.1	-	-	14.0	156.3	22.1	344.1
Case $b_2 = b_1$								
No arbitrage	48.5	41.6	6.9	14.5	16.4	153.9	1.6	287.3
Str. arbitrage	47.8	42.4	5.4	13.1	16.2	149.8	2.1	264.7
Wind 20%	48.0	42.1	5.9	13.6	16.3	146.1	1.9	272.9
Full Arbitrage	45.3	45.4	0.0	8.2	15.4	125.7	6.3	181.7
Case $b_2 < b_1$								
No arbitrage	47.3	40.8	6.4	14.9	15.2	142.0	7.6	246.8
Str. arbitrage	47.0	42.8	4.2	14.3	15.2	140.6	8.1	239.2
Wind 20%	46.9	44.1	2.9	13.9	15.1	138.2	8.4	236.2
Full Arbitrage	46.6	46.6	0.0	13.2	15.0	136.2	9.3	224.8
Original Data	51.8	49.7	2.1	12.6	14.0	-	-	-

Note: Welfare comparisons at 9pm during January 2010 to December 2011. Profits and costs represent average *hourly* costs. Profits are the sum of net profits across the four dominant firms. Total costs include both dominant firms production costs and fringe production costs.