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It's in the Data – Improved Market Power Mitigation in Electricity Markets

KEY MESSAGES

- **Some electricity markets use automated mitigation procedures against market power abuse**
- **This requires marginal cost estimates, which have to be derived from observed auction bids**
- **Current estimation procedures can be improved by using available auction data more systematically**
- **Our redesign delivers more precise estimates and reduces the risk of strategic manipulation by firms**
- **Precise mitigation allows for welfare gains and transfers to buyers in a simulation**

Limited storage capacities, inflexible demand, and high market concentration render power markets especially prone to market power exertion. Existing counter strategies by market regulators include the implementation of price caps (Wilson 2000), stringent application of antitrust policies (Green 1996; Borenstein et al. 1999), and structural market design measures (Mansur 2007; Bushnell et al. 2008; Allaz and Vila 1993; de Frutos and Fabra 2012). In several US markets, system operators go one step further and monitor and mitigate market power in real time in the wholesale auction markets. To that end, system operators implement automated mitigation procedures (AMPs), i.e., algorithms to screen all supply offers, detect undue market power, and override affected offers.

In electricity markets, market power is typically measured by the difference between observed offers and underlying marginal (variable) cost of power production. Therefore, marginal cost estimates should be as accurate as possible to ensure unbiased measurement of market power (Bushnell et al. 2008) and welfare-improving mitigation thereof. However, cost components and power plant characteristics are private information and firms have an incentive to overstate costs. Instead, system operators thus proxy marginal cost of power plants from past offers of the respective plant, which leaves room for strategic manipulation by firms (Shawhan et al. 2011).

We test the accuracy of this best-practice benchmark approach against multiple suggested alternative methods.[1] For this purpose, we employ hourly micro-level bidding data from the Iberian day-ahead electricity market. First, we calculate bottom-up engineering estimates of marginal cost of power production to obtain a unit-specific measure for "true" marginal cost. In a second step, we test the benchmark approach based on past offers and compare the outcomes to the true marginal cost we derived in the first step. We then proceed by testing the accuracy of three alternative estimation methods and assess their performance as compared to the benchmark approach. Finally, we use the best-performing approach for a market mitigation simulation and perform a welfare analysis on the data.

The results of our empirical analysis reveal a low estimation accuracy of the currently applied benchmark approach. For the sample of gas and coal power plants that we analyze, we find a mean deviation of EUR 11.53/MWh between marginal cost estimates following the benchmark approach and true marginal cost. All suggested alternative approaches deliver more precise estimates, with the best approach achieving a mean deviation of only EUR 2.77/MWh. This approach not only delivers the most precise estimates, but by design also limits the scope for strategic manipulation of estimates by firms. Applying this approach to an AMP simulation on the data, we find sizeable overall welfare gains and welfare transfers from supplier to buyer surplus.

AUTOMATED MARKET POWER MITIGATION IN US MARKETS

Overview and Procedure

Multiple independent system operators (ISOs) have implemented automated mechanisms for the mitigation of market power exertion in wholesale auction markets. These ISOs include for instance the California Independent System Operator (CAISO), the Independent System Operator New England (ISO-NE), the New York Independent System Operator (NYISO), and the Midcontinent Independent System Operator (MISO), whose network also covers parts of Canada. They use market observations such as historical bids and prices to construct so-called reference levels. Reference lev-

[1] The underlying working paper (Adelowo and Bohland 2022) can be accessed here: https://www.ifo.de/en/publications/2022/working-paper/redesigning-automated-market-power-mitigation-electricity-markets.

els serve as unit-specific proxies for marginal cost and simulate a competitive offer bid.

The basic condition for mitigation is a market situation that implies potential for market power. This is defined by the ISOs as a structural situation where supply is (temporarily) structurally constrained, e.g., in cases of inelastic excess demand or behind a transmission congestion. If this structural test fails, supply bids are tested against a conduct threshold in order to identify actual exercise of market power. This conduct threshold is usually defined as exceeding a unit's reference level by a certain margin (MISO 2019; ISO-NE 2020; NYISO 2020). However, to avoid excessive intervention, the bids are then tried against an impact test, which tests for the consequential price impact of the problematic bids. If a certain price impact is exceeded, automated mitigation takes place by overriding the respective bids by the unit-specific reference level.

Reference Levels

Our analysis focuses on the estimation of reference levels, which are crucial for efficient mitigation. The method most commonly applied by ISOs uses previously accepted bids from the past 90 days as a basis for a mean or median calculation and adjusts this for fuel price changes (MISO 2019; ISO-NE 2020; NYISO 2020).

Some ISOs impose additional conditions that narrow down the scope of relevant offers to certain periods or hours (e.g., excluding weekends), which reveals a lack of consistency in the definition of which categories of hourly bids are most appropriate as a basis for reference level calculation. The different approaches among the ISOs generally imply differing calculation results.

Further, the current approach bears risks of principal-agent problems arising from hidden information. Shawhan et al. (2011) find evidence in an experimental study that, in case of sufficiently high market power, bidders have an incentive to strategically raise their bids incrementally during unmitigated periods and thus manipulate the calculation basis for reference levels – so-called reference creep. Currently, this issue is addressed in none of the analyzed ISO tariffs; consequently, there are no measures in place to detect or account for reference creep.

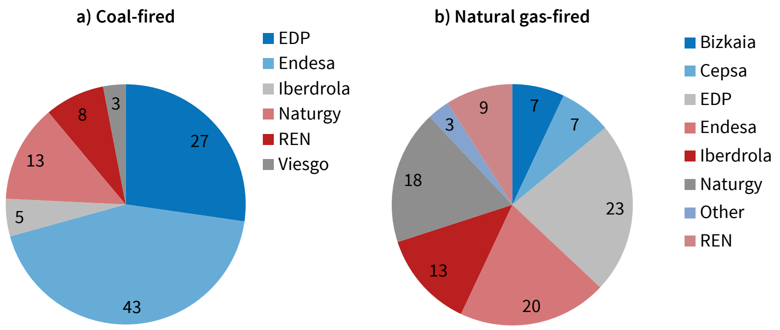
STUDY SETTING

Market Environment

We carry out our study in the Iberian electricity market, the fully integrated and joint administrative market of the geographical regions of Spain and Portugal. Our study concentrates on the market's day-ahead trading, which in 2017

Figure 1

Distribution of Fossil Power Generation across Firms



Note: Numbers in %. Data from 5th of September 2017 to 10th of December 2017.
Source: Authors' calculation.

(year of study) accounted for more than 73 percent of the total demand traded. It is managed by the nominated electricity market operator called Operador del Mercado Ibérico de Energía (OMIE).

On the day-ahead market, wholesale agents submit supply and demand (purchase) bids on electricity transactions for the following day. The daily scheduling horizon consists of 24-hour periods, which are all auctioned in a single session. The maximum possible bid price is regulated to EUR 180.30/MWh (OMIE 2015). Bids generally consist of a price and an amount of power for each scheduling period. OMIE then uses a common European algorithm that sorts all demand bids in order of descending price and all supply bids in order of ascending price for each scheduling hour. The intersection of these two resulting stepwise curves sets the uniform market clearing price (OMIE 2015). The day-ahead market is characterized by the presence of a few large players that dominate the market. Roughly two-thirds of generation can be accounted for by only five company groups that are also vertically integrated, i.e., also act as electricity resellers and retailers (Comisión Nacional de los Mercados y la Competencia 2019). Fossil fuel production, which is at the center of our research, is even more concentrated. Only seven companies accounted for 97 percent of natural gas-fired and 100 percent coal-fired generation in our sample period. Hence, market power concerns are well warranted in this market.

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Micro-level Data

The centerpiece of our data set stems from the Iberian market operator OMIE and comprises all hourly supply and demand side bids in the Iberian day-ahead market. Our analysis focuses on gas and coal power generation in an exemplary week in December 2017. As we need input data that stretches back 90 days, our sample includes all hourly bids from September onward and extends over a period of roughly three months. We focus on gas and coal-fired generation as these technologies are often the price-setting bids in the market and have distinct marginal cost.[2]

Our bottom-up calculation of marginal cost considers individual plant efficiencies and includes fuel costs, cost for carbon emissions, variable O&M costs (Global Energy Observatory 2018; Bloomberg 2019a and 2019b; MIBGAS 2020; Comisión Nacional de Energía 2013; EDP 2018; IEA/NEA 2015; United Nations 2015), as well as all relevant additional taxes and levies (Ley 15/2012 Título I, Título III; Decreto-Lei n.º 74/2013 Artigo 1.º). Generally, marginal cost of coal power plants is subject to less volatility than marginal cost of natural gas-fired plants, which is attributed to the higher volatility of natural gas prices as compared to hard coal prices.

Because part of our analysis is based on company behavior, we account for the company ownership structures behind each plant.

EXISTING AND NOVEL WAYS TO CALCULATE REFERENCE LEVELS

The NYISO Benchmark

To assess the relative performance of our proposed calculation approaches, we first define a best-practice benchmark procedure. To that end, we choose the NYISO method of calculating reference levels of plants' marginal cost, because compared to other ISOs the NYISO provides relatively more information on the composition of the calculation basis (i.e., the set of historical bids that is employed for the estimation of reference levels).

We calculate daily reference levels of fossil plants' marginal cost, which should optimally reflect the bottom-up calculated marginal cost for the respective plant and day. In line with the NYISO procedure, we use historical bids of the plant within the last 90 days as the calculation basis. Within the 90-day period, variation in the underlying fuel costs and cost for carbon emissions is substantial. The reference level calculation therefore includes a daily input price adjustment (for fuel and emission allowances) (NYISO 2020; Fabra and Reguant 2014), which we also empirically control for. Reference levels are then defined as the mean or median (whichever is lower) of all *adjusted* bids in competitive hours within the last 90 days.

Best-response Bidding

The second approach is based on Wolak (2003 and 2007), who derives underlying marginal cost directly from observed bids. We use his model of best-response pricing, which assumes, according to supply function equilibria (Klemperer and Meyer 1989), that a profit-maximizing firm will submit a set of bids that is ex post optimal given any demand shock. Assuming profit-maximizing behavior, we use a firm's hourly profit function to obtain a firm's marginal cost C' for observed residual demand RD, observed bids (optimal offer prices) p^* and its forward contracted quantity QC for any uncertain demand shock η – provided that the forward contracted quantity is known. This contracted quantity may be actual forward sales or resell obligations of vertically integrated retailers (Allaz and Vila 1993; Holmberg 2011; Kühn and Machado 2004; Mansur 2007; Bushnell et al. 2008):

$$(1)\ C'(RD(p^*, \eta)) = p^* - (QC - RD(p^*, \eta)) \,/\, RD'(p^*, \eta)$$

Last, we define daily reference levels for each plant as the mean of all calculated marginal cost estimates for the respective plant and day.

Accounting for Start-up Costs

We now present an extension of the benchmark NYISO method. By following the NYISO approach as presented above, we do not structurally incorporate additional cost components such as start-up costs. Yet, the bids in our calculation basis may partly be driven by the presence of start-up costs. Start-up costs occur when a thermal plant, which is not already running, has to start operation for the next scheduling hour. As our goal is to estimate short-run marginal cost without start-up costs, this is an undesired distortion. From bidding patterns, we can empirically infer which bids are not driven by start-up costs and include only those in the calculation base. Apart from this modification, we use the same calculation basis as in the NYISO benchmark approach and likewise account for changes in input prices.

Clustering

In our final approach, we address several additional shortcomings of the NYISO method, namely the large dispersion of results across power plants,[3] the missing calculation basis for a set of plants, and the potential occurrence of reference creep (i.e., strategic manipulation of the calculation base by firms). We tackle

[2] Unlike, say, hydro power units, whose bids represent the dynamic value of water, which is strongly driven by opportunity cost. For example, hydro plant operators bet on whether higher prices can be achieved if they empty their reservoirs at a later point in time.

[3] This pertains to plants that had been recently inactive in the market, e.g., due to maintenance or to new generating units entering the market.

these problems by departing from the calculation of unit-specific reference levels. Instead, we apply a machine learning algorithm to cluster the 89 power plants in our sample with respect to their two main characteristics relevant for marginal cost, i.e., efficiency (serving also as a simultaneous distinction by fuel type) and size. We use these clusters and calculate reference levels analogously to our start-up cost procedure below, yet not for each power plant individually, but at the cluster level. The cluster reference level is then applicable to all units that fall in the cluster. We thereby solve the problem of large dispersion of estimation errors across plants and receive a more concentrated distribution of results. Moreover, we solve the problem of missing calculation bases for new units entering the market. They can now simply be assigned to one of the clusters.

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

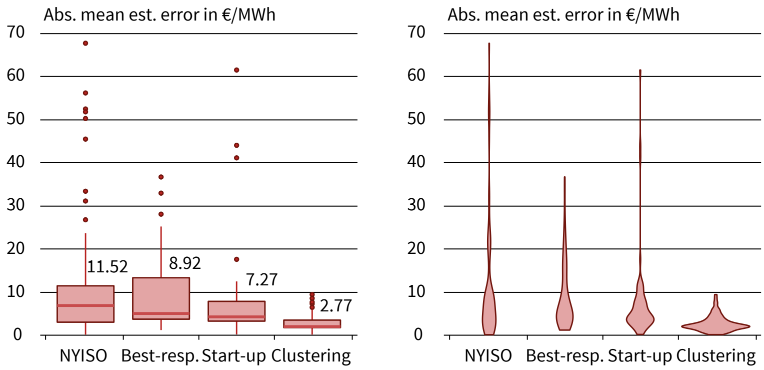
PERFORMANCE RESULTS

Estimation of Reference Levels

As described in detail above, we test the benchmark approach as well as three alternative approaches to calculate reference levels of marginal cost. We assess the performance of the approaches based on two quality criteria. First, we compare the mean absolute error between the derived reference levels and the true marginal cost. We deem absolute values of deviations from the underlying marginal cost to be better suited to assessing the performance of an approach than relative deviations. Ultimately, a regulator applying automated mitigation or a researcher who seeks to receive appropriate estimates of marginal cost is mainly interested in achieving precise estimation. Under- or overestimation are both undesired. The second criterion for the performance of each estimation method is the number of covered plants. The more we restrict the calculation basis within our empirical setting, the lower the number of plants for which we

Figure 2

Accuracy of Marginal Cost Estimation across Approaches in Absolute Terms



Source: Authors' calculation.

obtain reference levels. To ensure stable operation of an AMP, reference levels should at best be available for all power plants in the market.

The benchmark NYISO approach performs worst in precision, exhibiting a mean absolute error across plants of EUR 11.52/MWh (see Figure 2) and covering 82 plants. The best-response approach delivers smaller mean error terms as well as less dispersed outcomes across the coverage of 85 plants. For the start-up approach, we obtain an even lower mean error. This, however, comes at the price of a reduced set of only 72 covered plants due to the restricted calculation basis.

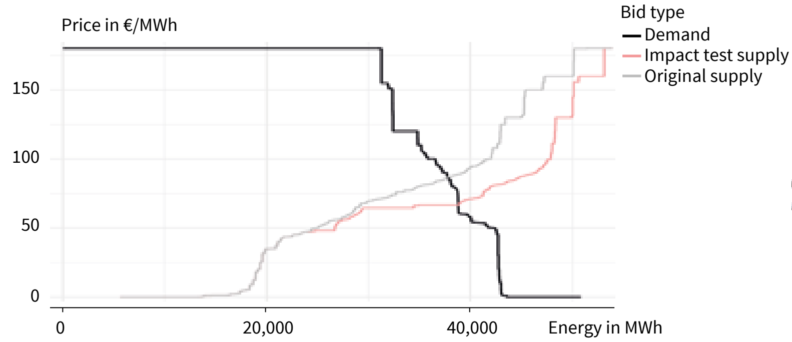
Our last approach overcomes this downside and delivers reference levels for all 89 fossil power plants in our sample. The clustering approach thus covers the broadest set of power plants, which is a crucial aspect for the potential application in AMPs. At the same time, it delivers reference levels that lead to the lowest mean error terms of just EUR 2.77/MWh.

Mitigation Simulation

We have now established the clustering approach as the best-performing way of calculating reference levels due to superiority in precision, coverage, and risk reduction of reference creep. In order to quantify welfare impacts that this mitigation mechanism would have on a previously unmitigated market like the Iberian day-ahead, we apply this approach in a simulation of automated mitigation. For our sample estimation week from December 4 to December 10, we apply the multi-step mitigation procedure laid out above.

Mitigation. For hours in which both the conduct test and impact tests fail, we perform actual bid mitigation of problematic bids to their respective reference levels. For mitigated hours, the new clearing price becomes the one calculated in the impact test, as illustrated in Figure 3. Out of the 168 hours in our weekly sample, mitigation occurs in 4 hours, which appears as a somewhat reasonable incidence of market interference.

Figure 3
Original and Resulting Market Clearing Curves of the Impact Test



Note: The impact test is for an exemplary hour: 2017-12-06 Hour 20. The respective clearing price is at the intersection with the demand curve. In mitigated hours, the supply curve and clearing price of the impact test become effective.
Source: Authors' calculation. © ifo Institute

Welfare impacts. For the 4 mitigated hours, we find a notable, deadweight-loss-decreasing rise in market efficiency, amounting to 6.57 percent increased social welfare for these hours. This goes along with sizeable welfare transfers from supplier surplus to buyer surplus.

Welfare robustness. We have to consider, however, that the reference levels to which non-competitive bids are mitigated are only a proxy for marginal cost. This may cause the true supplier surplus and true welfare impacts, based on true marginal cost, to deviate. We therefore calculate the true welfare impacts as a robustness check based on our bottom-up engineering estimates of marginal cost. The resulting true social welfare increase is of similar, sizeable magnitude at 6.51 percent.

POLICY CONCLUSION

Our findings contribute to improved automated mitigation of market power in electricity markets. Automated mitigation procedures (AMPs) find wide application in US power markets and are designed for real-time detection and mitigation of market power abuse. AMPs rely on so-called reference levels, supposed to approximate marginal cost, to evaluate the competitiveness of a bid and to mitigate it by overriding. We design alternative approaches to derive reference levels from producers' supply offers. Improved accuracy of marginal cost estimates allows for both facilitated detection of market power as well as refined and more targeted mitigation. Refined mitigation protects buyers from excessive redistribution of rents to suppliers, but in a given mitigation setting likewise protects suppliers from excessive and unjust mitigation of competitive offers.

By employing a large set of micro-level data from the Iberian day-ahead market, we can show that current best practices of AMPs can be redesigned to substantially improve mean errors in marginal cost estimation from EUR 11.52/MWh to EUR 2.77/MWh. Our suggested redesign builds on already existing instruments, which enhances its implementability. Our redesign not only delivers higher precision than existing approaches but also counteracts reference creep, i.e., the strategic manipulation of bids to evade mitigation. System operators should hence consider the adoption of this approach for AMP purposes. We finally apply our preferred redesign in a simulation setting of AMPs and find notable transfers from supplier to buyer surplus and overall welfare increases of roughly 6.5 percent. The surplus transfer to the buyer side can, if prices are passed through, allow for lower consumer retail prices.

Our study contributes to potential improvement of policies in electricity markets with market power issues, e.g., related to locational pricing, pivotal supply, and concentrated or integrated market structures. The EU, for instance, has signaled in light of REPowerEU initiatives that it will reassess locational pricing in the EU and "ensure an up-to-date and robust framework to protect against [market power] abuse [...] in periods of high prices and market volatility" (European Commission, Directorate-General for Energy 2022, 11). Any applied frameworks will have to make sure (1) that supply bids are fair and competitive, and (2) that underlying fluctuations in input prices are taken into account to not harm the profitability of producers. AMPs are a suitable tool to achieve both. The recent power crisis due to the Russo-Ukrainian war is just an extreme example of flexible fossil power generation being the marginal technology and causing high uniform clearing prices with high auction profits for cheap inframarginal producers (so-called windfall profits). This can potentially be exploited especially by firms who can strategically deploy a technology portfolio. These constellations will continue to occur in decarbonizing electricity systems, which will depend even more on flexible, quickly dispatchable generators at the price-setting margin to balance increasing shares of cheap, volatile renewables (if storage capacities are limited) – hence, raising the risk of market power abuse in uniform price auction markets. Graf et al. (2021) point out how this will heighten relevance of AMPs to work properly in increasingly decarbonized systems.

Our findings provide system operators with improved, easily implementable estimation techniques of power plants' marginal cost and with more accurate methods for monitoring and real-time mitigation of market power. Equipped with precise marginal cost estimates, system operators can apply automated mitigation more stringently, and achieve increased market efficiency and reduced costs for buyers. At the same time, improved accuracy benefits producers as the scope for unjust mitigation based on flawed marginal cost estimates is reduced. The main use cases for our approaches are automated procedures for market power mitigation in spot, balancing, and reserve electricity markets. Yet, they can likewise find application in other markets, e.g., for monitoring in renewable energy tenders or price and market power surveillance in rail and air traffic.

REFERENCES

Adelowo, J. and M. Bohland (2022), "Redesigning Automated Market Power Mitigation in Electricity Markets", *ifo Working Paper* 387.

Allaz, B. and J. L. Vila (1993), "Cournot Competition, Forward Markets, and Efficiency", *Journal of Economic Theory* 59, 1–16.

Bloomberg (2019a), *EEXX03EA Index via Bloomberg Terminal Access*.

Bloomberg (2019b), *MFE1 COMB Comdty Index via Bloomberg Terminal Access*.

Borenstein, S., J. B. Bushnell and C. R. Knittel (1999), "Market Power in Electricity Markets: Beyond Concentration Measures", *The Energy Journal* 20(4), 10.5547/ISSN0195-6574-EJ-Vol20-No4-3.

Bushnell, J. B., E. T. Mansur and C. Saravia (2008), "Vertical Arrangements, Market Structure, and Competition: An Analysis of Restructured US Electricity Markets", *American Economic Review* 98, 237–266.

Comisión Nacional de Energía (2013), *Spanish Energy Regulator's National Report to the European Commission*, https://www.cnmc.es/sites/default/files/1797558_8.pdf.

Comisión Nacional de los Mercados y la Competencia (2019), *Informe de Supervisión del Mercado Peninsular Mayorista al Contado de Electricidad Año 2017*, https://www.cnmc.es/sites/default/files/2322298_0.pdf.

De Frutos, M. A. and N. Fabra (2012), "How to Allocate Forward Contracts: The Case of Electricity Markets", *European Economic Review* 56, 451–469.

EDP (2018), *Annual Report 2017*, https://www.edp.com/sites/default/files/annual_report_edp_2017_with_minutes_.pdf.

European Commission, Directorate-General for Energy (2022), *Short-Term Energy Market Interventions and Long-Term Improvements to the Electricity Market Design – A Course for Action*, COM/2022/236 final, https://eur-lex.europa.eu/legal-content/EN/ALL/?uri=COM:2022:236:FIN.

Fabra, N. and M. Reguant (2014), "Pass-Through of Emissions Costs in Electricity Markets", *American Economic Review* 104, 2872–2899.

Global Energy Observatory (2018), *Power Plants*, https://globalenergyobservatory. org/.

Graf, C., E. La Pera, F. Quaglia and F. A. Wolak (2021), "Market Power Mitigation Mechanisms for Wholesale Electricity Markets: Status Quo and Challenges", *Program on Energy and Sustainable Development Working Paper*, https://fsi.stanford.edu/publication/market-power-mitigation-mechanisms-wholesale-electricity-markets-status-quo-and.

Green, R. (1996), "Increasing Competition in the British Electricity Spot Market", *The Journal of Industrial Economics* 44, 205-216.

Holmberg, P. (2011), "Strategic Forward Contracting in the Wholesale Electricity Market", *The Energy Journal* 32, 169-202.

IEA/NEA (2015), *Projected Costs of Generating Electricity* 2015, https://www.iea.org/reports/projected-costs-of-generating-electricity-2015.

ISO New England Inc. (ISO-NE, 2020), *Transmission, Markets, and Services Tariff*, https://www.iso-ne.com/static-assets/documents/regulatory/tariff/sect_3/mr1_append_a.pdf.

Klemperer, P. D. and M. A. Meyer (1989), "Supply Function Equilibria in Oligopoly under Uncertainty", *Econometrica* 57, 1243–1277.

Kühn, K. U. and M. Machado (2004), "Bilateral Market Power and Vertical Integration in the Spanish Electricity Spot Market", https://ssrn.com/abstract=608249.

Mansur, E. T. (2007), "Upstream Competition and Vertical Integration in Electricity Markets", *The Journal of Law and Economics* 50, 125–156.

MIBGAS (2020), *MIBGAS Data 2017, Trading Data, Product GDAES D+1*, https://www.mibgas.es/en/file-access?path=AGNO_2017/XLS.

MISO (2019), *Business Practices Manual – Market Monitoring and Mitigation, Manual No. 009-r15*, https://cdn.misoenergy.org//BPM percent20009 percent20 percent20Market percent 20Monitoring percent20and percent-20Mitigation49600.zip.

NYISO (2020), *NYISO Market Administration and Control Area Services Tariff*, https://nyisoviewer.etariff.biz/ViewerDocLibrary/MasterTariffs/9FullTariffNYISOMST.pdf.

OMIE (2015), *Daily and Intraday Electricity Market Operating Rules*, December, https://www.omie.es/sites/default/files/2019-12/20151223_reglas_mercado_ingles.pdf.

Shawhan, D. L., K. D. Messer, W. D. Schulze and R. E. Schuler (2011), "An Experimental Test of Automatic Mitigation of Wholesale Electricity Prices", *International Journal of Industrial Organization* 29, 46–53.

United Nations (2015), *2015 United Nations Energy Statistics Yearbook*, https://unstats.un.org/unsd/energy/yearbook/2015/08i.pdf.

Wilson, J. F. (2000), "Scarcity, Market Power, and Price Caps in Wholesale Electric Power Markets", *The Electricity Journal* 13(9), 33–46.

Wolak, F. A. (2003), "Identification and Estimation of Cost Functions Using Observed Bid Data", *Advances in Economics and Econometrics: Theory and Applications, Eighth World Congress* 2, 133.

Wolak, F. A. (2007), "Quantifying the Supply-Side Benefits from Forward Contracting in Wholesale Electricity Markets", *Journal of Applied Econometrics* 22, 1179–1209.