BIDDING BEHAVIOR IN SEQUENTIAL AUCTIONS FOR WHOLESALE ELECTRICITY: A CASE STUDY OF THE NYISO

by

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ABSTRACT

This paper investigates the process by which bidders in the NYISO (New York Independent System Operator) market update their bids between the Day-ahead and Hour-ahead markets. Observed bids for the ten largest bidders over the years 2002-2010 are used to investigate the extent to which observed bids into both the Day-ahead (DA) and Hour-ahead (HA) markets are consistent with joint profit maximization in the two markets. Theory about single period bidding behavior developed in the California spot electricity market (Wolak, 2003) and Texas electricity balancing market (Hortaçsu and Puller, 2008) is extended to the two-period case specific to the NYISO market. While uncertainty comes from both the behavior of competing firms and additive uncertainty in demand, bidder behavior is broadly consistent with expected profit maximization against a stochastic piece of demand that is additively separable.

CHAPTER 1

INTRODUCTION

This paper investigates the process by which bidders in the NYISO (New York Independent System Operator) market update their bids between the Day-ahead (DA) and Hour-ahead (HA) markets to maximize joint profits. Observed bids for the ten largest bidders over the years 2002-2010 are used to investigate the extent to which observed bids into both the Day-ahead and Hour-ahead markets are consistent with expectations based on a model of joint profit maximization in the two markets. Profit-maximization is not directly tested but rather an explicit assumption used to motivate behavioral expectations. Theory about single period bidding behavior developed in the California spot electricity market (Wolak, 2003) and Texas electricity balancing market (Hortaçsu and Puller, 2008) is extended to the two-period case specific to the NYISO market. The theoretical formulation allows each firm to incorporate information available after the DA auction but before the HA auction into bids submitted in the HA market. Bidders submit piecewise defined offer curves for each generator under their control, comprising a portfolio of generating assets. To aid the analysis, a piecewise-defined functional form was chosen to decompose bids into four parameters that reflect the theory behind optimal bid construction developed in Wolak (2007). Each firm's total bid, comprised of all generating assets under their control, is analyzed as a single strategy.

Using DA auction results and exogenous information available to bidders between the two auctions, this paper analyzes variation in the parameters from the curve fit to characterize bidder behavior. Six propositions developed as an extension of the model developed by Coase (1972) were tested; the results are largely inconclusive.

While most firms submit steeper bids into the DA market during hours when their market power as measured by a Lerner index, is higher, half of the sample did not discernibly respond. The Lerner index calculation indicates market power is present in the NYISO at levels consistent with other studies of domestic electricity markets. Half of the sample also did not appear to respond to results from the DA market simulation in their forward-market position price, P_B, as expected. The most convincing result from the study is the wholesale lack of impact of the net virtual supply cleared in the DA market, where zero of the ten firms in the sample had statistically significant results.

The mixed results could be due to the small sample size comprised solely of the ten largest firms in the NYISO. Because the New York generation portfolio is diverse, firm heterogeneity at the top is high and is driving the mixed results. This could also be due a misspecification of offer curves by the chosen parametrization. Both are likely fruitful directions for future research, where the sample size could be extended to include all firms bidding into the NYISO. It is likely that smaller firms own fossil-fuel based generators that match the theory established in this paper more directly than nuclear and hydroelectric generators that dominate the largest firms.

Electricity market outcomes have been a source of considerable interest in the last two decades, as wholesale markets in the U.S. transitioned to competitive auction markets. Understanding the nature of competition in these auction markets therefore has broad market design relevance. Previous empirical studies of electricity auctions have utilized observed bids along with firm marginal cost data to quantify the extent to which firms exercise unilateral market power[1] by simultaneously raising prices and restricting output. By simulating the price setting process using observed electricity

[1] Wolak (2003), Wolfram (1998).

loads cleared in the market, researchers can identify a firms ex post 'residual demand' and measure the extent to which observed bids capture monopoly rents[2]. Previous studies have focused on the balancing market for energy[3], when in fact the majority of electricity markets run two sequential auctions for energy procurement in each hour.

Previous studies of the New York electricity market have looked at the impact of virtual bidding on forward premiums[4], volatility[5] and market power[6] using price data. Zhang (2009) uses Day-ahead bids to study the mechanism by which generators in the NYISO choose into a bidding 'price group'. No studies have linked the two auctions by observing bids into the Day-ahead market and Hour-ahead market in sequence.

As modern electricity markets evolve, it is clear that restructuring has not abolished regulation but rather replaced direct rate-based regulation of vertically integrated firms with more nuanced regulation to mitigate the exercise of market power. Without understanding the mechanisms driving optimal bidding behavior in electricity auctions, regulation is difficult and creates costs both on the institutions charged with maintaining a competitive market, and participants who must identify bounds on behavior that allow for long-term profit and viability.

The results of this paper suggest that there is room to mitigate competition in the NYISO. Firms are using their market power to construct optimal bids over the two auctions, and thus extract additional rents from consumers. The introduction of additional players, whether speculators or new generators, would reduce the unilateral

[2]Wolak (2001) uses an inverse semi-elasticity to measure this under the assumption of profit maximization.

[3]Hortaçsu and Puller (2008) in Texas; Wolak (2001) in California.

[4]Hadsell (2007)

[5]Hadsell and Shawky (2006)

[6]Saravia (2003)

market power available in the auction and result in additional efficiency and price conversion. With location-specific data on these players, the NYISO could develop policy to induce market entry in specific locales where inefficiencies are most egregious.

This paper proceeds as follows: in Chapter 2, the origins and rules of the NYISO wholesale electricity auction are explained. in Chapter 3, an overview of previous studies about bidding behavior in wholesale electricity markets is given. Some related theoretical work to the exercise of market power in such auctions is also mentioned. In Chapters 4 and 5 summarize the data set used in this study and develop the intuition behind the model to be tested. Chapter 6 discusses the results and Chapter 7 concludes.

CHAPTER 2

BACKGROUND

2.1 NYISO Market Structure

The last twenty years has seen the dramatic transition of domestic electricity markets from vertically integrated, regulated monopolies to open and competitive markets. The forces that beget this transition are varied, but the critical piece of legislation that got the ball rolling was the Public Utilities Regulatory Policies Act of 1978 (PURPA)[1]. This legislation allowed the entrance of “qualifying facilities”, privately owned power producers, who were able to sell electricity to utilities at rates estimated to be equal to utilities’ avoided costs Hogan (2002). The success of PURPA, coupled with advances in technology, germinated the idea for a competitive market. The idea that regulated monopolies were the *only* way to reliably and cost-effectively run electricity markets was quickly dying Hogan (2002).

The movement further gained momentum and feasibility by the Energy Policy Act of 1992 and later with Federal Energy Regulatory Commission (FERC) Order 888, creating a new class of exempt wholesale generators and requiring “open access” to the electrical transmission infrastructure, effectively allowing independent private firms to generate and sell electricity through the power grid[2] Hogan (2002). Subsequently,

[1]Public Utilities Regulatory Policies Act of 1978, 16 U.S.C. section 2601 et seq.

[2]FERC Order No. 888 (May 10, 1996) required “all public utilities that own, operate or control interstate transmission facilities to offer network and point-to-point transmission services (and ancillary services) to all eligible buyers and sellers in wholesale bulk power markets, and to take transmission service for their own uses under the same rates, terms and conditions offered to others. In other words, it requires non-discriminatory (comparable) treatment for all eligible users of the

the New York State Public Service Commission (PSC) ordered the unbundling of services (generation & transmission) and encouraged the divestiture of generation and transmission assets to private owners[3] The New York Independent System Operator (NYISO), a non-profit company, was created to manage the restructured market; it gained authorization from FERC in 1998 and formally accepted control from the New York Power Pool on December 1st, 1999.

The NYISO runs several markets, including markets for Day-ahead electricity, ancillary services, capacity, transmission congestion contracts, and a spot market for electricity as well as managing imports and exports. The New York Control Area (NYCA) is divided into fifteen geographic zones (11 internal, 4 external), each with its own Location Based Marginal Price (LBMP)[4]. LBMPs are used to capture locational differences in prices due to thermal load loss and network congestion[5]. This ensures that the price properly signals investment by including both congestion and thermal load loss in the marginal price of electricity.

2.2 Bidding in the Day-ahead and Hour-ahead Markets

The Day-ahead (DA) market is the primary venue for clearing electricity in the NYISO. About 95% of the electricity produced is transacted in the Day-ahead market (half of which is forward contracts), and the remaining 5% clears in the real-time (RT)

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monopolists transmission facilities." Order Requiring Open Access Non-Discriminatory Transmission Services by Public Utilities (codified in 18 C.F.R. Part 35, March 14, 1997).

[3]from "Lighting The Way – A Decade of Progress: 1999-2009; http://www.nyiso.com.

[4]Prices are billed at a nodal level that is more granular than zonal. However, price data is published at the zonal level and is intrazonal price variation is minimal.

[5]$LBMP_{zone} = P_{reference} + MC_{losses} - MC_{congestion}$

market[6]. Generators submit sealed, piecewise-defined offers to supply various quantities of electricity at different prices. Similarly, Load Serving Entities (LSEs) submit sealed bids to buy electricity and the market is cleared via the Security Constrained Unit Commitment (SCUC) algorithm, a calculation administered by the NYISO that takes into consideration transmission constraints, generator startup costs, and bilateral contracts to serve demand at the least cost. When there is no system congestion, this is accomplished 'stacking' the bids into a merit order of increasing and decreasing price, for supply and demand, respectively (Zhang, 2009). Lower priced generators therefore will be scheduled before higher priced generators. When transmission constraints bind, auctions for each zone clear separately (Saravia, 2003). This price discovery mechanism is in stark contrast to the regulated market of the past, where prices were determined by regulators who set rates at annual or semiannual intervals.

Bids into the DA market are due by 5am the day before (day "$T-1$"), and the results of the auction are published by the NYISO six hours later at 11am (Support, 2011). The auction is a uniform-price, multi-unit auction, ensuring all generators (in the same zone), are paid the same price for electricity, regardless of their bids. The multi-unit auction format allows participants partially fulfill their orders, for accepted bids that are below the "stop out" price (Wang and Zender, 2002).

Electricity that clears in the DA market represents the expected needs of market participants 24 hours in advance of the 'strike' hour. However, conditions change in the intervening time period. This variation in actual load and supply necessitates a real-time market. The real-time market is cleared at five minute intervals over the course of each hour and matches sink and source loads on the network in all

[6] `http://www.nyiso.com/public/about_nyiso/understanding_the_markets/energy_market/index.jsp`

locations, maintaining system reliability and preventing brownouts (Saravia, 2003). Because managing the New York electricity market is a complex feat, the DAM serves the dual purpose of both a futures market and a scheduling market. This allows the NYISO to focus on unexpected changes in system conditions and maintain reliability in real time.

The Hour-ahead (HA) market is a residual market; loads cleared in the HA market are deviations from the load cleared in the DA market. Accepted bids into the Day-ahead market are copied as identical bids into the HA market, and the total real-time load clears the HA market. Because the HA market is a physical market and customers are not exposed to real-time prices[7], demand in the HA market is perfectly inelastic (Saravia, 2003). Bidders do, however, have the opportunity to update their bids (whether accepted or not) entering into the HA market auction to clear additional quantity.

In November of 2001 the New York wholesale market was opened to speculators via a virtual market for electricity. Prior to this, the market was open only to generators and load-serving entities, who had physical assets to back up their bids. Therefore, speculation on prices in the Day-ahead and Hour-ahead markets was limited by physical capacity (Saravia, 2003). After November 2001, the market was opened to speculators who could bid into the Day-ahead market as a generator to arbitrage prices between the DAM and spot markets. Currently, there are over 300 'generators'[8] bidding into the wholesale markets, and over 100 unique bidders[9].

[7]Most customers are charged a weighted average real-time price, but do not experience real-time prices and therefore do not respond by curtailing their usage.

[8]Because generator IDs are masked to the public and virtual bids are comingled with 'real' bids, it is not possible to differentiate between between the two.

[9]A single bidder can submit bids for multiple generators.

CHAPTER 3

REVIEW OF RELEVANT LITERATURE

3.1 Equilibrium Models of Bidding Behavior

The offers submitted by generators in wholesale electricity are essentially supply functions constrained in form: they must be piecewise-defined linear, monotonically increasing, and have a limited number of 'steps'. The literature contains several competing models to understand the strategic interaction of the bidders submitting supply functions. These are via Cournot competition, a Supply Function Equilibria, a multi-unit auction, and via a programming model, as well as others not mentioned in this review.

The Supply Function Equilibria (SFE) model developed by Klemperer and Meyer (1989) has been used extensively to predict market outcomes in wholesale electricity. SFE is a model of an oligopoly market where each firm can submit an infinite number of best responses, essentially a supply function mapping prices to quantities offered. It is not constrained to choosing only one price and quantity as in Bertrand and Cournot. The profit-maximizing bidder constructs its supply function as best response to realizations of residual demand. Residual demand is equal to total market demand with the supply offered by each of the other firms subtracted out. An equilibrium is found where each bidder is maximizing its profit given the residual demand curve it faces. Market power, then is the ability for a firm to submit a supply function that generates monopoly rents, or prices above its marginal cost at the quantity it 'wins'.

The SFE approach has, at its limits, the Cournot model (perfectly inelastic supply) and a Bertrand model (perfectly elastic supply). Bolle (1992) uses the SFE to predict outcomes in spot electricity auctions. Because demand is stochastic, the real-time reaction function must be specified beforehand to allow for multiple demand outcomes; a supply function allows for such flexibility. He finds that multiple equilibria in supply functions exist, and the profit-maximizing equilibrium holds prices above marginal costs even as the number of firms increases. The result predicts the presence of long-lasting unilateral market power (Market Lerner index > 0).

Baldick, Grant, and Kahn (2004) compares a Cournot model to a linear SFE in England and Wales (E&W) electricity market to predict the effect of generation divestitures. They find SFE match empirical evidence better than a static Cournot model. Borenstein, Bushnell, and Wolak (2002) use a Cournot model to predict competitive outcomes in the California market. von der Fehr and Harbord (1993); Wolfram (1999); Fabra, von der Fehr, and Harbord (2002); Garca-Daz and Marn (2003); and Hortaçsu and Puller (2008) model the electricity market using an auction format, looking for Nash equilibria in the multi-unit auction. Finally, Tamaschke, Docwra, and Stillman (2005) uses a programming model specific to the Queensland, Australia market to calculate a long-term competitive benchmark.

Supply Function Equilibria models are preferred because they mirror what happens in the actual market. Firms do indeed submit supply schedules, and this is important because of the considerable uncertainty in demand outcomes.

3.2 Multi-unit Auctions & Market Power

The NYISO procures electricity in a multi-unit (zonal) uniform-price auction. The auction is a multi-unit auction because each bid is not an ‘all-or-nothing’ proposition, but rather will have portions that are accepted and rejected. Multi-unit auctions have been used in recent history in other markets, namely to sell Outer Continental Shelf oil exploration leases and U.S. treasury notes.

Bidders in a uniform-price auctions, as shown by Ausubel and Cramton (2002) and more Wilson (1979), have an incentive to bid 'untruthfully' by overstating their costs (or shading their 'desire') when bidders are allowed to submit functions for fractions of the total offered quantity at different prices. When valuations are decreasing this results in a net positive surplus for all inframarginal units Cramton (2004). Wang and Zender (2002) demonstrate that almost all equilibriums in a multi-unit auction contain some strategic bidding.

Cramton (2004) investigates the incentives facing a bidder in a uniform-price, multi-unit auction and responds to the once popular notion that bidders would bid truthfully in a multi-unit auction. There should be no expectation that bidders offer at their marginal cost of production. Rather, bidders will maximize expected profits by weighing the trade-off between higher quantity and lower cost. By equating marginal revenue to marginal cost, bidders maximize profits against the specific residual demand they face. Cramton (2004) notes that this is exactly what we observe in wholesale electricity auctions: generators bidding above marginal cost.

de Castro and Riascos (2009) characterize a general class of multi-unit auctions, and look at behavior under a weak assumption about bidders' behavior: that each bidder plays a best response to the strategies that he believes the others are playing. Under this weak assumption, they prove the "basic principle of bidding": That is, a rational bidder maximizes profits by equating marginal benefit to marginal cost. de Castro and Riascos (2009).

3.3 Empirical Studies of Bidding Behavior

Wolfram (1998) studies the electricity spot market in England and Wales from an auction perspective, to see if the theory that bidders strategically withhold capacity holds under empirical scrutiny. She finds that (1) the largest participant in the electricity auction bids more than its smaller competitors for units with comparable costs; (2) suppliers submit higher-markup bids for units likely to be run after other units (e.g. speculative units); and (3) suppliers submit higher bids on days when more of their other units are available to produce electricity. This is consistent with the notion that large, strategic bidders will use a portion of their generating portfolio as 'speculative' capacity to attempt to drive up the winning price and thus all inframarginal units as well.

Green and Newbery (1992) develop a symmetric Cournot duopoly model of electricity supply in the UK electricity market that closely follows Klemperer and Meyer (1989). They develop upper and lower bounds on offer curves for the two-firm oligopoly that generalizes to n firms. The lower bound on optimal bids occurs when n is large; the bid intersects residual demand at the firm's marginal cost curve. The upper bound occurs when a firm faces the entire demand curve ($n = 1$); the optimal bid will intersect residual demand at the quantity where marginal revenue equals marginal cost. Green and Newbery (1992) use the elasticities at the point at which the residual demand facing the two largest firms equals the marginal cost versus the elasticity at the simulated equilibrium. The elasticity at equilibrium is a rough measure of market power, as the more inelastic the demand facing the firm, the greater the market power.

Wolak (2003) takes this idea a bit further by using the relationship between the Lerner index and the elasticity of residual demand facing an individual supplier.

Using data on the bids of the five largest firms in the California market, all the other suppliers, and load data, he constructs a firm-specific Lerner index that measures the market power facing that individual firm during the summer of 1998 and 1999. Wolak (2003) restricts his study to non-congested hours and to hours when the real-time price is above \$20/MWh because it is unlikely that market power is being exerted below this price point. It is also unlikely that the marginal bidder's cost of generation is below \$20, unless the load is being served by hydroelectric or nuclear power which are not strategic players in California.

Green and Newbery (1992) find that the duopolists in England & Wales (E&W) exercised substantial market power by bidding higher than marginal cost in all the years of the study. They also note that the transmission constraints in E&W empowered the duopolists with enhanced market power in some specific subregions of the network. They calculate deadweight losses to be £340 million per year, or 6% of total revenue if they produced at the competitive price and quantity.

Zhang (2009) studies bidding behavior in the New York day-ahead wholesale electricity market by looking at 'group choices' among bidders. Generators are divided into groups based on the highest price of their bid. Using hourly NYISO bidding data, she finds that grouping choices are persistent, and that generators in the high priced groups tend to strategically withhold capacity to drive prices higher, and while not the principal aim of the study, lends support for existence of market power in the NYISO.

Hortaçsu and Puller (2008) observe bidding in the Texas balancing energy market (ERCOT)[1], and develop benchmark bid functions that maximize both *ex post* and *ex ante*[2] profits based on a distribution of realizations of residual demand and a

[1]Using bids from uncongested weekdays from 6:00-7:00pm in the winter of 2001-2002.

[2]They call this the 'Naive Best-Response' bid.

firm's generation costs. They find that the largest firms' bids are close to the *ex post* profit-maximizing benchmark, but that smaller bidders deviate significantly from this benchmark, resulting in market efficiency losses. They speculate that this could be the result of institutional complexities in entering the auction: the smaller bidders are not equipped with sophisticated trading tools necessary to compute optimal bids for each hour of the day nor evaluate the profitability of historical bids.

Interestingly, the smaller bidders submit bids at offer prices higher than optimal. In other words, they error on the side of offering their capacity at too high a price and forgoing additional output (and profit). Hortaçsu and Puller (2008) calculate that these smaller bidders account for 81% of the efficiency losses due to all non-marginal cost bidding in ERCOT[3], an economically significant amount. This study implies that market inefficiency can be exacerbated by institutional complexity. That said, it is an open question whether these smaller firms improved their bidding performance over time which could be a fruitful area of future research.

Theoretical predictions of uniform-price auction behavior point to a result at odds with a competitive market: bidders have an incentive to shade bids. Through several studies in Texas, California, and New York, this notion has found support. However, more research into firm-specific bidding behavior and performance could shed light on the extent to which bids are constructed optimally to maximize expected profits.

3.4 Forward Premiums and Virtual Bidding

The primary reason for opening the Day-ahead (DA) market up to speculators is to reduce the forward premium in the DA market and thus stimulate conversion of

[3]As a group, they account for roughly 39% of capacity.

the DA and real-time (RT) price. Virtual bidders take a long or short position in the DAM that is then reversed in the RT market (Hadsell and Shawky, 2006). Virtual bidders are then “price takers” in the RT market because they must reverse their DA position at any cost. If the market were efficient, persistent differences in the DA price versus the RT price would be arbitraged away over time and overall volatility would decrease as market entry would ‘flatten’ both supply and demand schedules (Hadsell and Shawky, 2006).

The forward premium in electricity markets is analogous to conjecture outlined by Coase (1972) for a durable goods monopolist. Electricity is virtually nonstorable (not durable) and the ability for a firm to price discriminate between the DA and RT markets exists (Longstaff and Wang, 2004). Therefore, in the concentrated market, generators with local market power could segment the market to maximize profits. Furthermore, the ability of firms to pass on DA costs to customers provides an incentive for a risk averse load serving entity to purchase the majority of its energy needs in the DAM (Saravia, 2003). So, the existence of a positive and persistent forward premium would indicate an inefficient market (Hadsell and Shawky, 2007) and potentially market power (Willems, 2005).

Hadsell and Shawky (2006) find that the virtual bidding in the NYISO indeed is associated with reduced volatility in both the DA and RT markets while Hadsell and Shawky (2007) find that forward premiums did not disappear after the introduction of virtual bidding in the NYISO. Rather, forward premiums increased in off peak hours and decreased during peak hours. The findings suggest that while virtual bidding did impact DA and RT prices, the market is not efficient.

CHAPTER 4

DATA SUMMARY

4.1 Sources & Description

This study uses publicly available bidding data from the NYISO for the years 2002 through 2010 for the ten largest bidders in the DAM market measured by offered capacity. The NYISO publishes generator-specific bidding data in their "Gen Bids" data set at a three month lag[1]. This data set includes piecewise defined bid parameters, as well as masked identifying information. Each generator is assigned a masked generator ID and each bidder is assigned a masked bidder ID. A single bidder ID can submit bids for multiple generators, and the ten largest bidders studied here all submit multiple generator bids into the DAM and HAM.

The largest bidders were selected based on average monthly offered capacity[2].

4.1.1 Data Manipulation & Cleanup

The raw bidding data was not manipulated or cleaned up – all data for the years 2002-2010 was used, with the exception of bids between December 16, 2004 and January 21, 2006. This was a period of transition for the NYISO, and aggregate load

[1] Available at `http://mis.nyiso.com/public/P-27list.htm`

[2] The calculation is as follows: for each generator's hourly bid, I calculated the maximum of the k steps in their piecewise defined bid, representing their hourly offered capacity. Generator offered capacities were summed up to the bidder level, producing their hourly offered capacity. For each year 2002-2010, the mean offered capacity for each bidder was calculated. A list of the top 20 bidders for each year was created. The top 10 bidders that appeared on the list the most often were selected for this study.

data is not available at the hourly level during this time period. Because load-data is not available for this time period, the various regressors including q^*_{DAM} and L (Lerner index) could not be calculated and therefore observations in this time period are dropped.

4.1.2 Variables Used & Description

The primary data we use in this study is "Gen Bids" data set. See Table 4.3 for a description of the variables used from this data set. The "Gen Bids" data set includes a single bid for each row of data. Each bid includes information about the bidder, generator, and startup costs. Also included are the (up to) twelve price-quantity pairs that represent each bidder's piecewise-defined offer to supply electricity. The maximum number of price-quantity pairs used was eleven for any single bidder in this study, and prior to 2006 bids were capped at six price-quantity pairs. The more price-quantity pairs, the more 'smooth' bids can become. Essentially, this is each bidder's strategy space for the DA and HA auction.

The ten largest firms vary in the number of generators and amount of megawatts they bid for in the NYISO electricity auction. Tables 4.1 and 4.2 show the number of generators attached to each bidder and the average offered capacity. The median number of generators per bidder ranges from one (bidder A) to 15 (bidder F). Median offered capacities into the DA and HA markets ranges from 572 megawatts to 2,135 megawatts (bidder H).

The top ten bidders were chosen in this study because larger bidders are more likely to have and exercise market power. The models used in this paper assume bidders to be maximizing expected profit, and larger bidders are more likely to exhibit behavior that is expected profit maximizing (Hortaçsu and Puller, 2008). Furthermore, because of the time period involved, the choice of the top ten bidders was done

Table 4.1: Number of generators per bidder, 2002-2010

BIDDER	Mean	Median	StdDev
A	1.00	1.00	0.00
B	9.17	5.00	6.88
C	11.44	14.00	6.84
D	3.74	4.00	0.67
E	8.26	5.00	6.42
F	14.60	15.00	2.56
G	5.35	6.00	0.87
H	12.96	13.00	4.62
I	6.31	7.00	0.92
J	1.88	2.00	0.33

with a weight towards bidders that consistently participated in both the DA and HA markets. Participation in both markets is required in order to study behavior in the sequential auction.

Table 4.2: Median offer capacities for both markets by bidder.

BIDDER	OC_{DAM}	OC_{HAM}	OC_{diff}
A	572	572	0
B	2,271	1,625	4
C	1,699	1,566	0
D	1,008	1,008	0
E	1,853	1,624	0
F	1,874	1,888	35
G	1,688	1,700	0
H	1,995	2,135	76
I	1,245	1,265	0
J	1,744	1,745	0

4.1.3 Weather Data

Surface air temperature data from weather stations in the Global Historical Climatology Network was used in this study[3]. Maximum and minimum daily temperatures were collected from all weather stations within a 50 mile radius around the city of New York (NYC) to approximately weight temperatures by population. The majority of the population within the NYCA (New York Control Area) is located in the NYC metropolitan area and Long Island. Average daily heating degree days (HDD) and cooling degree days (CDD) were calculated as follows:

$$\mathrm{HDD}_t = \max\left\{\frac{1}{N}\sum_{i}^{N} 65 - (\mathrm{TMIN}_{it} + \mathrm{TMAX}_{it}) \div 2, 0\right\}$$

$$\mathrm{CDD}_t = \max\left\{\frac{1}{N}\sum_{i}^{N} (\mathrm{TMIN}_{it} + \mathrm{TMAX}_{it}) \div 2 - 65, 0\right\}$$

where TMIN_{it} and TMAX_{it} are minimum and maximum temperatures in degrees Fahrenheit for weather station i at time t; N represents the number of stations within a 50 mile radius of NYC.

4.1.4 Fuel Prices

The daily #2 Heating Oil spot price delivered to New York harbor, measured in dollars per gallon, is used in this study to capture variation in one of the primary fuels used by power plants in New York state. The data is made publicly available by the U.S. Energy Information Administration[4].

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[3] More information can be found at `http://www.ncdc.noaa.gov/oa/climate/ghcn-daily/`.

[4] Available at `http://www.eia.gov/dnav/pet/hist/LeafHandler.ashx?n=PET&s=EER_EPD2F_PF4_Y35NY_DPG&f=D`

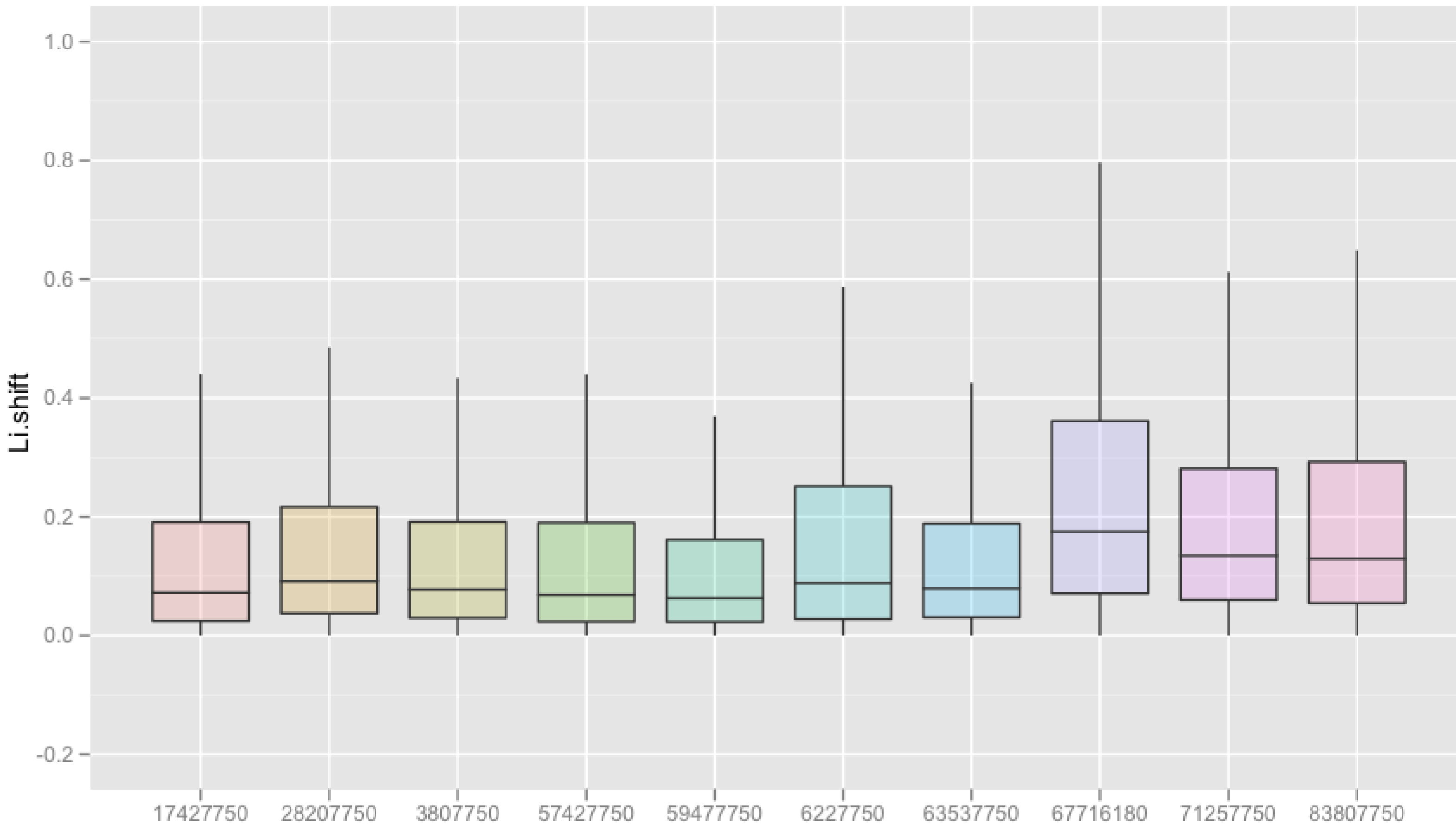


Figure 4.1: Boxplot of DA market Lerner indices for top 10 bidders in the NYISO. [boxplot.r]

4.1.5 A Firm-specific Lerner Index

Following the calculation methodology implemented by Wolak (2003) for the California electricity market, a firm level Lerner index is calculated in the NYISO Day-ahead market, using actual bidding data and clearing the auction with total DA load published in the NYISO Daily Energy Report. To account for inaccuracies in simulating the SCUC (Security Constrained Unit Commitment algorithm), out-of-sample adjacent-hour fixed effects were included to simulate the impact of startup costs and any other unobservables. This adjustment brought Lerner index results broadly in line with results from Wolak (2003), albeit showing less market power than California. See by bidder Lerner indices in Figure **??**. While all ten firms exhibited nonzero market power, this is typical for electricity markets and are only a piece of evidence that should be used to determine if the amount of market power is excessive and calls for action.

The DA market in the NYISO becomes segmented during congested hours, complicating the construction of a market-wide supply stack. Because of this, hours where the average congestion rent across all 11 NYISO zones was larger (in absolute value) than 2% of the reference bus price for electricity, were excluded from this study. Lerner index serves to broadly capture variation in the ability of firms to raise prices by withholding output.

Developing a firm-specific Lerner index relies crucially on the assumption that a firm is profit-maximizing and acts as a monopolist against the residual demand curve it faces. The firm's maximization problem is as follows:

$$\max_{p} \Pi_i = p * \breve{D}_{it}(p) - C(\breve{D}_{it}(p))$$

where $\breve{D}_{it}(p)$ is the residual demand curve, a function mapping prices to quantities demanded, facing firm i at time t, and $C(\cdot)$ its cost function. Taking the first order conditions,

$$\frac{d\Pi_i}{dp} = p \cdot \breve{D}'_{it}(p) + \breve{D}_{it}(p) - C'(\breve{D}_{it}(p)) \cdot \breve{D}'_{it}(p) = 0$$

$$p - C'(\breve{D}_{it}(p)) = \frac{-\breve{D}_{it}(p)}{\breve{D}'_{it}(p)}$$

then dividing both sides by p and changing notation yields the following relationship:

$$\frac{p - C'(\breve{D}_{it}(p))}{p} = \frac{-\breve{D}_{it}(p)}{\breve{D}'_{it}(p)} \cdot \frac{1}{p}$$

$$\frac{p - MC}{p} = \frac{-q}{\frac{dq}{dp}} \cdot \frac{1}{p}$$

$$L_{it} = \frac{-1}{\varepsilon_{pit}} \tag{4.1}$$

where L_{it} is firm i's Lerner index at time t. In sum, the negative inverse semi-elasticity of residual demand represents firm i's markup of price over its marginal costs of production. This procedure is used in Wolak (2003) and Wolak (2007) for the largest bidders in the California and New Zealand electricity markets. The primary difference in the calculation methodology used by Wolak (2003) is that the addition of out-of-sample shifters, akin to hourly fixed effects, was used in this paper while it was not used by Wolak (2003) or Wolak (2007).

Table 4.3: Brief Explanations of Variables Provided in NYISO Bidding Data

Masked Gen ID	Identifies unique generating units.
Date Time	Hourly time stamp.
Duration	Always equal to one hour.
Market	Either Day-ahead market or Hour-ahead.
Expiration	Bid expiration date/time
Upper Oper Limit	A unit's operating limit under normal system conditions.
Emer Oper Limit	A unit's operating limit under *extraordinary* system conditions.
Zero Start-Up Cost	'Yes' or 'No'
On Dispatch	'Yes' or 'No'
Fixed Min Gen MW	Minimum start-up production (in Megawatts)
Fixed Min Gen Cost	Minimum start-up costs (in $)
Bid Curve Format	BLOCK (only pre 2005) or CURVE
Dispatch MW1 - MW12	Incremental offer quantities.
Dispatch $/MW1 - $/MW12	Incremental offer prices.
Masked Bidder ID	Identifies unique bidders in the auction.

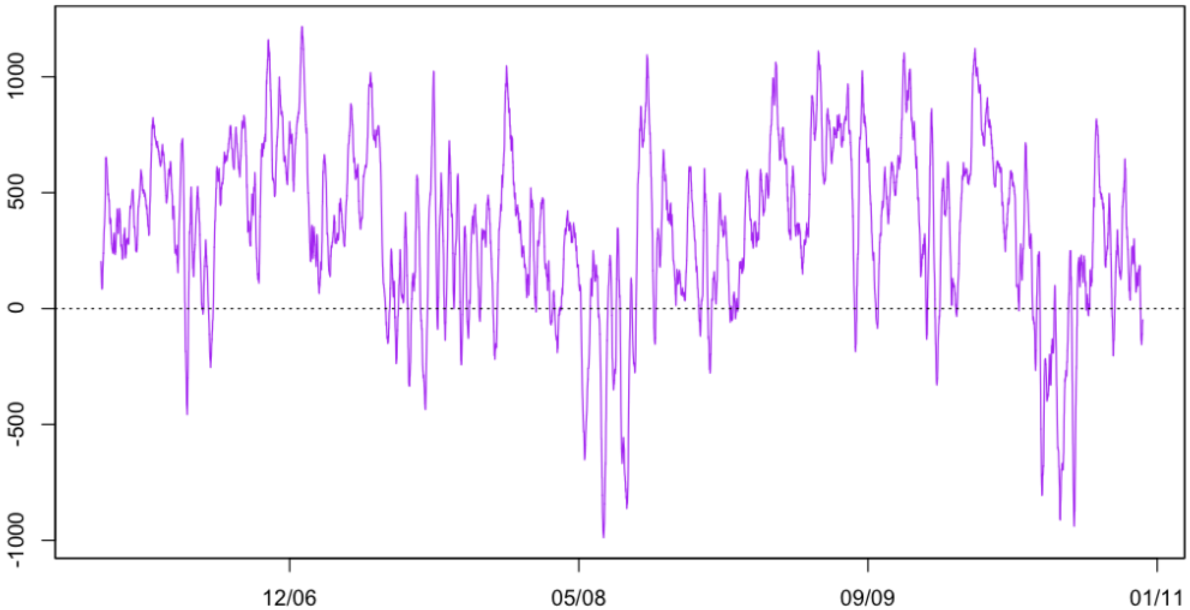


Figure 4.2: Time Series: The net virtual supply (netsupp) cleared in the NYISO Day-ahead market (weekly simple moving average) [virtual-supply.r].

4.1.6 Net Virtual Supply

In November, 2001, the NYISO introduced virtual bidding in the Day-ahead market. Private firms and individuals meeting the credit requirements can submit bids just like generators to arbitrage prices between the DA market and HA market. The idea is that different prices in the DA and HA markets is symptomatic of a noncompetitive market. Virtual traders whose bids are accepted in the DA market to supply electricity automatically take a long position for an equal amount of electricity in the spot market. Because the spot market is close both in time and nature to the balancing market, the forces affecting demand and supply in this critical hour are highly related. A net short position by virtual traders in the DA market, in the aggregate, results in a net long position the HA market. This position, in the aggregate, is made available by the NYISO after the close of the Day-ahead auction.

The net virtual supply, (i.e., 'netsupp') is simply virtual supply bids accepted minus virtual load bids accepted. The Daily Energy Report started reporting this data as of January 16, 2006. A weekly simple moving average of the 'netsupp' time series from 2006 through 2010 is shown in Table 4.2. The simple moving average was shown for illustrative purposes due to the volatility of 'netsupp'. Summary statistics are shown in Table 4.4.

Table 4.4: Summary Statistics: Virtual bidding

	Obs	Mean	Median	Std.Dev	Min	Max
Virtual Loads Scheduled	86,782	1628.34	1522.00	676.26	86.00	5641.00
Virtual Supply Scheduled	86,782	1974.51	1929.00	532.05	50.00	4996.40
netsupp	86,782	346.16	406.00	646.74	-3293.00	3094.00

CHAPTER 5

A MODEL OF SEQUENTIAL AUCTIONS

5.1 A Model of Joint Profit Maximization Over Two Auctions

The following section models bidding behavior for a participant in the sequential NY wholesale electricity auction.

5.1.1 Uncertainty in the Day-ahead Market

Following the market equilibrium formulation developed in Hortaçsu and Puller (2008) to explain generator bidding behavior in the ERCOT[1] balancing market, a simplified model is used here to illustrate how differences in the slope of residual demand affect how bidders construct their offer curves in the face of additive demand uncertainty.

Assuming that a firm has at least some market power, it will set the market price where its offer curve (i.e., bid) intersects residual demand. The market clearing condition occurs at the price p_t^c where the horizontally summed bids from all market participants (i.e., total supply) equals total load demanded:

$$\sum_{i=1}^{N} S_{it}(p_t^c, QC_{it}) = \tilde{D}_t(p) = D_t(p) + \rho_t \ ,$$

where $S_{it}(p)$ represents generator i's bid as a function of price p; p_t^c is the market clearing price at time t; QC_{it} is the quantity already dedicated to a forward contract position for firm i at time t; and $\tilde{D}_t(p)$ is the total demand for electricity at time t that includes a deterministic component $D_t(p)$ and a stochastic component ρ_t. The term ρ_t is a stochastic demand shifter representing weather or other random events

[1] Electricity Reliability Council Of Texas.

that can increase or decrease electricity load from its expected level. The sum of all N generators' bids represents the wholesale electricity supply function and the market clears where supply equals demand. Each generator gets paid $S_{it}(p_t^c) \times p_t^c$ and earns a profit of $\Pi_{it} = S_{it}(p_t^c) \cdot p_t^c - C_{it}(S_{it}(p_t^c)) - (p_t^c - PC_{it}) \cdot QC_{it}$, where $C_{it}(q)$ is each firm's cost function, and PC_{it} is the "locked-in" price of firm i's forward contract quantity at time t of QC_{it}.

Assuming that each bidder has knowledge of the physical attributes of the other generators within the market consistent with Hortaçsu and Puller (2008), a firm can formulate its competitors' marginal cost curve with reasonable accuracy[2]. A firm's bid is structured around its marginal costs of generation. Firm i is assumed to have a reasonable prediction of the total demand for electricity for any day based on its experience in the market. However, generator i faces some uncertainty when placing his bid in the market coming from two sources:

(1) $\tilde{D}_t(p) = D_t(p) + \rho_t$: unsystemic event uncertainty.

(2) $\{(QC_{jt}, PC_{jt}), j \in -i\}$: forward position of all competing generators $j \neq i$.

The two unknowns from the perspective of bidder i are: the stochastic component of demand (1), and the forward contract prices and quantities of all the other bidders (2). Without these uncertainties, generator i could perfectly forecast the residual demand it faces at time t and bid (with certainty) as a monopolist to maximize profits. While uncertainty in the forward contract level QC_{jt} will impact the slope of residual demand, the stochastic shock to demand will not. Forward contract levels are thought to be fixed in the short run and persistent. Because the Day-ahead auction is repeated every hour, we assume that the uncertainty around QC_{jt} is limited when

[2]These attributes include fuel type, fuel cost, operation and maintenance (O&M) costs and heat rate (or generation technology).

bidders construct their offer curves and collapse both types of uncertainty into an additively separable stochastic demand shifter ε_t. Total demand becomes:

$$\tilde{D}_t(p) = D_t(p) + \varepsilon_t$$

where $D_t(p)$ is the deterministic component of demand as mentioned above. Next, we can define firm i's deterministic residual demand $\breve{D}_{it}(p)$ as composed of total deterministic demand with the supply offered by all competing firms (i.e., $S_{-i}(p)$ at price p) subtracted out:

$$\breve{D}_{it}(p) = D_t(p) - S_{-i}(p)$$

It follows that the realization of firm i's residual demand, including the random variable ε_t becomes:

$$\tilde{D}_t(p) - S_{-i}(p) = \breve{D}_{it}(p) + \varepsilon_t \tag{5.1}$$

5.1.2 A Supply Function Equilibria Formulation

To model the role of uncertainty in the construction of offer curves, we will start with firm i's profit maximization program with deterministic residual demand:

$$\max_p \Pi_{it} = p \cdot \breve{D}_{it}(p) - C(\breve{D}_{it}(p)) \tag{5.2}$$

where the bidder chooses p to maximize profits. In reality, the firm chooses a function $S_{it}(p)$ that maps multiple prices to multiple offered quantities. The reconciliation of this formulation is that the profit maximizing firm will choose p to maximize profits against multiple realizations of residual demand, each with a specific probability. The optimal bid (i.e., supply function) will 'connect the dots' by running through all optimal combinations of price and quantity[3].

[3]See figure 5.1.

Proposition 1: *Bidders facing steeper residual demand curves in the DA market will submit steeper offer curves to connect the locus of profit-maximizing points in response to additive uncertainty in the realization of residual demand.*

Proof: To build residual demand uncertainty into the maximization problem (5.2) above, we now introduce the random variable ε_t discussed above. Because ε_t can take on positive and negative values, we simplify our formation by allowing ε_t to take on two values $(\varepsilon_t^+, \varepsilon_t^-)$ with probabilities $(q, 1-q)$. Now the expectation of total demand becomes[4]:

$$E[\tilde{D}_t(p)] = D_t(p) + q \cdot \varepsilon_t^+ + (1-q) \cdot \varepsilon_t^-$$

Following equation (5.1), firm i's expectation of residual demand becomes:

$$E[\tilde{D}_t(p) - S_{-i}(p)] = \breve{D}_t(p) + q \cdot \varepsilon_t^+ + (1-q) \cdot \varepsilon_t^-$$

Let $\varepsilon_t^+ = \varepsilon_t$ and $\varepsilon_t^- =$ -ε. Suppressing i and t subscripts for brevity, firm i's maximization problem becomes[5]:

$$\begin{aligned} \max_p E[\Pi(p)] = &\left[p \cdot (\breve{D}_R(p) + \varepsilon) - C(\breve{D}_R(p) + \varepsilon)\right] \cdot q \\ &+ \left[p \cdot (\breve{D}_R(p) - \varepsilon) - C(\breve{D}_R(p) - \varepsilon)\right] \cdot (1-q) \end{aligned}$$

where p is chosen to maximize expected profits $E[\Pi(p)]$.

<u>First-order condition:</u>

$$\frac{\partial E[\Pi(p)]}{\partial p} = p \cdot \left(\frac{\partial \breve{D}_R(p) + \varepsilon}{\partial p}\right) + \breve{D}_R(p) + (2q-1) \cdot \varepsilon \tag{5.3}$$
$$+ (q-1) \cdot \left(\frac{\partial C(\breve{D}_R(p) - \varepsilon)}{\partial \breve{D}_R(p)}\right)\left(\frac{\partial \breve{D}_R(p) - \varepsilon}{\partial p}\right) - q \cdot \left(\frac{\partial C(\breve{D}_R(p) + \varepsilon)}{\partial \breve{D}_R(p)}\right)\left(\frac{\partial \breve{D}_R(p) + \varepsilon}{\partial p}\right) = 0$$

[4]This follows the formulation used in Rothschild and Stiglitz (1976).

[5]The bidder is assumed to be risk neutral.

The sufficient condition for a maximum, that $\frac{\partial^2 E[\Pi]}{\partial p^2} < 0$, is satisfied. By using the implicit function theorem at the optimum and taking the derivative of the first-order conditions with respect to the parameter ε, it can be shown that[6]

$$\frac{\partial p^*}{\partial \varepsilon} \geq 0 \tag{5.4}$$

and

$$\frac{\partial \left(\frac{\partial p^*}{\partial \varepsilon} \right)}{\partial \breve{D}(p)} \geq 0 \ . \tag{5.5}$$

The result of this relationship is shown in Figure 5.1. As the stochastic shock increases, the optimal price increases (consistent with Figure 5.1). This results in offer curves that are upward sloping. If the derivative of $\frac{\partial p^*}{\partial \varepsilon}$ is taken with respect to $\frac{\partial \breve{D}_R(p^*)}{\partial p^*}$ (equation 5.5), it can be shown to be positive . In short, as $\frac{\partial \breve{D}_R(p^*)}{\partial p^*}$ increases, $\frac{\partial p^*}{\partial \varepsilon}$ increases. Because we've linked the inverse semi-elasticity of residual demand to unilateral market power (see equation (4.1) in Section 4.1.5), and the slope of residual demand is a key component in this measure, this is akin to saying "as market power increases, the rate at which the optimal price changes with response to an additive stochastic shift ε increases". The result is that if the optimal bid connects the locus of points that maximize profits as we expect, the bid must be constructed in a way that accounts for the potential of a stochastic demand shock. The offer curve itself must be steeper for firms facing a steeper demand curve, as shown in Figure 5.1.

5.1.3 Hour-ahead Bids as a Function of Day-ahead Results

Bidders in the wholesale electricity auction have the option to update their bids in the Hour-ahead (HA) balancing market in response to the results of the Day-ahead (DA) market as well as other changes that occur after submission of the DA bid.

[6]The proof of equations (5.4) and (5.5) is shown in Appendix A.

Results from the DA market include the price and quantity that the firm cleared. This is important data for the firm because it gives it a point on the residual demand curve (i.e., p^*_{it},q^*_{it}) as well as total system load cleared (i.e., Q^*_t). Taking the results from the DA market as given, the firms will attempt to maximize their profits entering the spot market.

Proposition $2(a)$**:** *Conditional on clearing the Day-ahead auction at a quantity greater than their forward market position, firms will increase the quantity they offer at marginal cost.*

Proposition $2(b)$**:** *Entering into the Hour-ahead market, a bidder will, conditional on clearing a quantity less than its forward market position, reduce the price at which it offers its capacity.*

Proof: (see Figure 5.2) Following the durable goods monopolist described by Coase (1972), there is an incentive for a monopolist to charge different prices in different periods to maximize profit. The monopolist would like to charge a higher price in period one, and a lower price in period two, extracting additional rents in the process. To see how there is an incentive to reduce prices offered in the second auction, it is necessary to look at the firm's objective function in period 2[7].

$$\max_p \Pi^2(p) = p \cdot \breve{D}(p) - C(\breve{D}_R(p)) + FQ \cdot (FP - p) \tag{5.6}$$

where FP and FQ represent the forward price and forward quantity (sold prior to period two). Because the quantity sold in the DA market represents a sunk cost, the variables FP and FQ are fixed in period 2. To see how the existence of a forward position reduces the incentive to reduce the price in period 2, consider term 3 in equation (5.6). This term represents the gain or loss from the firm's forward contract

[7]This formulation simplifies the formulation by assuming certainty of residual demand.

position. The negative sign on the price p in period 2 means that as you raise the price, you decrease the profit on your forward contract position. This increases the incentive to reduce prices in period 2 versus period 1. The natural question that arises in such a formulation is that no rational consumer will purchase any quantity in period 1 without some contractual arrangement preventing the firm from selling additional quantity in period 2 (Coase, 1972). In electricity markets, there are advantages to buyers securing quantity in the DA market. Buyers may be risk averse, and therefore are willing to pay a premium on quantity secured ahead of the spot market. In addition, arbitrage between the two markets is relatively inexpensive. The introduction of virtual bidding in November 2001 invited firms and speculators to arbitrage between the two markets[8].

As noted in Hadsell and Shawky (2007), the introduction of speculation between these two markets has resulted in decreased forward premiums in some hours, but not in all hours. Overall, a DA market premium persists in the NYISO (Hadsell, 2007). The persistency of these premiums indicates a market that is not perfectly efficient. This inefficiency would allow for behavior consistent with Coase (1972), where firms may purposefully clear different prices between the two auctions.

In addition, the NYISO requires that all LSEs (Load Serving Entities) purchase their forecasted load in the DA market. This ensures that reliability standards will be met during the strike hour, and gives the NYISO ample time to enlist additional resources if available generating capacity in NY is likely to be inefficient. The NYISO schedules generators in the DA market, and then focuses on meeting deviations from the DA market quantity in the spot market the following day. Because market rules

[8] The barriers to entry in the virtual market are the filing of an application to become a market participant, and the proof of specified credit requirements in proportion to the volume of virtual bidding.

require this level of participation in the DA market, LSEs do not have the option to wait for the spot market to buy their electricity and therefore are exposed to the DA market price.

Proposition $2(c)$**:** *In order to bid optimally in the HA auction, where residual demand is steeper, bidders will submit steeper bids in the strategic portion of their bid functions.*

Proof: Consider that buyers in the DA market have more flexibility in the DA market than the HA market. In the HA market, if LSEs are net long on electricity, they must purchase the difference between load demand in their area and the amount purchased in the DA market. LSEs are extremely unresponsive to price because the majority of their customer base is unaware of real-time electricity prices. This translates into a much steeper residual demand in the HA market. Shown with weakly convex marginal costs, Figure 5.4 illustrates this point. After clearing quantity q_1 in the DA market, the firm's best response to the the HA residual demand curve is to clear additional quantity at a lower price, exactly as explained in our base example related to Coase (1972). Uncertainty exists in the HA market that makes submitting a steeper bid optimal, analogous to the DA market shown in Figure 5.1.

This same effect can be compounded by convex marginal costs. See Figure 5.5, where an example of a piecewise-defined linear marginal cost function is shown. Because the difference in marginal costs is larger between points q_{DA} and q_{HA} than between any two points on either of the two 'pieces', the relationship is analogous to a convex marginal cost function. This abstraction is not uncommon in power generation, especially when a firm submits bids for a variety of power plants with different technologies. Any heterogenous mix of generation technologies will exhibit this type of convexity.

Convex marginal costs means that there is a higher cost 'penalty' for increasing production than for constant marginal costs. The result is that variation in the realization of residual demand in the positive direction has incrementally less impact on the optimal quantity. This translates into a steeper optimal bid function in period 2 versus period 1.

5.1.4 Other Exogenous Impacts on Bid Formation (Propositions 3 & 4)

Proposition 3**:** *The temperature, measured in cooling-degree-days should not impact formation of firms' Hour-ahead bids.*

Extreme hot and cold weather increases the demand for electricity. Because the majority of homes in New York state heat their home using heating oil or natural gas, extreme cold weather has less impact on electricity demand than extreme hot weather[9]. Temperature is important to generators as they construct bids into the Day-ahead market, because higher temperatures portend higher demand for electricity.

Bids into the DA market are made in advance of the strike hour, so the actual temperature (i.e., load) that is realized is unknown. Firms may update their knowledge of the temperature when submitting their HA bids. However, the level of realized temperature, measured in cooling-degree-days on the day of production, should not impact the formation of HA bids because the variation in changes to the forecast between day $T-1$ and day T will have mean zero.

Proposition 4**:** *As the net virtual supply increases, bidders will be more aggressive in the HA market by submitting steeper-sloped bids because residual demand will be more inelastic.*

[9]Only 9% of homes in NY use electricity for heating purposes according to the U.S. Census (2000). `http://bit.ly/sZgWxO`)

The NYISO virtual market allows speculators to purchase or sell virtual load in the DA market and reverse their purchase or sale in the spot market. If more virtual supply is sold than is bought in the DA market, virtual traders will be net short of electricity going into the spot market. This implies a net increase in demand in the spot market. Bidders, anticipating this extra demand in the spot market, will adjust their bids accordingly. Assuming weakly convex marginal costs, in order to bid optimally against the same uncertainty (mean zero, as in ε_t mentioned in Section 5.1.1), at a higher level of demand (than the DA residual demand), requires a steeper bid. This is illustrated in Figure 5.4.

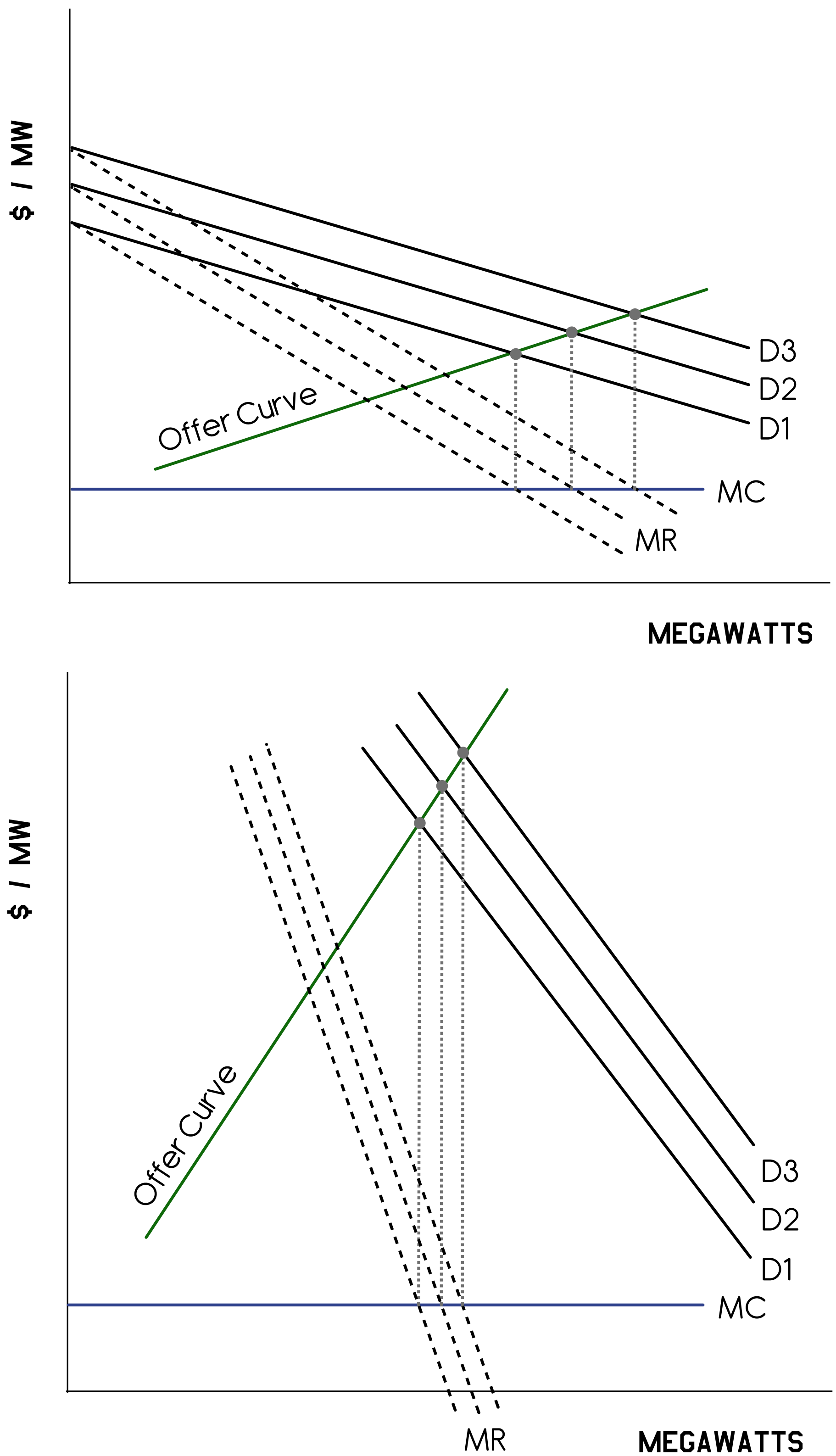


Figure 5.1: Residual demand variation of a low (top) and high (bottom) market power bidder.

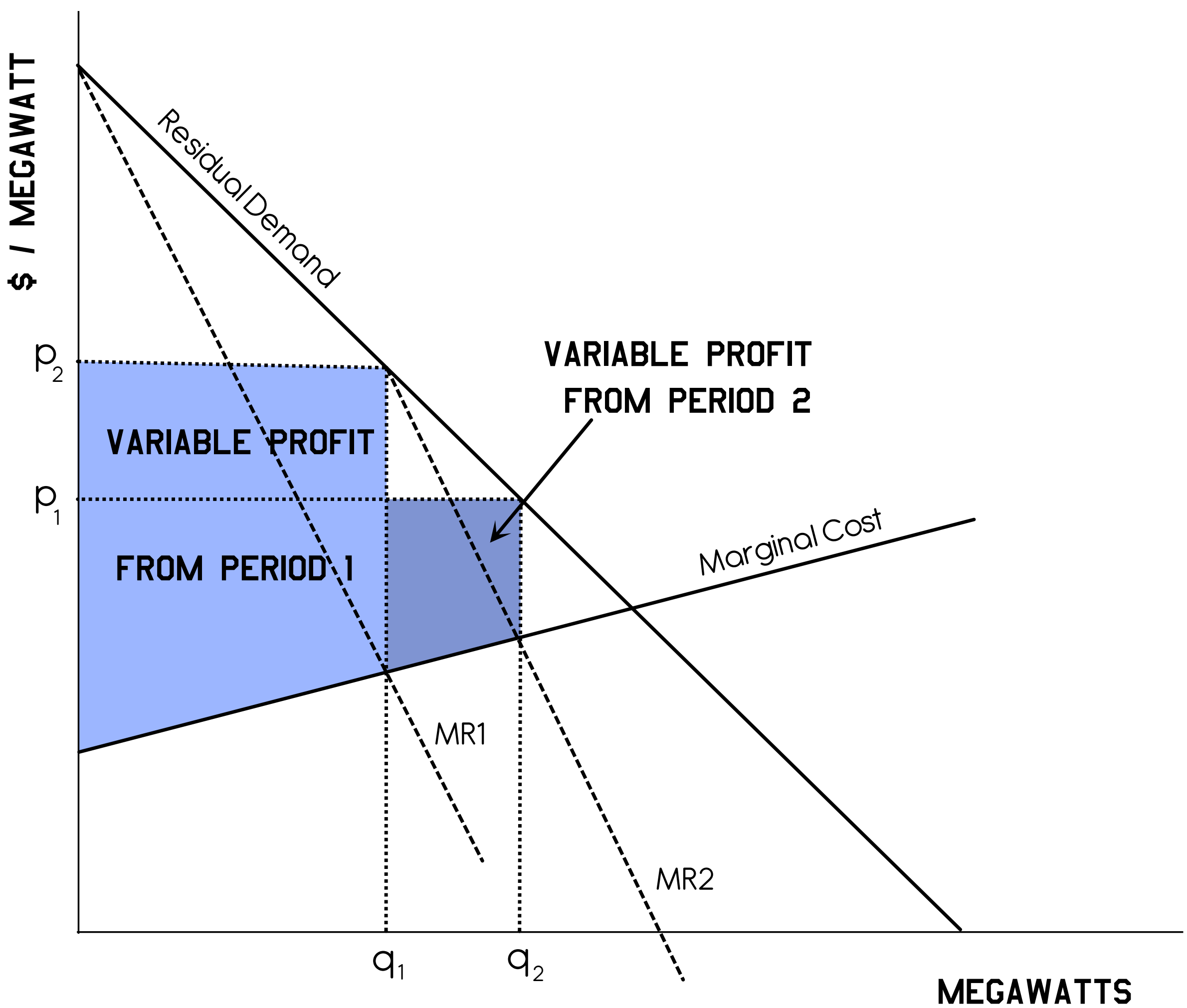


Figure 5.2: Price discrimination over a two-period auction, loosely following Coase (1972).

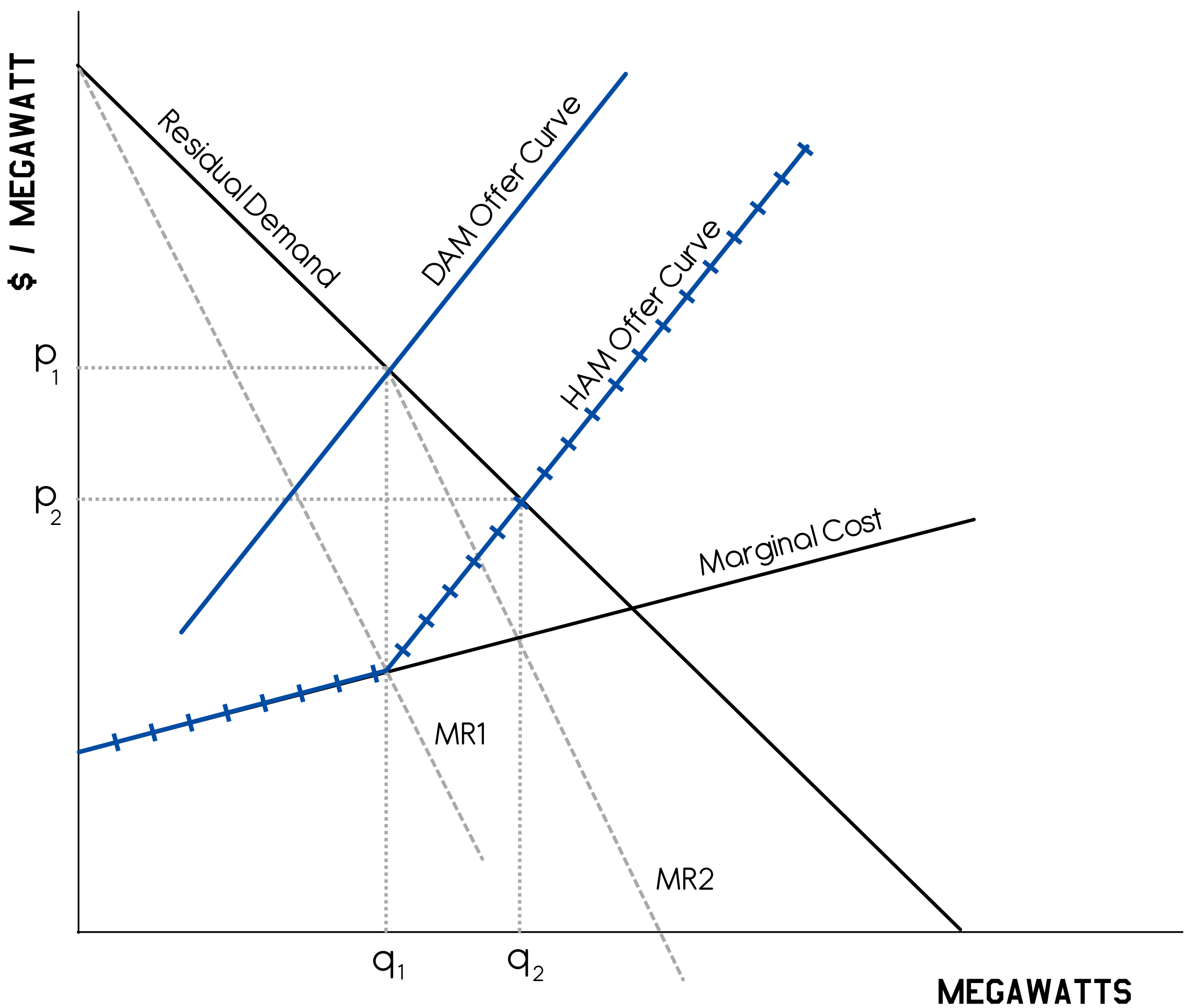


Figure 5.3: Offer curves implied by Figure 5.2.

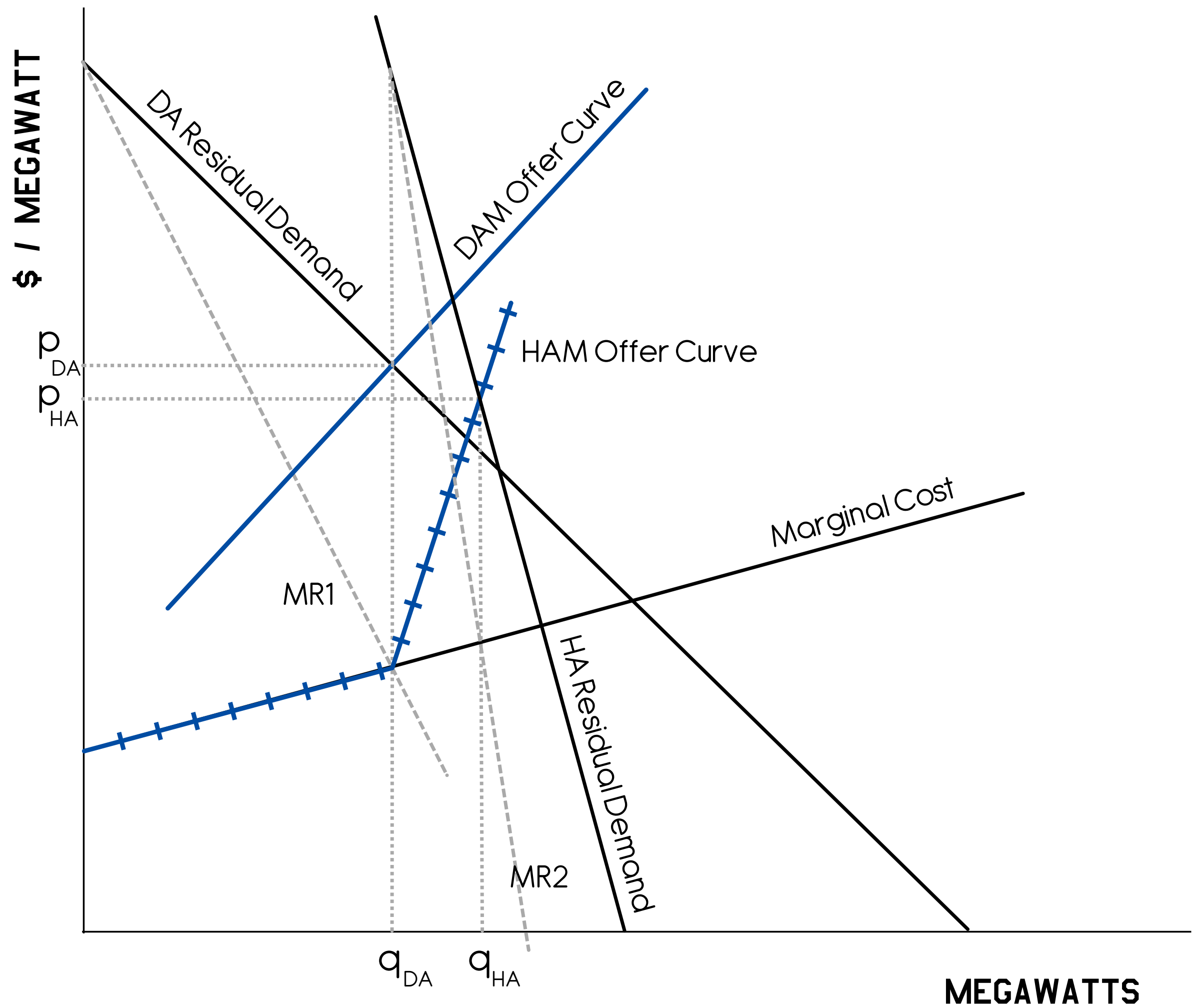


Figure 5.4: Sequential bids by a firm facing a more inelastic Hour-ahead (HA) residual demand as compared to Day-ahead (DA) residual demand.

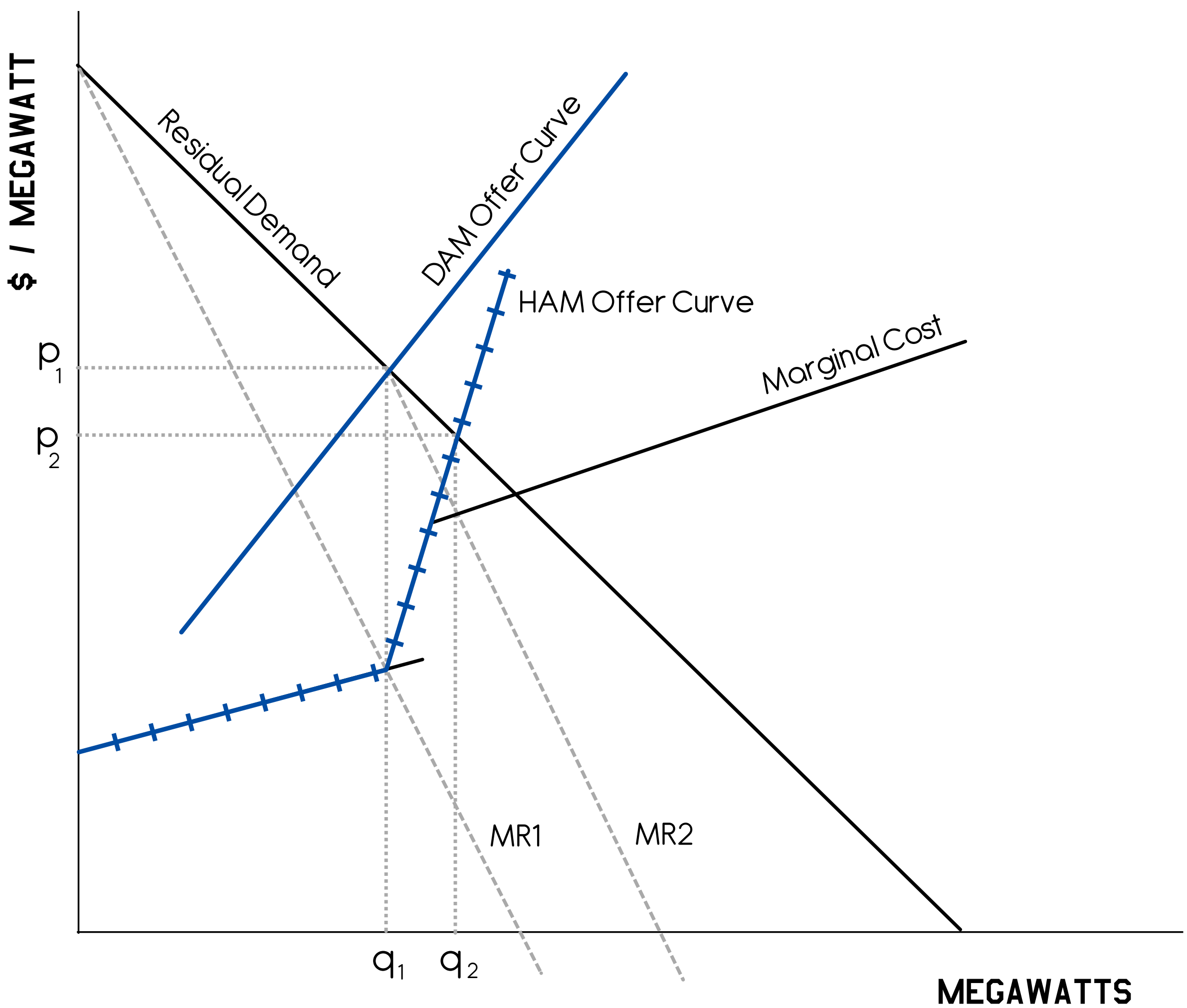


Figure 5.5: Sequential bids by a firm with convex marginal costs of production.

CHAPTER 6

EMPIRICAL SPECIFICATION AND RESULTS

The propositions outlined in Chapter 5 aim to characterize bidding behavior in both the Day-ahead (DA) auction and (HA) auctions by addressing the following question: Is firm bidding behavior consistent with expected profit maximization? The outline of the following empirical application is as follows: first, an offer curve functional form is used to extract salient features from each bidder's piecewise-defined offer curve. Next, a model is constructed that allows us to test propositions 1 through 4 (from Chapter 5). Finally, results from the model are discussed.

6.1 Conceptualizing an Ideal Experiment

6.1.1 Profit-maximizing Behavior

The ideal experiment to measure if firms were maximizing expected profit would be to form a joint distribution of the outcomes of both the DA and HA markets. With firm-specific marginal cost data and forward contract positions, optimal bids could be constructed for each firm[1]. This would involve knowing where in the network

[1] Wolak (2007) has shown that with careful specification of the firm's maximization problem, marginal cost data is not required to test the null hypothesis of expected profit maximization by bidders. A set of moment conditions, based on well defined market rules that constrain bid form, can be defined. When the number of moment restrictions is greater than the number of unknown parameters specifying the variable cost function, the parameters can be identified using Generalized Method of Moments (GMM). The test of profit maximization follows directly. Wolak (2007) and Wolak (2010) explains this approach in further detail and tests profit maximization directly using data from the National Energy Market (NEM) in Australia.

each generator is located and applying the SCUC algorithm[2] currently being used at the NYISO to clear the auction at least cost. A comparison could be made between observed bids and the optimal bids to see if they are statistically different.

Then, with some measure of market power (such as a firm-level Lerner index), we could see if the amount of market power attributed to each bidder had any bearing on the extent to which bids were optimal. Similar to the results in Hortaçsu and Puller (2008), we would expect that larger bidders are better able to form optimal bids due to their ability to amortize the cost of figuring out an optimal strategy (e.g., creating an internal trading department) over a larger capacity. The expected gains of bidding optimally for a larger firm are likely to be higher than a smaller firm.

6.1.2 Offer Curves in the Hour-ahead Market

Researching the way in which firms update their bids in the HA market involves identifying changes in a firm's information set between the DA auction and the HA market auction. Since the DA and HA auctions take place 24 and 2 hours in advance of the strike hour, respectively, there is opportunity for a bidder with a portfolio of generating assets to glean information from the outcome of the DA auction and fashion its HA bid accordingly. In practical terms, firms will use the results of the DA market to form their expectation of the HA residual demand. The residual demand in the HA market, ceteris parabus, has more variance than the unconditional expectation of the HA market residual demand curve (Hadsell and Shawky, 2007). Other factors increase variability in HA residual demand including unexpected outages and unexpected (extreme) load variation. With this updated information, firms can alter

[2]The Security-Constrained Unit Commitment algorithm is the NYISO's proprietary optimal power flow (OPF) calculation. It is unavailable to the public.

their bids into the HA market to capture any profits left on the table from non-optimal bidding in the DA market.

To examine variation across bidders in addition to across time, it would be useful to observe two bidders of different sizes and/or different portfolios of generation technology (e.g., marginal costs of production). With this cross-section, similarities or differences in firms' ability to construct an optimal bid could be inferred, given their size and complexion.

In this paper, firm-level NYISO bidding data is used to test if behavior is consistent with the theory outlined in Chapter 5 over the period from 2002 through 2010. Controlling for exogenous factors that impact a firm's marginal cost of production, the model identifies how the information set available after the DA market but before the HA market is used in the construction of both the DA and HA offer curves.

A firm-level Lerner index, calculated using the method developed in Wolak (2003) and McRae and Wolak (2009), is used to proxy variation in market power attributable to changes in the residual demand curve each firm faces[3].

6.2 Parametric Fitting of Firm Offer Curves

The approach taken in this paper deviates from the ideal experiment because of data availability. The NYISO masks firm identifying information to the public so that the anonymity of bidders is maintained. Without the ability to identify specific generating units, it becomes problematic to match marginal cost data and other observables at the firm level from other sources. Because masked generator and bidder IDs are kept to the same bidder, it is possible to track firms over time,

[3]See Section 4.1.5.

even without speculating on their true identity. This is helpful for two reasons: (1) generating units can be grouped into bidders; and (2) bidder participation in the Day-ahead and Hour-ahead wholesale electricity auctions can be tracked over time.

Identifying optimal bidding behavior is problematic without marginal cost data. Specifically, it is difficult to determine whether firms are equating marginal revenue to marginal costs in their bid structure, thereby exercising market power and collecting associated rents. Furthermore, proprietary forward contract data that enters the firm's objective function is unobservable to the public. But by inferring a conservative structure on firms' marginal cost, and isolating the effect of exposure to forward markets to the result of the day-ahead market results, the optimal bidder will exhibit certain characteristics observable in the masked bidding data.

Earlier work done by Zhang (2009) grouped generators (not bidders) into five groups determined by the highest price offered in each generator's respective bid. With these groups, the chosen functional form was an inverse logistic function[4],

$$P_{jk,t} = \frac{d_j}{1 + exp\Big[a_{j,t} - b_{j,t} \times (q_{jk,t}/OC_{j,t})\Big]} + e_{j,t} \ ,$$

where $P_{jk,t}$ is the offer price for the k^{th} level of offer quantities from group j at time t; $d_j \in \{50, 150, 400, 1000\}$ represents the highest price that determines each generator's grouping; $a_{j,t}$ and $b_{j,t}$ are the parameters to be estimated; $q_{jk,t}$ is the first k levels of offer quantities from group j at time t; $OC_{j,t}$ is the total capacities offered by group j at time t; and $e_{j,t}$ is a normally distributed error term.

The logistic functional form used by Zhang (2009) has some advantages in curve fitting bids: it is bounded above by d_i and below by zero; like offer curves, it is monotonically increasing[5]; and finally, its curvature resembles the bid shape observed

[4]My re-creation of this method is available in the file "Gen_grouping.r".

[5]NYISO market rules require all bid functions to be monotonically increasing in quantity.

for each group. However, it was not chosen in this analysis because the economic intuition behind the shape is lost in its functional form. Because the curve is fitted over the entire capacity offered, it is influenced equally by low price offers and higher priced offers. This is not ideal because the theory around submitting optimal offer curves suggests a bifurcation between the construction of the lower priced portion and higher priced portion of a bid. Additionally, the logistic functional form requires unwarranted symmetry in the neighborhood around the point $q_{ik,t}/OC_{i,t} = a_{i,t}/b_{i,t}$. The simplicity of this functional form comes at a cost: by constraining offer curve shape to this smooth functional form, we risk losing valuable information contained both at the high-priced and low-priced portion of the offer curve.

While capacity offered at lower prices may be made due to operational constraints (e.g., it is very costly to decrease output under 60%), forward contract positions, or risk preferences (e.g. operators/owners do not want to 'gamble' with this capacity), megawatts offered at higher prices may represent capacity offered strategically to influence the market clearing price for all inframarginal units. These high priced megawatts offered have attracted public interest, especially in the early stages of the NYISO wholesale market[6].

The curve chosen for this analysis stems from the theory behind optimal offer construction outlined in Hortaçsu and Puller (2008)[7] and Wolak (2007). Expected profit maximization is an assumption used in the development of the firm-level Lerner

[6]See the white paper "The New York Independent System Operators Market-Clearing Price Auction Is Too Expensive for New York", (McCullough Research; March 3 , 2009) and its responses: "McCulloughs Critique of the New York Electricity Market" (Hogan & Harvey; December 22, 2009) and "An Evaluation of the McCullough Research Report on New Yorks Wholesale Power Market" (Analysis Group; March 25, 2009).

[7]See figure 1 in Hortaçsu and Puller (2008).

index (Section 4.1.5) and is an assumption used in this paper for the DA market. To find out if bidders are expected profit-maximizing going into the HA market involves looking at the strategic portion of HA offer curves: namely, the megawatts offered at higher prices. Combining the lower priced and higher priced bids into a single functional form could potentially pollute our analysis of strategic bidding behavior. In response to this, a functional form (6.1) is chosen that reflects this dichotomy.

Because we are studying strategic behavior, our analysis is at the firm level versus the 'price grouping' done by Zhang (2009). While many generators offer bids that fall into the same price group, the incremental changes in response to market conditions would be drowned out by the numerous other competing firms in the same group. Furthermore, it is likely that firms own a portfolio of generating assets around the state of New York and implement bidding strategies based on location and generation technology. It could be that the price grouping serves mainly to divide up generators by technology (e.g., coal, nuclear, hydro, natural gas) rather than by bidding behavior. Furthermore, a generator choosing into a 'bidding group' as in Zhang (2009) is not relevant if it is a minor piece of a firm's generation portfolio and may reflect decisions by risk managers at the aggregate level rather than strategic decisions at the unit level. All of these features make this grouping unsuitable for an analysis of strategic bidding behavior at the firm level.

6.2.1 A Strategic Functional Form

To capture the relevant features of firm offer curves, this study parametrizes bids at the firm level by horizontally summing all generators for each bidder. The bid is then separated into a baseload portion and a strategic portion, where the slope of the strategic portion is allowed to vary whereas the baseload offered price is fixed for each hour and auction. The offered quantities were normalized as a percentage of total offered capacity[8] so that bids could be directly compared across bidders in the NYISO.

A piecewise defined functional form (shown in Figure **??**) is chosen to fit each bidder's offer curve in order to account for the previously mentioned features. The offer price for the first $\frac{q_{ita}}{Q_{MAX,it}}$ portion of offered capacity from bidder i at time t is modeled as:

$$P_{ita} = \begin{cases} \mathrm{P}_{B,ita} & \text{when } \frac{q_{ita}}{Q_{MAX,it}} < Z \\ \tilde{\beta}_{0,ita} + \tilde{\beta}_{1,ita} \cdot \left(q_{ita}/Q_{MAX,it}\right) & \text{when } \frac{q_{ita}}{Q_{MAX,it}} \geq Z \ , \end{cases} \tag{6.1}$$

where P_{ita} is the price the bidder is willing to accept for supplying q_{ita} megawatts of electricity; $a \in \{DAM, HAM\}$ represents the Day-ahead and Hour-ahead auctions respectively; $Q_{MAX,ita}$ is the maximum quantity offered across both auctions; Z, $P_{B,ita}$, $\tilde{\beta}_{0,ita}$ and $\tilde{\beta}_{1,ita}$ are parameters to be estimated.

6.2.2 Nonlinear Least Squares Estimation

The specification outlined above was estimated using the Gauss-Newton method to minimize the sum of squared residuals of the fit. To find the optimal breakpoint, Z^*, a grid-search approach was used. The curve was fit for all values of Z between 0 and 1 at increments of 0.0025, or at each quarter percent of offered capacity. This approach was used because the model is overspecified when Z is included in the nonlinear least squares optimization problem. The increment of 0.25% of capacity was chosen as a granular enough approach to adequately fit the model, while also being computationally efficient. To put this in perspective, the largest capacity into

[8] Total offered capacity is the maximum offered capacity submitted between the DA and HA auctions.

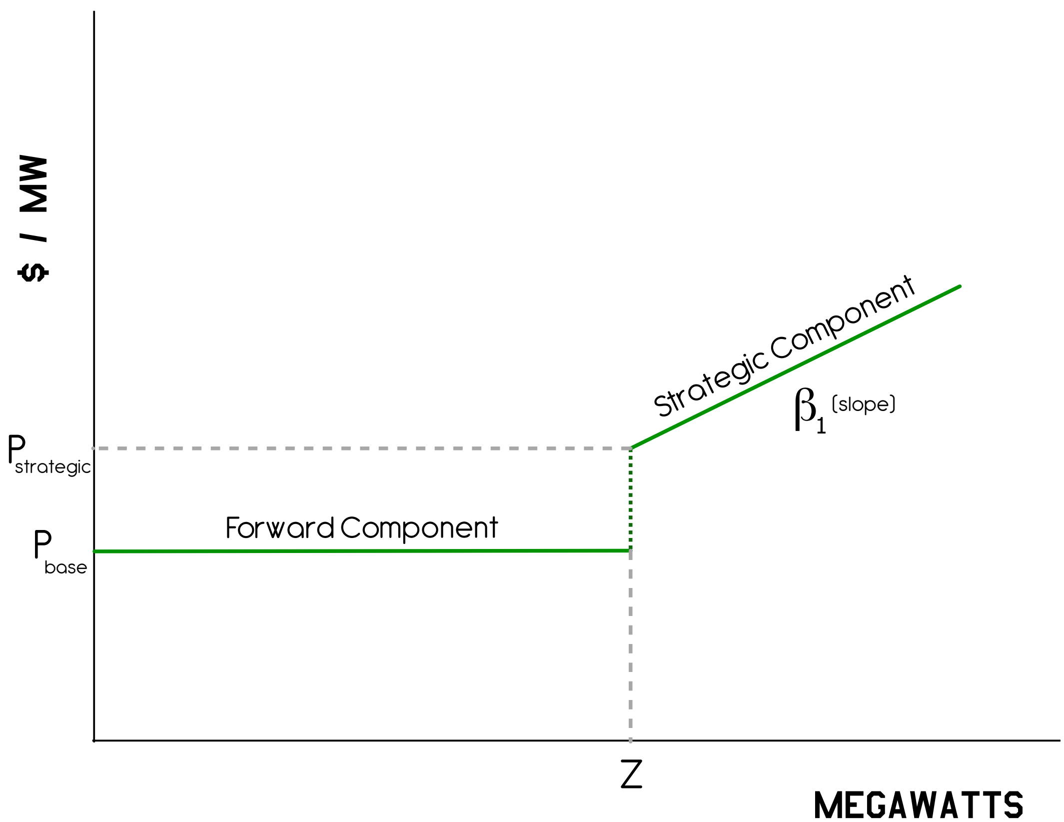


Figure 6.1: The parameterization of bidder offer curves via a piecewise-defined function.

the Day-ahead market is 14,672 megawatts; this means that values of Z were searched at a maximum of every 37 megawatts of capacity[9].

Each of the ten largest bidders' offer curves for both the Day-ahead market and Hour-ahead market were fit using the piecewise defined function (6.1) defined above using nonlinear least squares estimation[10].

[9]Furthermore, 99.8% of bidders offered less than or equal to 5,000 megawatts; this implies granularity of 12.5 megawatts on the value of Z.

[10]The calculation methodology is explained in more detail in Appendix B.

6.2.3 How Parameters Reflect Firm Strategic Decision Making

From Wolak (2007) and Hortaçsu and Puller (2008), the shape of a bidder's offer curve reflects three important components: (1) the firm's own marginal costs of production; (2) its forward contract position entering the auction; and (3) its expectation of the residual demand curve it is facing.

Notion (3) above is arguably the most important because with absolute certainty of the realization of residual demand, the shape of the a firm's offer curve, at all quantities except for the quantity (q^*) where the bid intersects residual demand, is arbitrary. Recall that for the marginal bidder, the auction clears at precisely one point: the intersection of residual demand and the firm's offer curve. With absolute certainty, the shape of an offer curve over the entire domain excluding q^* does not change the result of the auction as long as the offer curve intersects residual demand at (q^*, p^*).

Firms do not behave in an environment of certainty. Therefore, the shape of a firm's offer curve matters. The profit maximizing firm constructs its offer curve to provide the best chance at intersecting residual demand at the profit maximizing price and quantity. It is likely larger bidders are sophisticated enough to construct offers that closely mirror an optimal, expected-profit-maximizing bid. The sample used in this analysis consists of the ten largest firms bidding into the NYISO Day-ahead market. Therefore, this offer curve specification should capture the realization of these key factors in the construction of a bid.

6.2.4 The Optimal Breakpoint Z_{it}

Recall that the optimal breakpoint Z_{it} is found by curve fitting 400 different iterations[11] of each offer curve, and selecting the Z that resulted in the best fit. This parameter is important because it reflects the transition of megawatts offered at a constant, lower base price, to megawatts offered in a changing sequence of prices. The incentive to offer lower, base price quantities at varying prices depends on marginal costs of production, the forward contract of the firm, and any "must use" capacity. As described in Wolak (2007), when firm forward contract position increases the optimal bid is to produce the contracted quantity only if the firm is the least cost producer. This translates into bidding at marginal cost for quantities less than Z_{it}.

6.2.5 The Base Price $P_{B,it}$

The estimated parameter P_B is directly related to marginal costs of production. In fossil fuel-fired generating units, P_B (i.e., marginal cost) is determined by fuel prices and heat rates; in hydroelectric plants it could be the increasing opportunity cost of exercising the "option" of stored water (potentially nonrenewable in the short run). In all generating plants, operating and maintenance costs generally increase incrementally and monotonically over capacity. Summing up into a portfolio of generating assets, marginal costs of production will change due to heterogenous generation technology (e.g., switching from oil to natural gas). Because more efficient generation technology serves the initial load, and more expensive generating technology is turned on later, there is expected to be some convexity to a firm's marginal cost function.

That said, my contention is that this variation (of marginal costs over quantity) is minimal for the majority of a firm's capacity. Allowing for sloped curve fits for

[11] $400 \times 0.25\% = 100\%$.

capacity less than Z makes it more difficult to discern the switch between baseload capacity and 'strategic' capacity. This is why the first interval of megawatts offered is modeled as a single unchanging price P_B.

6.2.6 The Strategic Slope $\tilde{\beta}_{1,it}$

In the functional form chosen to fit the offer curves, the latter portion of a firm's offer capacity is allowed to vary with respect to price. In my model its slope, $\tilde{\beta}_{1,it}$, represents capacity that a firm is willing to use to influence the outcome of the market-clearing price. This is the piece where market power is likely to be exerted by a firm raising the last few megawatts of its capacity to nudge the market price up and increase the price received for all inframarginal units[12].

6.2.7 The Strategic Price P_S

In equation 6.1, the starting price of the strategic portion of the bid is allowed to vary. This variation is captured in the parameter $\tilde{\beta}_{0,ita}$. Because the value of this parameter depends not only on the structure of the strategic portion of a firm's bid, but also on the breakpoint, Z, this parameter is converted into a 'starting price' for the strategic portion of the bid P_S, equal to $\tilde{\beta}_0 + Z \cdot \tilde{\beta}_1$. This value represents the price level where a bidder starts its strategic offer.

Table 6.1: Summary statistics for Curve fit [ACF_analyses.r].

Day-ahead Market

	Obs	**Mean**	**Median**	**Std.Dev**	**Min**	**MAX**
Z	492,435	0.55	0.64	0.36	0.00	1.00
P_B	492,435	-71.77	24.39	311.70	-999.00	997.00
P_S	491,928	47.43	60.15	398.15	-1,218.33	1,041.89
$\tilde{\beta}_1$	492,435	5769.95	300.47	27,739.58	-0.00	1,446,413.25
pseudo R^2	492,435	0.91	0.93	0.07	0.40	1.00
OC	492,435	1,551.70	1,270.00	1,052.73	2.00	14,672.00

Hour-ahead Market

	Obs	**Mean**	**Median**	**Std.Dev**	**Min**	**Max**
Z	512,159	0.52	0.52	0.36	0.00	1.00
P_B	512,159	-75.58	14.98	306.31	-999.00	1,000.00
P_S	510,605	17.21	44.96	377.54	-995.89	1,000.00
$\tilde{\beta}_1$	512,159	8,579.56	199.25	58,402.10	-0.02	2,897,743.04
pseudo R^2	511,960	0.89	0.91	0.09	0.47	1.00
OC	512,159	1,562.76	1,273.00	1,027.44	2.00	5,120.00

Change in Parameters Between Auctions: HAM minus DAM

	Obs	**Mean**	**Median**	**Std.Dev**	**Min**	**Max**
Z	470,175	-0.03	0.00	0.27	-0.99	0.99
P_B	470,175	-8.79	0.00	64.49	-1,097.00	999.82
P_S	468,994	-34.03	0.00	216.04	-1490.27	1,154.77
$\tilde{\beta}_1$	470,175	3,263.60	0.00	63,123.04	-1,446,373.71	2,845,318.81

6.2.8 Estimating Curve Fit Parameters P_B, Z, P_S, & $\tilde{\beta}_1$

Summary statistics of the parameters estimated via nonlinear least squares, pooled for the 10 largest bidders, are shown in Table 6.1 on page 52. Parameter means by

[12] The estimated slope parameter $\tilde{\beta}_{1,it}$ exhibited extreme dispersion as compared to the regressors that had the potential to introduce bias in parameter estimates. For this reason, it was transformed using the shifted power transformed outlined in Box and Cox (1964). From hereafter, all discussion of the parameter $\tilde{\beta}_{1,it}$ in both the DA and HA market will refer to the transformed data.

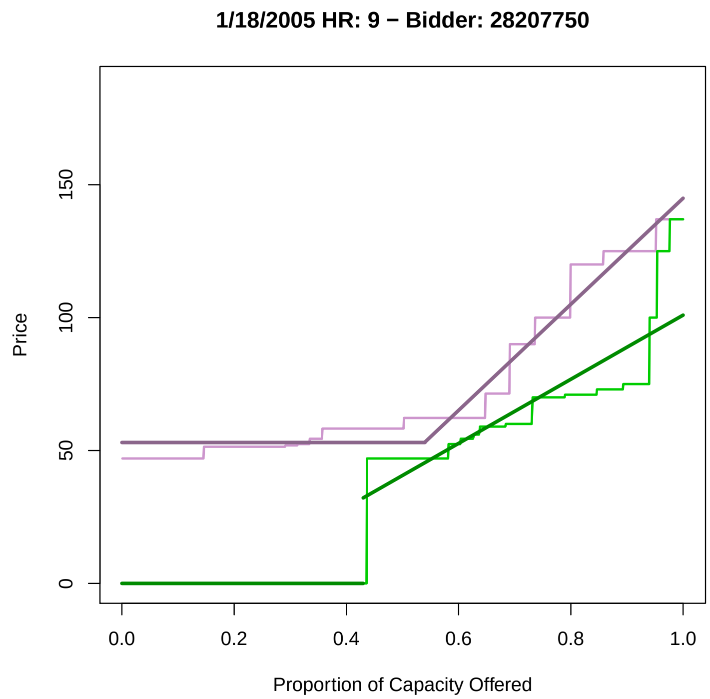
bidder are shown in Table 6.2 on page 55 [13]. The maximum and minimum prices of P_B and P_S are close to the allowable range of prices in the NYISO (+/-$\$1,000$), and median prices for P_B are reasonably close to what a baseload generator might have as marginal cost, although a bit lower due to some of the larger hydro generators likely in our sample.

The parameter $\tilde{\beta}_1$ shows extreme variation, and its value in absolute terms is not easily recognizable because it has been normalized across maximum offered capacity. Because offered capacity varies, and proportion of offered capacity lies on the interval [0,1] these become high quickly. For example, a bidder with a slope (exactly analogous to $\tilde{\beta}_1$) on the strategic portion of its offer curve of $5 per megawatt, whose total offered capacity is 800 megawatts, would be fit a $\tilde{\beta}_1$ of $4,000$ – it would be multiplied by a factor of 800.

The median Z parameter lies at 64% of capacity. This implies that the median bidder is offering slightly more than half of its capacity at a lower price, perhaps marginal cost. This is broadly consistent with NYISO figures that roughly 47.5% of quantity cleared in the Day-ahead market is through bilateral contracts.

Differences in summary statistics between the DA and HA market show that the median bidder does not change its parameters at all. However, variation does exist and it is negative for Z, P_B and P_S, while positive for $\tilde{\beta}_1$. This suggests that bidders are offering steeper bids overall, but bids that start at a lower price. In the empirical section, other factors will be controlled for to isolate these changes.

[13] A lookup table that matches NYISO masked bidder IDs to the letters used in this study is available in Appendix D.



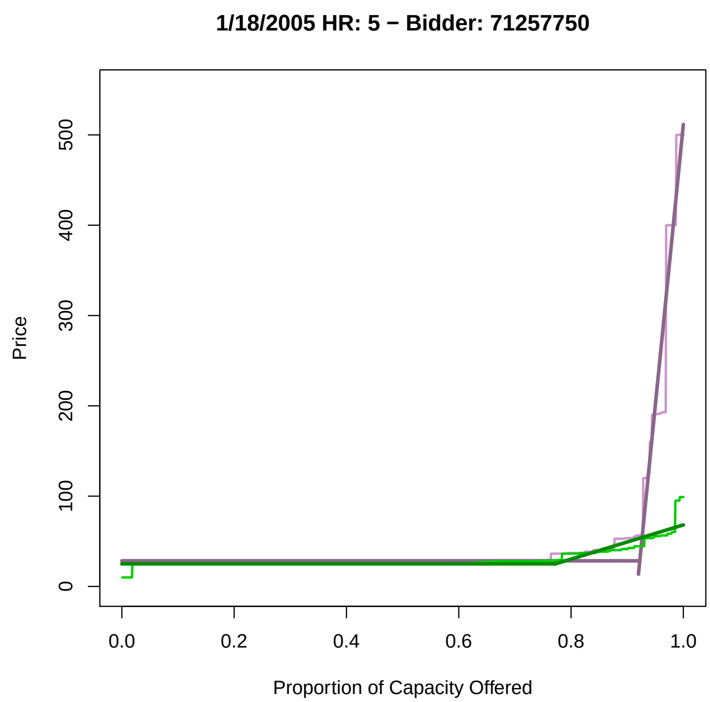


Figure 6.2: Curve fitting the DAM and HAM offer curves using a 2-step piecewise functional form (DAM = purple, HAM = green).

Table 6.2: Mean of estimated parameters of curve fit by bidder [ACF_analyses_IV.r].

Day-ahead Market

BIDDER	Z	P_B	P_S	$\tilde{\beta}_1$	R^2	**OC**
A	0.10	-998.86	-981.28	0.06	0.98	549.72
B	0.38	33.26	91.92	7,435.76	0.90	2,736.93
C	0.35	44.39	112.42	403.35	0.91	2,419.34
D	0.85	47.94	88.15	752.52	0.92	963.35
E	0.42	33.50	91.91	3,537.25	0.90	2,633.71
F	0.63	73.23	125.52	263.60	0.94	1,727.39
G	0.50	48.57	81.71	694.30	0.87	1,510.03
H	0.71	2.51	331.66	24,149.70	0.92	1,758.23
I	0.93	28.08	292.66	6,531.70	0.93	1,164.30
J	0.10	-9.91	-4.32	7.79	0.87	1,636.72

Hour-ahead Market

BIDDER	Z	P_B	P_S	$\tilde{\beta}_1$	R^2	**OC**
A	0.10	-998.85	-982.05	0.07	0.98	546.79
B	0.36	25.84	70.11	2,736.06	0.89	2,707.79
C	0.34	40.36	101.94	3,772.12	0.91	2,182.10
D	0.77	42.95	81.07	742.86	0.90	964.17
E	0.46	39.01	86.78	558.52	0.89	2,281.88
F	0.51	46.70	133.21	688.24	0.86	1,620.48
G	0.45	40.16	79.04	990.02	0.85	1,509.88
H	0.72	-19.32	291.87	41,963.24	0.89	1,936.73
I	0.90	24.05	139.02	9,503.06	0.88	1,182.46
J	0.09	-9.95	-5.00	6.86	0.86	1,648.96

Table 6.3: Mean of the difference between parameters of curve fit by bidder between the Hour-ahead and Day-ahead market (HAM minus DAM) [ACF_analyses_IV.r].

BIDDER	Z	P_B	P_S	$\tilde{\beta}_1$
A	-0.00	-0.00	0.00	-0.77
B	-0.03	-4,720.56	-7.07	-20.62
C	0.01	4,975.46	-7.07	-13.51
D	-0.08	-10.38	-5.00	-7.00
E	0.01	-3,958.71	3.24	-2.07
F	-0.12	481.65	-29.11	15.23
G	-0.05	271.03	-8.38	-1.83
H	0.01	17,845.44	-21.64	-37.24
I	-0.03	2,974.22	-4.02	-153.61
J	-0.00	-0.92	-0.04	-0.68

6.2.9 Goodness of Fit

Table 6.4: The pseudo-R^2 for bidder curve fits were above 0.85 a majority of the time.

BIDDER	% R^2 over 0.85
A	99.99
B	78.87
C	83.49
D	83.69
E	78.44
F	76.72
G	58.86
H	80.61
I	80.5
J	68

The goodness of fit for our chosen model is based on a visual inspection (see Figure **??**) and a psuedo R^2 measure[14]. The median of this measure is 0.93 and 0.91 for the

[14] pseudo-$R^2 = 1 - \text{SSR}_{model}/((n-1)\cdot \text{Var}[Y])$

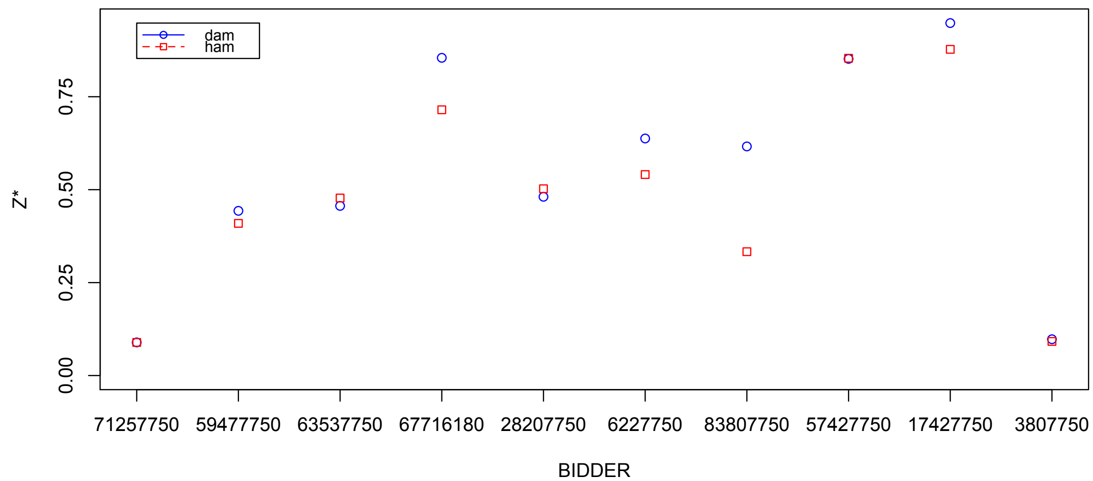


Figure 6.3: Mean of Breakpoint Z by Bidder by Market

DA and HA markets, respectively. The pseudo-R^2 was no less than 0.85 the majority of the time (see Table 6.4) for all ten bidders in the sample.

Bidders in the day-ahead market are strategic players, but they are also operators taking into account "the particular circumstances of time and place"[15]. This might translate into a need to commit a certain portion of capacity in the Day-ahead market. Risk preference and operational considerations would limit the size of the strategic portion of the bid, and the likelihood of setting the marginal price for the auction.

6.3 Testing the Theoretical Predictions

In order to test the theoretical predictions outlined in Chapter 5, an empirical model of bidding behavior in the DA and HA markets is developed. Next, the method

[15]Hayek, F.A. *The Use of Knowledge in Society.* American Economic Review. XXXV, No. 4. pp. 519-30.

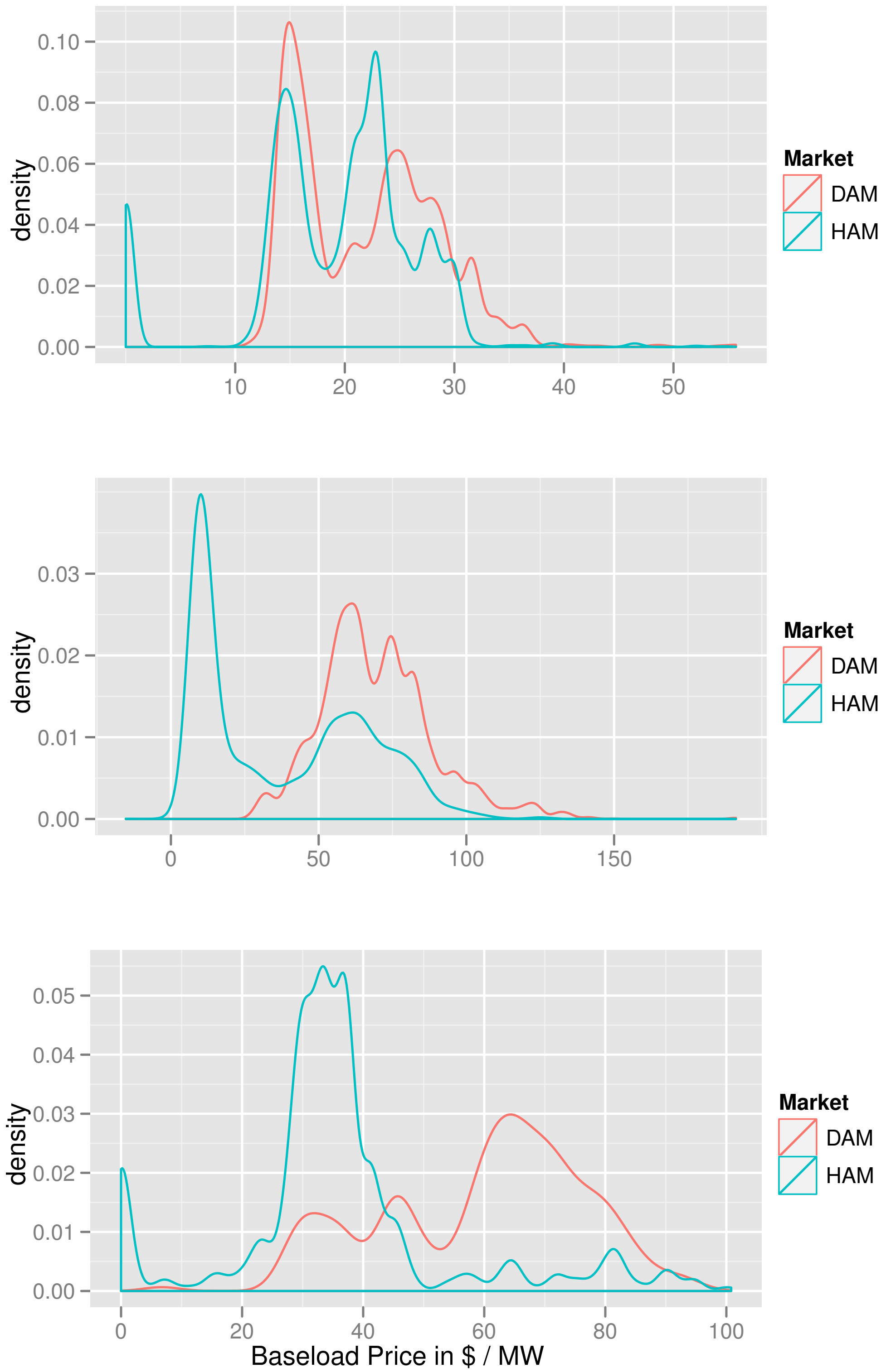


Figure 6.4: Baseload price density by bidder (1 of 4). Bidders are 71257750, 59477750, & 63537750 (top to bottom) [ACF_analyses.r].

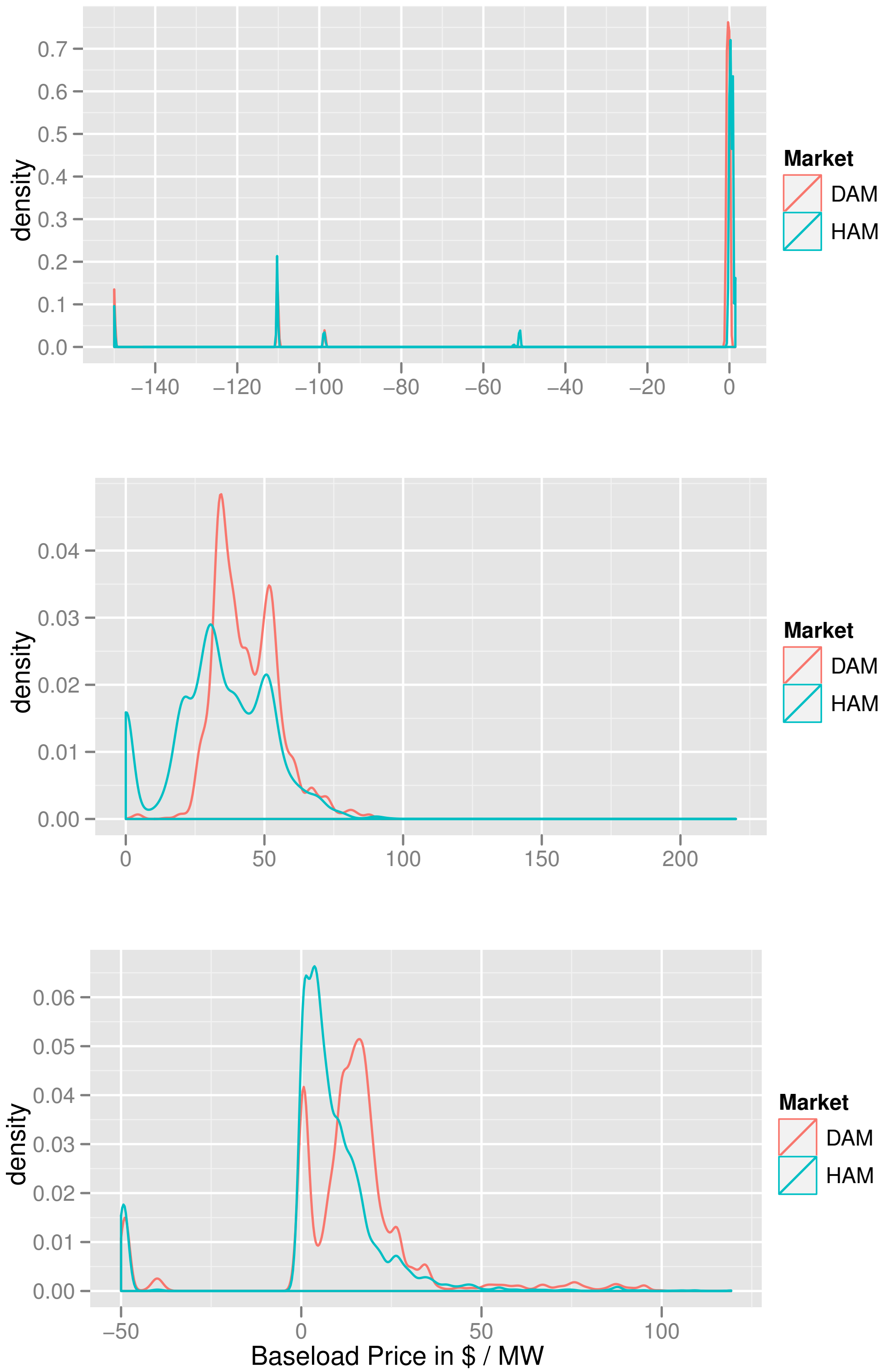


Figure 6.5: Baseload price density by bidder (2 of 4). Bidders are 67716180, 28207750, & 6227750 (top to bottom) [ACF_analyses.r]

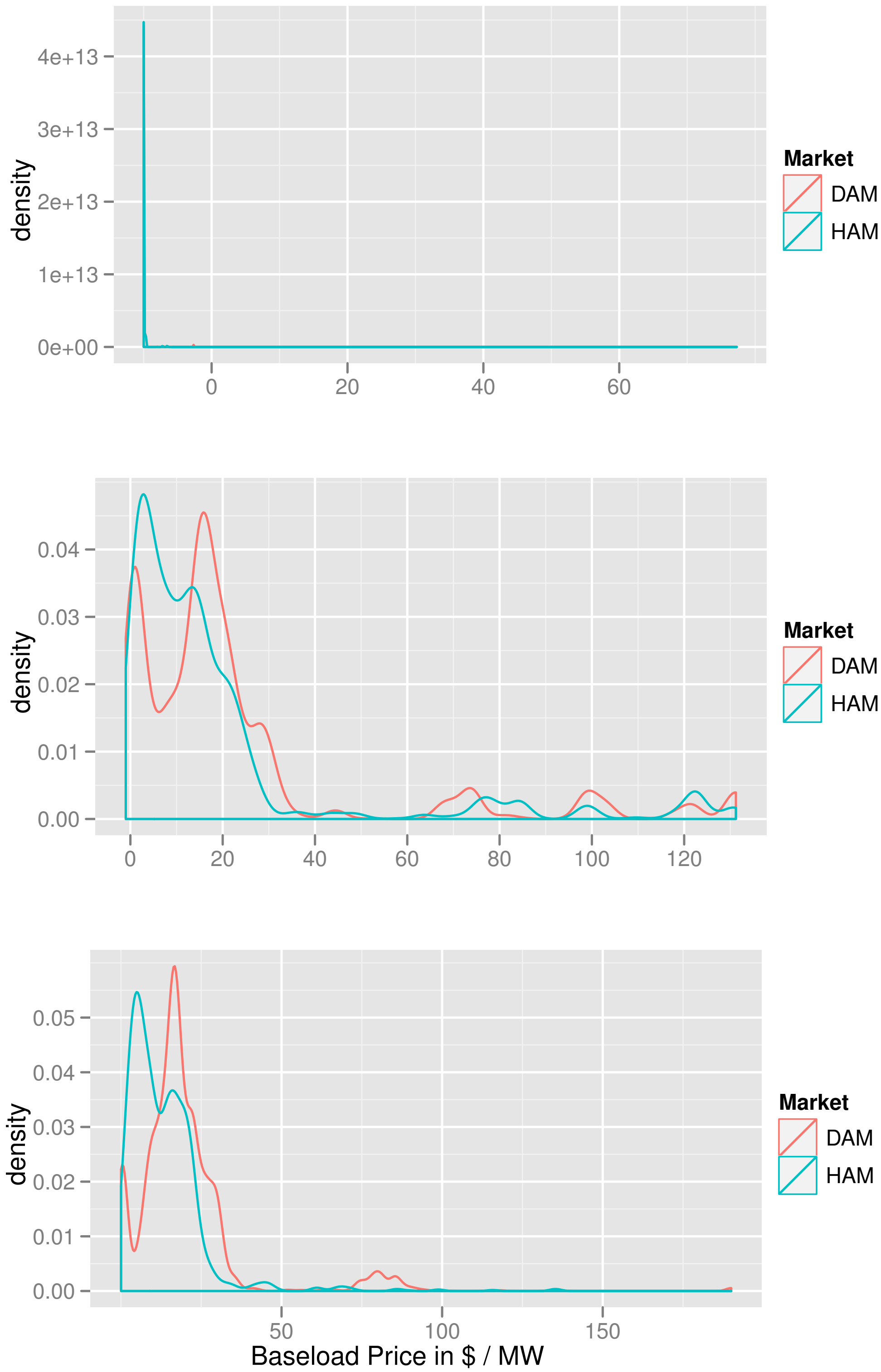


Figure 6.6: Baseload price density by bidder (3 of 4). Bidders are 83807750, 57427750, & 17427750 (top to bottom) [ACF_analyses.r]

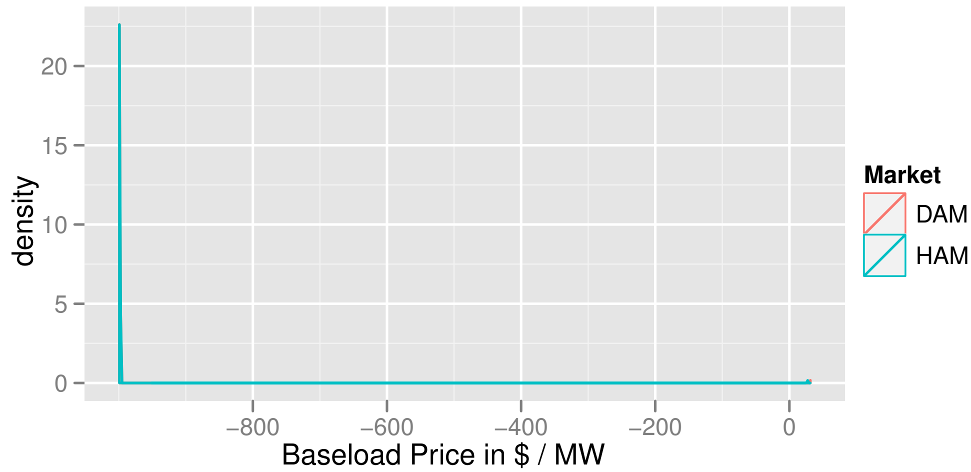


Figure 6.7: Baseload price density by bidder (4 of 4). Bidder is 3807750 [ACF_analyses.r]

by which the theoretical predictions will be tested is discussed. Finally, the results of the estimation are discussed in the context of the theoretical tests.

6.3.1 Four Empirical Models of Offer Curve Parameters

Between the two auctions, a bidder updates its information set with (1) the price and quantity sold in the Day-ahead market; (2) updates on the load forecast (normally a function of weather); and (3) changes in the spot price of natural gas (the marginal fuel in the NYISO (Tierney et al., 2008)); and (4) the virtual supply conditions heading into the HAM. The model for the Hour-ahead offer curve is then

$$\hat{S}_{it}^{DAM}(p) = h(\Omega_{it}) \tag{6.2}$$

$$\hat{S}_{it}^{HAM}(p) = g(\hat{S}_{it}^{DAM}) + f_i(\theta_t) \tag{6.3}$$

where $\hat{S}_{it}(p)$ is the supply function (i.e. bid) mapping prices to quantity offered by firm i in the Day-ahead and Hour-ahead markets for hour t; $h(\cdot)$ is a function relating how information available prior to the DA market (Ω_{it}) is incorporated into the DA bid; $g(\cdot)$ is a function representing how results from the DA market endogenous to the choice of $\hat{S}_{it}^{DAM}(p)$ impact the bid into the HA market; θ_t is a vector of observables representing new information available prior to the strike hour; and $f_i(\cdot)$ is a bidder specific function that converts this new information into the optimal HA bid.

Because bidder offer curves have been decomposed into a set of four parameters $\{P_B, Z, P_B, \beta_1\}$ using the piecewise defined fit defined in (6.1), our notion of both $\hat{S}_{it}^{HAM}(p)$ and $\hat{S}_{it}^{DAM}(p)$ is described by a vector of length four. So, to further investigate the response $f_i(\cdot)$ that bidders have to changes in the information available between the Day-ahead and Hour-ahead market, model (6.3) will be estimated as

$$\Phi_{it}^a = \vec{\beta}_0 \cdot \Omega_{it} + \vec{\beta}_1 \cdot 1\{\Omega_{it}\}^{HAM} + \vec{\beta}_2 \cdot 1\{\theta_t\}^{HAM} + \vec{\beta}_3 \cdot 1\{g(\hat{S}_{it}^{DAM})\}^{HAM} \tag{6.4}$$

where $\Phi \in \{P_B, Z, P_S, \tilde{\beta}_1\}$ represents the parameters estimated in the curve fit described in Section 6.2 for bidder i at time t; $a \in \{DAM, HAM\}$; $h(\cdot)$, $g(\cdot)$ and $f_i(\cdot)$ are linear; and $1\{\cdot\}^{HAM}$ is the indicator function that turns on for Hour-ahead market observations. Separate models are estimated for each left hand side variable.

Table 6.5: Additional variables with descriptions.

Variable	**Type**	**Description**	**Range of values**
CDD	Integer > 0	Cooling-degree Days	0 - 35
NTHO	Number > 0	Price of No. 2 Heating Oil (daily)	\$ 0.507 - 4.083
L	Number	Lerner index	0 - 5.25
peak	Dummy	Peak hours of the day (11a.m. - 5 p.m.)	0/1
wknd	Dummy	Weekends	0/1
q^*_{DAM}	Integer	Estimated quantity cleared in the DAM	> 0
WP$_{DAM}$	Number	Load-weighted DAM electricity price	\$10 - \$520/MWHr
LTZ	Dummy	q^*_{DAM} in $[0, Z]$ range	0/1
netsupp	Integer	Net DA virtual supply	-3,293 to 3,094

The objective here is to understand how bidders use information not available to them prior to the clearing of the Day-ahead auction to update their bids going into the Hour-ahead market. Because there is considerable heterogeneity across bidders, as evidenced by the distribution of the dependent variable $\tilde{\beta}_{1,it}$ a fixed effects model was insufficient to capture the heterogeneity stemming from bidders' heterogenous reaction to each of the regressors[16].

Therefore, the empirical model outlined in (6.4) will be estimated separately for each bidder and curve fit parameter, as follows.

6.3.2 Heteroskedasticity and Autocorrelation

Because many bidders do not update their bids every hour of every day, the sample used in these regressions is highly serially correlated and is also heteroskedastic. Because this can bias standard errors in regression results, heteroskedasticity and autocorrelation adjusted standard errors from Newey and West (1987) were used in the regression results. Since sample size used in this paper is large, these are preferred to explicitly modeling the structure of autocorrelation and heteroskedasticity.

6.3.3 Congestion

Network congestion occurs when wires transporting electricity can no longer fit additional load. When these constraints bind, the wholesale electricity market becomes segmented into multiple regional markets. Because firm and generator identifying information is masked, it is difficult to determine where on the NY electricity network each generator is located. In order to reliably calculate firm Lerner indices, the entire NYCA must be treated as a single market, i.e. it must be uncongested. Therefore, all the regressions estimated below exclude hours when average zonal congestion rents, in absolute value, were more than 2% of the reference bus base price of electricity.

[16] A Chow test of the null hypothesis that the restricted fixed effects model is equal to separate models for each bidder was soundly rejected (F-stat $= 87,025$) lending support for estimating separate models.

This occurred in slightly more than half of the hours between 2002 and 2010. 2% was chosen because it indicates a congestion rent that is an insignificant portion of the total price of electricity, so should not factor into the strategic bidding decisions at the firm level.

Much literature has focused on the interaction between congestion and market power (Joskow and Tirole, 2000; Bushnell, 1999; Stoft, 1999); this topic is out of the scope of this paper.

6.3.4 The Strategic Slope Parameter β_1

The regression equation for β_1 will be:

$$
\begin{aligned}
\tilde{\beta}_{1,it} = {} & \beta_0 + \beta_1 \cdot \mathrm{L} + \beta_2 \cdot (\mathrm{HAM} \times \mathrm{L}) + \beta_3 \cdot (\mathrm{HAM} \times \mathrm{WP}) \\
& + \beta_4 \cdot (\mathrm{HAM} \times q^*_{DAM}) + \beta_5 \cdot \mathrm{CDD} + \beta_6 \cdot (\mathrm{HAM} \times \mathrm{CDD}) + \beta_7 \cdot (\mathrm{HAM} \times \mathrm{LTZ}) \\
& + \alpha_1 \cdot \mathrm{HAM} + \alpha_2 \cdot \mathrm{peak} + \alpha_3 \cdot \mathrm{wknd} + \vec{\gamma}_1 \cdot \bar{\mathrm{YR}} + \vec{\gamma}_2 \cdot \bar{\mathrm{SE}} + e_{it}
\end{aligned} \tag{6.5}
$$

where the dependent variable $\tilde{\beta}_{1,it}$ is the parameter used to fit the strategic slope of bidders' offer curves; HAM is an indicator variable equal to one when the dependent variable refers to a bid into the Hour-ahead market; $\bar{\mathrm{YR}}$ and $\bar{\mathrm{SE}}$ are matrices of year and seasonal fixed effects, respectively; α coefficients denote dummy variable regressors equal to 1 or 0; and e_{it} is a zero-mean error term[17]. The results of the estimation are shown in Table 6.7.

[17] Refer to Table 6.5 for a description of all regressors used.

6.3.5 The Strategic Price Parameter P_S

The regression equation for P_S will be:

$$\begin{aligned} P_{S,it} &= \beta_0 + \beta_1 \cdot \mathrm{L} + \beta_2 \cdot (\mathrm{HAM} \times \mathrm{L}) + \beta_3 \cdot (\mathrm{HAM} \times \mathrm{WP}) \\ &+ \beta_4 \cdot (\mathrm{HAM} \times q^*_{DAM}) + \beta_5 \cdot \mathrm{CDD} + \beta_6 \cdot (\mathrm{HAM} \times \mathrm{CDD}) + \beta_7 \cdot (\mathrm{HAM} \times \mathrm{LTZ}) \\ &+ \beta_8 \cdot \mathrm{NTHO} + \alpha_1 \cdot \mathrm{HAM} + \alpha_2 \cdot \mathrm{peak} + \alpha_3 \cdot \mathrm{wknd} + \vec{\gamma}_1 \cdot \bar{\mathrm{YR}} + \vec{\gamma}_2 \cdot \bar{\mathrm{SE}} + e_{it} \end{aligned} \tag{6.6}$$

where the dependent variable $P^{HAM}_{S,it}$ is the parameter used to fit the intercept price on the strategic slope of bidders' offer curves in the HAM (see Figure **??**); NTHO is the daily price of #2 heating oil; and the remaining regressors mirror model (6.5). The estimation results for this model are shown in Table 6.9. #2 heating oil is included in this regression to control for variation in a major input into power generation for fossil fuel plants.

6.3.6 The Marginal Cost Parameter P_B

The regression equation for P_B will be:

$$\begin{aligned} P_{B,it} &= \beta_0 + \beta_1 \cdot \mathrm{L} + \beta_2 \cdot (\mathrm{HAM} \times \mathrm{L}) + \beta_3 \cdot (\mathrm{HAM} \times \mathrm{WP}) \\ &+ \beta_4 \cdot (\mathrm{HAM} \times q^*_{DAM}) + \beta_5 \cdot \mathrm{CDD} + \beta_6 \cdot (\mathrm{HAM} \times \mathrm{CDD}) + \beta_7 \cdot (\mathrm{HAM} \times \mathrm{LTZ}) \\ &+ \beta_8 \cdot \mathrm{NTHO} + \alpha_1 \cdot \mathrm{HAM} + \alpha_2 \cdot \mathrm{peak} + \alpha_3 \cdot \mathrm{wknd} + \vec{\gamma}_1 \cdot \bar{\mathrm{YR}} + \vec{\gamma}_2 \cdot \bar{\mathrm{SE}} + e_{it} \end{aligned} \tag{6.7}$$

where the dependent variable $P^{HAM}_{B,it}$ is the parameter used to fit the intercept price on the baseload portion of bidders' offer curves in the HAM (see Figure **??**); and the remaining regressors mirror model (6.6). The estimation results for this model are shown in Table 6.11.

6.3.7 The Breakpoint Parameter Z

The regression equation for Z will be:

$$\begin{aligned} Z_{it} = {} & \beta_0 + \beta_1 \cdot \mathrm{L} + \beta_2 \cdot (\mathrm{HAM} \times \mathrm{L}) + \beta_3 \cdot (\mathrm{HAM} \times \mathrm{WP}) \\ & + \beta_4 \cdot (\mathrm{HAM} \times q^*_{DAM}) + \beta_5 \cdot \mathrm{CDD} + \beta_6 \cdot (\mathrm{HAM} \times \mathrm{CDD}) + \beta_7 \cdot (\mathrm{HAM} \times \mathrm{LTZ}) \\ & + \alpha_1 \cdot \mathrm{HAM} + \alpha_2 \cdot \mathrm{peak} + \alpha_3 \cdot \mathrm{wknd} + \vec{\gamma}_1 \cdot \bar{\mathrm{YR}} + \vec{\gamma}_2 \cdot \bar{\mathrm{SE}} + e_{it} \end{aligned} \tag{6.8}$$

where the dependent variable $P^{HAM}_{B,it}$ is the parameter used to fit the intercept price on the baseload portion of bidders' offer curves in the HAM (see Figure **??**); and the remaining regressors mirror model (6.7). The estimation results for this model are shown in Table 6.10.

Underlying this representation of bidders' sensitivity to exogenous conditions is that the bid constructed in the Day-ahead market should include all relevant information known at hour $t = T - 24$. This includes an accurate forecast of weather data resulting in a load forecast, fuel prices that directly impact variable production costs, and the results of all auctions prior to day $t = T$. In this type of oft repeated auction, players have ample opportunity to learn based on prior experience. Bidders learn both by the updating their beliefs about other bidders' types from previous auction outcomes, but also by better understanding the impact of their own bids on the auction outcome (Jeitschko, 1998). Because the NYISO wholesale electricity market has been in existence over a decade[18] our data spans a time period, 2002-2010, where bidders have been through at least a full year of auctions and thus are well educated entering each hourly auction. Bidders are both sophisticated and have nontrivial stakes in the auction outcome.

[18] The NYISO wholesale auctions began in December 1999.

Bidders use the information collected in the period between auctions to "true up" their understanding of the available strategy space, and maximize expected profits in the final period (i.e. balancing market). This information set includes all the regressors included in model 6.5. Clearly, the regressors used in model 6.5 is a subset of the myriad information available to the technically adroit bidder. Extensive reporting obligations ensure that detailed market information will be made available by the NYISO in a timely manner. In addition, several vendors provide other real-time market information such as location specific loads at a cost.

6.3.8 Testing Proposition 1

Proposition 1 stated that if expected profit maximizing firms face a steeper residual demand, their optimal offer curve will also be steeper. In response to additive uncertainty, many realizations of residual demand are possible. In order to bid optimally, the firm will connect the locus of profit maximizing points on different realizations of residual demand. If Proposition 1 is indeed correct, the sign of the coefficient β_1 on the regressor L in (6.5) will be positive. In other words, as the Lerner index increases, bids in the DA market get steeper.

In our sample, this turns out to be the case for 5 of the 10 bidders. Bidder A is the only bidder with a negative estimate for β_4 that is statistically different from zero with 95% confidence (Table 6.7). Our regression suggests that more market power, represented by our inverse semi-elasticity (Lerner index), is concomitant with a steeper strategic portion of firm offer curves. This result lends support for Proposition 1, that firms with market power account for noise in DA demand by constructing their bids accordingly.

6.3.9 Testing Proposition 2(a)

Proposition 2(a) stated that the amount offered at price P_B in the HA market would be larger than the quantity offered at that same price in the DA market. To test this hypothesis, we need to look at the estimation of parameter Z (equation 6.8). If breakpoint Z is getting larger in the HA market as we suspect, the sign on α_1, the coefficient for the HA market dummy variable, should be positive.

In general, this is not the case. We find that the Z decreases from the DA market to the HA market more often than it increases. Four of the bidders in our sample have statistically significant results for this parameter in the negative direction, while bidder H has the only positive and statistically significant sign. This means that bidders are offering a larger portion of their capacity strategically in the HAM, on average, controlling for other factors influencing the offer curve. One interpretation of this result is that firms may be net buyers in the HA market, having undersold quantities in the DA market. This would cause them to offer their quantity at a lower price to drive prices down, and we would expect that the sign α_1 in the regression on P_B would be negative for these bidders as well.

Bidders C, D, F, and I were the four bidders with negative signs on α_1 in the regression on $\tilde{\beta}_1$ (Table 6.7). If these bidders are simultaneously offering the baseload portion of their bids at a lower price in the HA market, this may induce the bid fit to find a smaller Z in the HA market. Two of the four bidders (D & I) do indeed have negative signs on α_1 in regression (6.8)[19]. This may explain better the counter intuitive results in the regression on $\tilde{\beta}_1$; as bidders change one part of their bid, the curve fit adjusts.

[19] All have point estimates less than zero, but estimates for bidders C & F are not statistically different from zero.

6.3.10 Testing Proposition 2(b) & 2(c)

Proposition 2(b) states that the price bidders offer their baseload quantity in the HA market will be lower if the estimated quantity cleared in the DA market is less than Z^{DAM}. The regressor LTZ is a dummy variable that equals one when this is the case (i.e., $q^*_{DAM} < Z_{DAM}$). In order to test the veracity of this proposition, we can look at the sign on the coefficient β_7 from regression (6.7). A negative sign on β_7 will lend support to proposition 2(b).

The regression results on P_B (Table 6.11) show that out of four statistically significant results, only one is negative as expected.

Proposition 2(c) states that bids should get steeper in the HA market, based on the theoretical discussion in Chapter 5. To test this, we can look at the sign on the coefficient for HAM (i.e., α_1) in the regression on $\tilde{\beta}_1$ (6.5), which should be positive after controlling for other parameters that affect the strategic slope parameter. The results are mixed. While five of the bidders had statistically significant coefficient estimates for α_1, only two were in the positive direction. This could mean that for the bidders with a negative sign, all of the factors that affected the bid slope in this way were captured in the other interaction terms with HAM.

6.3.11 Testing Proposition 3

Proposition 3 states that cooling degree-days (CDD) should not, on their own, impact bids into the HA market because firms' predictions about the weather (and thus load) are equally accurate at all temperatures. Though the firm's idea about the temperature in the strike hour will likely be more accurate when the HA market bid is constructed, there should be no consistent effect because it is equally likely to be higher and lower.

Table 6.6: Statistically significant coefficient estimates on $(HAM \times CDD)$.

Regression	**# Statistically Significant**
$\tilde{\beta}_1$	4
P_S	2
Z	3
P_B	1

To test this proposition, we expect that the coefficient (β_6) on the interaction term $(HAM \times CDD)$ should not be statistically different from zero. This would be consistent for all regressions, if indeed this did not impact offer curve formation in any way. This was largely the case. The number of coefficient estimates (out of ten total) that were statistically different from zero was small, and never more than 5 of the 10 bidders had statistically significant results (see Table 6.6).

These results tend to support our claim, because out of 40 possible coefficient estimates, three quarters were not statistically significant.

6.3.12 Testing Proposition 4

Recall that Proposition 4 stated that as virtual supply increased, residual demand in the spot market would become steeper. In response, the expected profit maximizing bidder will submit a steeper offer curve. To test this proposition, we would expect the sign on the coefficient of 'netsupp' regressed on $\tilde{\beta}_1$ to be positive. Because the Daily Energy report containing virtual trading information was not made available to bidders in the Hour-ahead market until January 16, 2006[20] including this data invariably cuts off samples taken prior to this date. This impacts some bidders more than others, as some did not participate in the DA market and HA market until or

[20]The NYISO revamped its 'OASIS' reporting system during 2005; this update included publishing a more detailed Daily Energy Report.

after 2006. A second model, exactly the same as (6.5) but including the variable 'netsupp', was estimated; the results are shown in Table 6.8.

The results are strikingly counterintuitive. Zero of the ten bidders had statistically significant results in response to 'netsupp'. It could be that net virtual supply is not information used by bidders in the HA market at all. Or rather, this information could be redundant to other DA market results, such as price and quantity.

Table 6.7: Regression results: $\tilde{\beta}_1$ (Newey-West corrected).

Bidder:	A	B	C	D	E	F	G	H	I	J
	Estimate (S.E.)	Estimate (S.E.)	Estimate (S.E.)	Estimate (S.E.)	Estimate (S.E.)	Estimate (S.E.)	Estimate (S.E.)	Estimate (S.E.)	Estimate (S.E.)	Estimate (S.E.)
(Intercept)	-4.638*	2.412*	3.092*	13.625*	2.153*	13.443*	2.51*	27.097*	128.801*	2.457*
	(0.343)	(0.016)	(0.03)	(0.848)	(0.05)	(1.625)	(0.044)	(1.208)	(5.164)	(0.353)
HAM	-1.899	-0.061*	0.052	-0.176	0.004	9.038*	0.038*	-1.769	-41.002*	-4.889*
	(1.606)	(0.02)	(0.047)	(0.825)	(0.014)	(4.264)	(0.018)	(1.792)	(10.408)	(0.962)
L	-0.373*	0.013*	0.069*	0.423	0.016*	-0.253	0.003	3.083*	-0.82	0.377*
	(0.098)	(0.005)	(0.013)	(0.323)	(0.004)	(0.666)	(0.008)	(0.497)	(1.549)	(0.095)
(HAM $\times$ L)	0.024	-0.01	-0.065*	-0.471	-0.014	-1.584	-0.004	-5.452*	4.602	-0.172
	(0.133)	(0.008)	(0.018)	(0.476)	(0.007)	(2.241)	(0.014)	(0.863)	(3.835)	(0.127)
(HAM $\times q^*_{DAM}$)	0.003	0*	0*	0.001	0*	0.003*	0	0.001*	0.053*	0.003*
	(0.003)	(0)	(0)	(0.001)	(0)	(0.001)	(0)	(0.001)	(0.007)	(0.001)
(HAM $\times$ WP)	0.002	0	-0.001	-0.018	0	-0.118	-0.001*	-0.029	-0.282	0.004
	(0.003)	(0)	(0.001)	(0.014)	(0)	(0.061)	(0)	(0.023)	(0.144)	(0.003)
CDD	-0.08*	-0.001	-0.01*	0.252*	0	0.263*	-0.001	-0.015	0.425	0.103*
	(0.032)	(0.002)	(0.002)	(0.061)	(0.001)	(0.133)	(0.001)	(0.144)	(0.496)	(0.035)
(HAM $\times$ CDD)	0.007	0.001	-0.001	-0.235*	-0.003*	0.09	-0.001	-0.213	-1.818*	-0.063*
	(0.04)	(0.002)	(0.003)	(0.073)	(0.001)	(0.42)	(0.002)	(0.21)	(0.71)	(0.027)
(HAM $\times$ LTZ)	.	-0.011	-0.053	-0.191	-0.012	0.354	0.002	2.076	39.04*	.
		(0.015)	(0.031)	(0.616)	(0.015)	(1.182)	(0.01)	(5.331)	(8.11)	
peak	-0.101	0.04*	0.052*	-0.828*	0.018*	0.157	0.001	0.207	-0.329	0.03
	(0.067)	(0.005)	(0.008)	(0.273)	(0.006)	(0.21)	(0.004)	(0.274)	(1.178)	(0.059)
wknd	0.109	-0.007	-0.027*	0.464	-0.003	-0.711	-0.009*	-0.493	-2.124	-0.039
	(0.113)	(0.006)	(0.013)	(0.278)	(0.006)	(0.478)	(0.004)	(0.573)	(2.178)	(0.085)
N	29,035	18,471	17,651	33,107	7,165	19,160	39,570	52,496	52,782	30,322
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Seasonal F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$RMSE$	1.817	0.145	0.231	8.649	0.081	11.526	0.138	13.529	61.384	1.424
R^2	0.303	0.287	0.224	0.157	0.1	0.092	0.583	0.116	0.267	0.34

* $p \leq 0.05$

Table 6.8: $\tilde{\beta}_1$ with 'netsupp' (Newey-West)

Bidder:	A	B	C	D	E	F	G	H	I	J
(Intercept)	-4.632*	2.41*	3.091*	22.183*	2.234*	19.979*	3.015*	34.366*	103.648*	2.478*
	(0.317)	(0.015)	(0.023)	(1.061)	(0.011)	(1.189)	(0.014)	(1.368)	(7.087)	(0.331)
HAM	-1.892	-0.065*	0.048	-0.441	0.005	-4.726	0.036*	0.105	-18.893	-4.858*
	(1.599)	(0.021)	(0.037)	(0.977)	(0.014)	(4.441)	(0.017)	(2.494)	(10.725)	(0.944)
L	-0.368*	0.011*	0.067*	0.314	0.016*	-0.202	0.018	2.022*	1.559	0.394*
	(0.111)	(0.005)	(0.01)	(0.379)	(0.004)	(1.142)	(0.01)	(0.597)	(1.985)	(0.091)
(HAM × L)	0.022	-0.01	-0.064*	-0.471	-0.013	4.264	-0.004	-2.412*	-4.45	-0.18
	(0.154)	(0.008)	(0.014)	(0.547)	(0.008)	(3.007)	(0.015)	(0.967)	(4.027)	(0.12)
(HAM $\times q^*_{DAM}$)	0.003	0*	0*	0.001	0*	0	0*	0.003*	0.021*	0.003*
	(0.003)	(0)	(0)	(0.001)	(0)	(0.005)	(0)	(0.001)	(0.005)	(0.001)
(HAM × WP)	0.002	0	-0.001*	-0.02	0	0.042	-0.001*	-0.041	-0.425*	0.004
	(0.003)	(0)	(0)	(0.017)	(0)	(0.069)	(0)	(0.028)	(0.109)	(0.003)
CDD	-0.081*	-0.001	-0.01*	0.246*	0	0.106	0	-0.012	0.058	0.101*
	(0.032)	(0.002)	(0.002)	(0.068)	(0.001)	(0.13)	(0.001)	(0.191)	(0.65)	(0.035)
(HAM × CDD)	0.007	0.001	-0.001	-0.225*	-0.003*	0.656	0	-0.354	-2.01*	-0.063*
	(0.04)	(0.002)	(0.002)	(0.084)	(0.001)	(1.212)	(0.001)	(0.26)	(0.633)	(0.026)
netsupp	0	0	0	0	0	0	0	-0.001	-0.002	0
	(0)	(0)	(0)	(0)	(0)	(0.001)	(0)	(0.001)	(0.002)	(0)
peak	-0.104*	0.041*	0.054*	-0.95*	0.017*	-0.309	0.004	0.075	4.002*	0.021
	(0.049)	(0.005)	(0.009)	(0.316)	(0.005)	(0.404)	(0.004)	(0.319)	(1.925)	(0.063)
wknd	0.11	-0.008	-0.027*	0.49	-0.003	-0.736	-0.015*	-0.535	-1.735	-0.036
I(HAM * underZDAM)	.	-0.011	-0.054*	-0.091	-0.012	-0.587	-0.012	.	23.856*	.
		(0.015)	(0.022)	(0.739)	(0.015)	(2.023)	(0.011)		(7.7)	
N	29,035	18,471	17,651	30,438	7,158	6,664	30,430	30,450	30,448	30,322
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Seasonal F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$RMSE$	1.817	0.145	0.231	8.987	0.081	11.314	0.127	11.707	51.538	1.424
R^2	0.303	0.287	0.224	0.123	0.1	0.049	0.666	0.079	0.14	0.34

* $p \leq 0.05$

Table 6.9: P_S (Newey-West)

Bidder:	A	B	C	D	E	F	G	H	I	J
(Intercept)	-968.767*	135.395*	76.012*	102.304*	121.77*	19.097	53.731*	287.534*	492.385*	-4.006*
	(19.293)	(8.141)	(10.492)	(8.594)	(29.775)	(13.223)	(6.089)	(40.11)	(25.54)	(1.077)
HAM	-0.439	-5.65	7.095	15.241*	-43.828*	15.012	-10.683*	-114.02*	-229.761*	0.916
	(44.036)	(8.427)	(9.182)	(5.942)	(18.516)	(13.503)	(2.607)	(49.926)	(29.791)	(0.49)
L	-1.935	-7.84*	-32.254*	-4.935*	-16.391*	-2.178	1.19	14.511	0.302	-0.406
	(3.545)	(2.326)	(3.307)	(2.269)	(7.89)	(4.144)	(1.354)	(14.638)	(6.055)	(0.322)
(HAM $\times$ L)	1.279	7.361*	39.804*	5.905	5.565	0.571	-0.964	15.408	21.702*	0.218
	(3.674)	(3.342)	(4.38)	(3.7)	(8.945)	(8.483)	(2.21)	(23.163)	(9.926)	(0.26)
(HAM $\times q^*_{DAM}$)	-0.005	-0.013*	-0.016*	-0.01	-0.015*	-0.045*	0.001	-0.03*	0.008	0
	(0.091)	(0.002)	(0.002)	(0.006)	(0.004)	(0.01)	(0.003)	(0.015)	(0.025)	(0)
(HAM $\times$ WP)	0.052	0.047	-0.016	-0.392*	0.746*	0.243	0.158*	1.737*	1.104*	-0.008
	(0.184)	(0.128)	(0.145)	(0.118)	(0.23)	(0.257)	(0.048)	(0.536)	(0.378)	(0.009)
CDD	2.662	1.692*	1.627*	-0.609	0.777	0.379	-0.056	3.296	0.924	0.156
	(2.854)	(0.7)	(0.553)	(0.483)	(1.182)	(0.866)	(0.22)	(3.842)	(1.507)	(0.247)
NTHO	2.576	6.406	-18.456*	38.038*	9.475	145.649*	13.026*	-81.014*	57.08*	-0.007
	(2.877)	(3.649)	(4.083)	(4.504)	(10.57)	(19.078)	(1.589)	(24.053)	(16.572)	(0.294)
(HAM $\times$ CDD)	-0.121	-1.748*	1.152	0.071	1.336	1.266	-0.186	7.044	-5.187*	-0.114
	(2.575)	(0.816)	(0.685)	(0.582)	(1.314)	(1.387)	(0.275)	(5.176)	(1.894)	(0.17)
peak	5.068	-22.59*	-14.397*	7.767*	-29.436*	-5.781*	0.29	-5.656	2.214	0.37
	(4.521)	(2.357)	(2.223)	(1.711)	(5.783)	(1.848)	(0.712)	(7.42)	(3.676)	(0.397)
wknd	3.545	2.973	5.048	0.752	6.567	1.16	1.901	29.705*	-1.301	0.195
	(3.918)	(2.744)	(3.38)	(1.765)	(8.032)	(3.54)	(1.046)	(13.068)	(6.043)	(0.264)
(HAM $\times$ LTZ)	.	8.107	-3.488	-6.963	22.556	-22.218*	3.523	-181.324*	52.044*	.
		(8.309)	(7.06)	(4.23)	(13.559)	(6.102)	(2.269)	(75.535)	(20.015)	
N	29,035	18,467	17,338	33,097	7,127	19,079	39,570	52,456	52,782	30,322
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Seasonal F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$RMSE$	60.695	71.923	66.03	60.483	102.682	70.595	38.164	333.815	182.062	4.147
R^2	0.059	0.365	0.362	0.361	0.141	0.156	0.187	0.114	0.363	0.038

* $p \leq 0.05$

Table 6.10: Z (Newey-West)

	A	B	C	D	E	F	G	H	I	J
(Intercept)	0.116*	0.246*	0.369*	0.864*	0.353*	0.666*	0.668*	0.597*	0.942*	0.095*
	(0.019)	(0.024)	(0.034)	(0.012)	(0.057)	(0.02)	(0.039)	(0.029)	(0.006)	(0.013)
HAM	0.047	-0.058	-0.099*	-0.077*	0.036	-0.144*	0	0.112*	-0.148*	0.021
	(0.043)	(0.031)	(0.039)	(0.018)	(0.049)	(0.04)	(0.026)	(0.035)	(0.026)	(0.018)
L	-0.002	0.026*	0.011	-0.018*	0.011	-0.061*	-0.018	0.136*	0.001	0
	(0.003)	(0.007)	(0.017)	(0.006)	(0.012)	(0.015)	(0.012)	(0.013)	(0.002)	(0.003)
(HAM $\times$ L)	0.001	-0.068*	-0.063*	0.008	-0.014	0.073*	-0.009	-0.126*	0.019*	-0.001
	(0.003)	(0.011)	(0.021)	(0.011)	(0.021)	(0.025)	(0.019)	(0.018)	(0.005)	(0.003)
(HAM $\times q^*_{DAM}$)	0	0	0*	0	0	0	0*	0*	0*	0
	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)
(HAM $\times$ WP)	0	0	0	0	0	-0.001	-0.001*	0.002*	0	0
	(0)	(0)	(0.001)	(0)	(0.001)	(0.001)	(0)	(0)	(0)	(0)
CDD	0.002	-0.008*	-0.008*	-0.001	-0.001	0.014*	-0.001	-0.007	0.001	0.002
	(0.002)	(0.003)	(0.002)	(0.001)	(0.003)	(0.003)	(0.002)	(0.004)	(0.001)	(0.002)
(HAM $\times$ CDD)	0	0.005	0.005	-0.003	-0.01*	-0.011*	0	0.006	-0.004*	-0.001
	(0.002)	(0.003)	(0.003)	(0.001)	(0.004)	(0.004)	(0.002)	(0.004)	(0.001)	(0.001)
peak	0.004	0.053*	0.087*	0.028*	0.057*	0.001	0.023*	0.008	-0.001	0.004
	(0.004)	(0.009)	(0.008)	(0.003)	(0.014)	(0.006)	(0.006)	(0.005)	(0.002)	(0.003)
wknd	0.003	0.008	-0.024*	0.014*	-0.013	-0.004	-0.019*	-0.003	0.001	0.004
	(0.003)	(0.011)	(0.008)	(0.004)	(0.016)	(0.012)	(0.006)	(0.013)	(0.003)	(0.003)
(HAM $\times$ LTZ)	.	-0.013	0.074*	-0.011	-0.043	0.009	0.029	-0.086	0.103*	.
		(0.031)	(0.034)	(0.014)	(0.052)	(0.018)	(0.017)	(0.079)	(0.029)	
N	29,035	18,471	17,651	33,107	7,165	19,160	39,570	52,496	52,782	30,322
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Seasonal F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$RMSE$	0.049	0.254	0.232	0.168	0.24	0.22	0.21	0.297	0.088	0.044
R^2	0.104	0.138	0.115	0.142	0.225	0.191	0.477	0.143	0.147	0.03

* $p \leq 0.05$

Table 6.11: P_B (Newey-West)

Bidder:	A	B	C	D	E	F	G	H	I	J
(Intercept)	-998.766*	68.42*	30.065*	58.159*	21.958*	13.035	36.682*	7.001	10.291*	-9.886*
	(0.145)	(3.79)	(10.215)	(2.4)	(10.341)	(6.742)	(2.31)	(22.501)	(0.49)	(0.075)
HAM	0.085	-5.666	-10.103	-4.095*	-14.525	-6.283	-8.236*	-23.933	-4.202*	0.221*
	(0.353)	(3.166)	(9.138)	(1.762)	(7.539)	(7.718)	(2.055)	(23.333)	(0.968)	(0.104)
L	-0.001	-2.261*	-9.179*	0.759	-9.632*	-3.143	0.929	-18.665*	-0.223	-0.022
	(0.026)	(0.745)	(2.067)	(0.573)	(2.667)	(2.355)	(1.981)	(5.518)	(0.186)	(0.024)
(HAM × L)	0.006	2.881*	11.244*	-0.814	4.071	7.295	0.337	16.231*	0.48	-0.005
	(0.027)	(1.24)	(3.258)	(1.134)	(4.039)	(3.874)	(3.104)	(5.554)	(0.337)	(0.024)
(HAM $\times q^*_{DAM}$)	0	0	0.002	-0.008*	-0.002	-0.004	-0.003	-0.006	0.002*	0
	(0.001)	(0.001)	(0.003)	(0.002)	(0.002)	(0.004)	(0.002)	(0.005)	(0.001)	(0)
(HAM $\times WP$)	0	-0.058	0.018	0.071	0.371*	-0.221	0.06	0.254	-0.027*	-0.001
	(0.001)	(0.05)	(0.145)	(0.036)	(0.13)	(0.127)	(0.036)	(0.207)	(0.007)	(0.001)
CDD	0.023	0.854*	2.275*	0.439*	0.834	-0.598	-0.018	-0.157	0.049	0.012
	(0.021)	(0.346)	(0.5)	(0.109)	(0.552)	(0.504)	(0.132)	(0.92)	(0.042)	(0.017)
NTHO	0.038	-4.8*	-5.501	7.464*	-0.16	57.713*	-3.387	-16.32	6.196*	-0.021
	(0.022)	(1.564)	(4.508)	(1.218)	(5.325)	(9.061)	(1.905)	(13.284)	(0.511)	(0.027)
(HAM $\times CDD$)	0	-0.573	-0.967	-0.076	-1.664*	0.671	-0.255	0.668	-0.086	-0.01
	(0.019)	(0.423)	(0.705)	(0.124)	(0.696)	(1)	(0.153)	(1.188)	(0.061)	(0.012)
peak	0.042	-6.216*	1.063	-0.26	-5.217*	-1.35	1.974*	-0.552	0.13	0.031
	(0.033)	(1.112)	(1.705)	(0.249)	(2.105)	(0.771)	(0.422)	(1.422)	(0.087)	(0.023)
wknd	0.023	-0.22	-0.008	0.806*	-3.148	-0.021	0.855*	4.532	0.123	0.042
	(0.031)	(1.319)	(2.468)	(0.317)	(3.153)	(1.577)	(0.41)	(4.102)	(0.135)	(0.025)
(HAM × LTZ)	.	8.997	24.109*	0.073	29.596*	-1.99	4.568*	-51.739*	1.259	.
		(4.763)	(7.589)	(1.086)	(9.091)	(3.321)	(1.209)	(15.503)	(0.837)	
N	29,035	18,471	17,651	33,107	7,165	19,160	39,570	52,496	52,782	30,322
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Seasonal F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$RMSE$	0.465	35.921	50.063	12.416	42.832	28.368	15.015	90.382	4.333	0.394
R^2	0.091	0.338	0.152	0.464	0.086	0.243	0.383	0.094	0.764	0.041

* $p \leq 0.05$

CHAPTER 7

CONCLUSION

This analysis of the NYISO Day-ahead and Hour-ahead market yields inconclusive results. While several of the tests against theoretical predictions yielded results consistent with expectations, the results taken as a whole do not adequately resolve bidder behavior but rather expose the extent of bidder heterogeneity in our sample of the largest NYISO firms. Because the sample includes only the largest firms, this analysis necessarily captures markedly different generation technologies that evidently impact bidding behavior to such a degree that a single model is insufficient to predict behavior for each firm. Specifically firms dominated by large hydroelectric and or nuclear generators, whose strategic incentives are driven by factors varying in the medium and long term rather than the short term are pulling the results in this paper in different directions.

The natural extension to this research is to include a broader cross section of firms that may be more closely related in generation technology and thus bidding strategies. Similarly, a parallel study of bidding at the generator level would bolster my hypothesis that the strategic unit of interest is at the firm level rather than the generator level.

Firms in the NYISO participate in multiple related energy markets in addition to wholesale electricity auctions such as the capacity market, ancillary services, and transmission congestion contracts. It is possible that the strategy space available to firms includes bids into these related markets. When bids into the wholesale electricity market are jointly determined with bids into other markets, looking at a single market as done in this study could exclude salient strategic behavior. Studying the interaction of these markets within firms objective function could also be a fruitful area for future research.

This paper developed a new way to decompose piecewise-defined offer curves by fitting them around a two-piece functional form. The functional form relies on the assumption of profit maximization and attempts to capture the salient features of a strategic bidders offer curve. Firms facing different residual demands offer bids that are reflective of the market power available during that specific hour. By directly calculating market power in the Day-ahead auction using an inverse semi-elasticity developed by Wolak (2003), I find that firms with more market power in a specific hour bid more aggressively. This is consistent with expectations and suggest that efforts to mitigate market power in the NYISO over the past decade have not completely eliminated it. Rather, firms routinely exercise available market power to opportunistically maximize their profits.

The results of the other hypotheses tested are mixed. While certain hypotheses consistent with expected profit maximization were not confirmed, the sample used in this study includes only a subset of bidders into the NYISO. With competitive electricity markets evolving world- wide, methods for analyzing bidding behavior is a very important tool for monitoring and understanding competitive electricity markets. Anticipating the strategic motives of firms bidding into these markets can assist regulators in obviating noncompetitive outcomes and inform policy development and implementation. This paper has attempted to further this analytical approach using a large publicly available data on the top firms in the New York electricity market.

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APPENDICES

APPENDIX A

PROOF OF COMPARATIVE STATIC RESULTS

Second-order condition:

Representing $\frac{\partial \breve{D}_R(p)}{\partial p}$ as $\breve{D}'$ and $\frac{\partial^2 \breve{D}_R(p)+\varepsilon}{\partial p^2}$ as $\breve{D}''$:

$$\frac{\partial^2 \Pi}{\partial p^2} = 2\breve{D}' + p\breve{D}'' - \left(\frac{\partial^2 C(\breve{D}_R(p))}{\partial \breve{D}_R(p)^2}\right)(\breve{D}')^2 - \left(\frac{\partial C(\breve{D}_R(p)+\varepsilon)}{\partial \breve{D}_R(p)}\right)\breve{D}''$$

At the maximum ($p = p^*$), where the first-order condition is satisfied, we can check that $\frac{\partial^2 \Pi}{\partial p^2} \neq 0$, by the implicit function theorem p^* can be rewritten as a function of exogenous parameters, $p^* = p^*(\varepsilon)$ and evaluated in the neighborhood of its maximum[1]. Accordingly, the first-order condition at the optimum becomes an identity, from which the comparative static can be calculated as follows:

$$p^*\left(\frac{\partial \breve{D}_R(p^*)}{\partial p^*}\right) + \breve{D}_R(p^*) + (2q-1)\cdot\varepsilon - \left(\frac{\partial C(\breve{D}_R(p^*)+\varepsilon)}{\partial \breve{D}_R(p^*)}\right)\left(\frac{\partial \breve{D}_R(p^*)}{\partial p^*}\right) \equiv 0$$

$$\left(\frac{\partial \breve{D}_R(p^*)}{\partial p^*}\right)\left(p^* - \frac{\partial C(\breve{D}_R(p^*)+\varepsilon)}{\partial \breve{D}_R(p^*)}\right) \equiv -\breve{D}_R(p^*) - (2q-1)\cdot\varepsilon$$

$$p^* - \frac{\partial C(\breve{D}_R(p^*)+\varepsilon)}{\partial \breve{D}_R(p^*)} \equiv \frac{-\breve{D}_R(p^*) - (2q-1)\cdot\varepsilon}{\frac{\partial \breve{D}_R(p^*)}{\partial p^*}}$$

This is the familiar formulation used in the process of calculating the firm-level Lerner index. Comparative statics can be used to determine the effect of ε_t on the optimal slope of the offer curve. First, equation (5.3) can be represented by f as follows:

---

[1]From Chiang (p. 206):

> Given $F(y, x_1, ..., x_n) = 0$, if (1) the function F has continuous partial derivates and if (2) at a point $(y_0, x_{10}, ..., x_{n0})$ satisfying the equation, F_y is nonzero, then there exists an n-dimensional neighborhood of $(x_{10}, ..., x_{1n})$, N, in which y is an implicitly defined function of the variables $(x_1, ..., x_n)$ in the form of $y = f(x_1, ..., x_n)$.

$$f(p^*(\varepsilon),\varepsilon) \equiv 0$$

and

$$\frac{\partial f(p^*(\varepsilon),\varepsilon)}{\partial \varepsilon} \equiv \frac{\partial f}{\partial p}\frac{\partial p^*}{\partial \varepsilon} + \frac{\partial f}{\partial \varepsilon}\frac{\partial \varepsilon}{\partial \varepsilon} \equiv 0 \ .$$

Substituting the full representation of f back into the equation, the formulation above becomes

$$\left\{\partial\left(p^*\breve{D}' + \breve{D} + \varepsilon - \frac{\partial C(\cdot)}{\partial \breve{D}}\breve{D}'\right)\Big/\partial p\right\}\frac{\partial p^*}{\partial \varepsilon} + \partial\left(p^*\breve{D}' + \breve{D} + \varepsilon - \frac{\partial C(\cdot)}{\partial \breve{D}}\breve{D}'\right)\Big/\partial \varepsilon \equiv 0$$

$$\left\{\partial\left(p^*\breve{D}' + \breve{D} + \varepsilon - \frac{\partial C(\cdot)}{\partial \breve{D}}\breve{D}'\right)\Big/\partial p\right\}\frac{\partial p^*}{\partial \varepsilon} + 1 - \frac{\partial^2 C(\cdot)}{\partial \breve{D}\partial \varepsilon}\breve{D}' \equiv 0$$

$$\left\{2\breve{D}' + p\breve{D}'' - \left(\frac{\partial^2 C(\cdot)}{\partial \breve{D}^2}\right)(\breve{D}')^2 - \left(\frac{\partial C(\cdot)}{\partial \breve{D}}\right)\breve{D}''\right\}\frac{\partial p^*}{\partial \varepsilon} + 1 - \frac{\partial^2 C(\cdot)}{\partial \breve{D}\partial \varepsilon}\breve{D}' \equiv 0$$

Which yields the fraction:

$$\frac{\partial p^*}{\partial \varepsilon} \equiv \left\{-1 + \frac{\partial^2 C(\cdot)}{\partial \breve{D}\partial \varepsilon}\breve{D}'\right\}\Big/\left\{2\breve{D}' + p\breve{D}'' - \left(\frac{\partial^2 C(\cdot)}{\partial \breve{D}^2}\right)(\breve{D}')^2 - \left(\frac{\partial C(\cdot)}{\partial \breve{D}}\right)\breve{D}''\right\} \quad \text{(A.1)}$$

To show that equation (A.1) is equal to a positive number, the following relationships will be used:

$$\frac{\partial \breve{D}_R(p^*)}{\partial p} \leq 0$$

$$\frac{\partial^2 C(\cdot)}{\partial \breve{D}\partial \varepsilon} = \frac{\partial^2 C(\cdot)}{\partial \breve{D}^2} \geq 0$$

The derivative of residual demand with respect to price p is less than or equal to zero. This is a result of the market rule that all bids, and thus the supply stack, must be monotonically increasing over quantity. The second relationship assumes convex total costs, which is consistent with increasing marginal costs of generation[2]. This yields:

$$\begin{array}{lcccccccccccc} \text{sign:} & & - & + & - & & - & ? & + & + & + & ? \\ \frac{\partial p^*}{\partial \varepsilon} \equiv & \Big\{ & -1+ & \frac{\partial^2 C(\cdot)}{\partial \breve{D} \partial \varepsilon} & \breve{D}' \Big\} & \Big/ & \Big\{ 2\breve{D}'+ & p\breve{D}''- & \left(\frac{\partial^2 C(\cdot)}{\partial \breve{D}^2}\right) & (\breve{D}')^2 & -\left(\frac{\partial C(\cdot)}{\partial \breve{D}}\right) & \breve{D}'' \Big\} \end{array}$$

No assumptions are made about the second derivative of residual demand with respect to price. In practice, this might be both positive and negative over the quantity domain. If we approximate residual demand in the neighborhood of q^* as a straight line, the reduces of signing the comparative static reduces:

$$\begin{array}{lcccccccc} \text{sign:} & & - & + & - & & - & + & + \\ \frac{\partial p^*}{\partial \varepsilon} \equiv & \Big\{ & -1 \;+ & \frac{\partial^2 C(\cdot)}{\partial \breve{D} \partial \varepsilon} & \breve{D}' \Big\} & \Big/ & \Big\{ 2\breve{D}' \;- & \left(\frac{\partial^2 C(\cdot)}{\partial \breve{D}^2}\right) & (\breve{D}')^2 \Big\} \end{array}$$

So, $\frac{\partial p^*}{\partial \varepsilon}$ reduces to a fraction with a negative number in both the numerator and denominator, thus indicating a positive result.

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[2]Convex total costs means variable costs of generation are either increasing or constant over quantity. This is consistent with profit-maximizing behavior where cheaper generators will be used before older or less efficient generators. Within a specific unit, marginal costs of production in general will track the costs of fuel and heat rate, both of which increase over capacity. See Wolfram (1999) and Wolak (2010).

APPENDIX B

NONLINEAR LEAST SQUARES ESTIMATION OF OFFER CURVES

The following is an outline of the calculation process:

1. Subset all bidding data to pull out a single bidder's Day-ahead and Hour-ahead offer curve.

2. Using the defined offer 'steps', build out a new set of data where each observation represents a single megawatt offered at a single price. The number of observations, then, will equal the number of megawatts offered by bidder i at time t. This is to reflect the equal weighting of each offered megawatt.

3. Normalize each observation so that each cumulative megawatt is converted into a % of total offered capacity in that specific auction. Total offered capacity is the sum of the offered capacity of all generators included in the bid.

4. Calculate the minimum and maximum offered price for both the DAM and HAM.

5. If the minimum offered price equals the maximum offer price – in other words, if the offer curve is flat, run an OLS regression over the entire domain of offered capacity (the slope parameter will necessarily equal zero); otherwise,

6. Use the Gauss-Newton algorithm fit via nonlinear least squares the model (6.1) for each 0.0025 increment of Z between 0 and 1, collecting the sum of squared residuals (SSR) for each of the 400 fits. Choose Z^* such that the model with the minimum SSR is chosen. $\forall \mathbb{Z}, Z \in [0, 400] \times 0.0025$, choose ϕ, β_0 and β_1 such that SSR $= \sum_{k=1}^{OC} e_k^2$ is minimized. Then choose Z that has smallest SSR.

7. Collect parameter values Z, ϕ, β_0 and β_1 for each auction.

APPENDIX C

OLS REGRESSION RESULTS.

The following tables show regression results for equations (6.5) through (6.8) prior to the correction of standard errors using Newey-West variance-covariance matrix (Newey and West, 1987).

Table C.1: $\tilde{\beta}_1$ 12 - 2 - 2011

	A Estimate (S.E.)	B Estimate (S.E.)	C Estimate (S.E.)	D Estimate (S.E.)	E Estimate (S.E.)	F Estimate (S.E.)	G Estimate (S.E.)	H Estimate (S.E.)	I Estimate (S.E.)	J Estimate (S.E.)
(Intercept)	-4.638*	2.412*	3.092*	13.625*	2.153*	13.443*	2.51*	27.097*	128.801*	2.457*
	(0.044)	(0.004)	(0.008)	(0.239)	(0.031)	(0.271)	(0.004)	(0.228)	(1.01)	(0.032)
HAM	-1.899*	-0.061*	0.052*	-0.176	0.004	9.038*	0.038*	-1.769*	-41.002*	-4.889*
	(0.153)	(0.006)	(0.009)	(0.316)	(0.006)	(0.646)	(0.004)	(0.326)	(2.007)	(0.067)
Li.shift.15	-0.373*	0.013*	0.069*	0.423	0.016*	-0.253	0.003	3.083*	-0.82	0.377*
	(0.045)	(0.003)	(0.006)	(0.225)	(0.002)	(0.487)	(0.003)	(0.203)	(0.879)	(0.028)
I(HAM * Li.shift.15)	0.024	-0.01*	-0.065*	-0.471	-0.014*	-1.584*	-0.004	-5.452*	4.602*	-0.172*
	(0.065)	(0.005)	(0.009)	(0.326)	(0.005)	(0.7)	(0.005)	(0.296)	(1.273)	(0.04)
I(HAM * qfirm2)	0.003*	0*	0*	0.001*	0*	0.003*	0*	0.001*	0.053*	0.003*
	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0.002)	(0)
I(HAM * Price)	0.002*	0*	-0.001*	-0.018*	0*	-0.118*	-0.001*	-0.029*	-0.282*	0.004*
	(0.001)	(0)	(0)	(0.004)	(0)	(0.009)	(0)	(0.005)	(0.022)	(0.001)
CDD	-0.08*	-0.001*	-0.01*	0.252*	0	0.263*	-0.001*	-0.015	0.425*	0.103*
	(0.004)	(0)	(0.001)	(0.019)	(0)	(0.039)	(0)	(0.025)	(0.112)	(0.003)
I(HAM * CDD)	0.007	0.001	-0.001	-0.235*	-0.003*	0.09	-0.001*	-0.213*	-1.818*	-0.063*
	(0.005)	(0.001)	(0.001)	(0.023)	(0)	(0.051)	(0)	(0.03)	(0.135)	(0.004)
I(HAM * underZDAM)	.	-0.011	-0.053*	-0.191	-0.012	0.354	0.002	2.076*	39.04*	.
		(0.007)	(0.009)	(0.282)	(0.006)	(0.37)	(0.003)	(0.894)	(2.953)	
N	29035	18471	17651	33107	7165	19160	39570	52496	52782	30322
$RMSE$	1.817	0.145	0.231	8.649	0.081	11.526	0.138	13.529	61.384	1.424
R^2	0.303	0.287	0.224	0.157	0.1	0.092	0.583	0.116	0.267	0.34

* $p \leq 0.05$

Table C.2: $\tilde{\beta}_1$ with variable 'netsupp'

	A	B	C	D	E	F	G	H	I	J
(Intercept)	-4.632*	2.41*	3.091*	22.183*	2.234*	19.979*	3.015*	34.366*	103.648*	2.478*
	(0.045)	(0.004)	(0.008)	(0.209)	(0.004)	(0.441)	(0.003)	(0.28)	(1.214)	(0.033)
HAM	-1.892*	-0.065*	0.048*	-0.441	0.005	-4.726*	0.036*	0.105	-18.893*	-4.858*
	(0.153)	(0.006)	(0.01)	(0.342)	(0.006)	(1.238)	(0.004)	(0.363)	(1.963)	(0.068)
Li.shift.15	-0.368*	0.011*	0.067*	0.314	0.016*	-0.202	0.018*	2.022*	1.559	0.394*
	(0.046)	(0.003)	(0.006)	(0.247)	(0.002)	(1.277)	(0.003)	(0.246)	(1.051)	(0.028)
I(HAM * Li.shift.15)	0.022	-0.01*	-0.064*	-0.471	-0.013*	4.264*	-0.004	-2.412*	-4.45*	-0.18*
	(0.065)	(0.005)	(0.009)	(0.351)	(0.005)	(1.894)	(0.005)	(0.353)	(1.507)	(0.04)
I(HAM * qfirm2)	0.003*	0*	0*	0.001*	0*	0	0*	0.003*	0.021*	0.003*
	(0)	(0)	(0)	(0)	(0)	(0.001)	(0)	(0)	(0.002)	(0)
I(HAM * Price)	0.002	0*	-0.001*	-0.02*	0*	0.042*	-0.001*	-0.041*	-0.425*	0.004*
	(0.001)	(0)	(0)	(0.005)	(0)	(0.018)	(0)	(0.006)	(0.025)	(0.001)
CDD	-0.081*	-0.001	-0.01*	0.246*	0	0.106	0	-0.012	0.058	0.101*
	(0.004)	(0.001)	(0.001)	(0.02)	(0)	(0.058)	(0)	(0.026)	(0.116)	(0.003)
I(HAM * CDD)	0.007	0.001	-0.001	-0.225*	-0.003*	0.656*	0	-0.354*	-2.01*	-0.063*
	(0.005)	(0.001)	(0.001)	(0.024)	(0)	(0.075)	(0)	(0.031)	(0.137)	(0.004)
I(HAM * underZDAM)	.	-0.011	-0.054*	-0.091	-0.012	-0.587	-0.012*	.	23.856*	.
		(0.007)	(0.009)	(0.307)	(0.006)	(0.606)	(0.003)		(2.641)	
netsupp	0	0*	0	0	0	0	0*	-0.001*	-0.002*	0*
	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0.001)	(0)
N	29035	18471	17651	30438	7158	6664	30430	30450	30448	30322
$RMSE$	1.817	0.145	0.231	8.987	0.081	11.314	0.127	11.707	51.538	1.424
R^2	0.303	0.287	0.224	0.123	0.1	0.049	0.666	0.079	0.14	0.34

* $p \leq 0.05$

Table C.3: Z

	A	B	C	D	E	F	G	H	I	J
(Intercept)	0.116*	0.246*	0.369*	0.864*	0.353*	0.666*	0.668*	0.597*	0.942*	0.095*
	(0.001)	(0.006)	(0.008)	(0.005)	(0.092)	(0.005)	(0.007)	(0.005)	(0.001)	(0.001)
HAM	0.047*	-0.058*	-0.099*	-0.077*	0.036*	-0.144*	0	0.112*	-0.148*	0.021*
	(0.004)	(0.01)	(0.009)	(0.006)	(0.017)	(0.012)	(0.006)	(0.007)	(0.003)	(0.002)
Li.shift.15	-0.002	0.026*	0.011	-0.018*	0.011	-0.061*	-0.018*	0.136*	0.001	0
	(0.001)	(0.005)	(0.006)	(0.004)	(0.007)	(0.009)	(0.005)	(0.004)	(0.001)	(0.001)
I(HAM * Li.shift.15)	0.001	-0.068*	-0.063*	0.008	-0.014	0.073*	-0.009	-0.126*	0.019*	-0.001
	(0.002)	(0.008)	(0.009)	(0.006)	(0.014)	(0.013)	(0.007)	(0.006)	(0.002)	(0.001)
I(HAM * qfirm2)	0*	0*	0*	0*	0*	0*	0*	0*	0*	0*
	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)
I(HAM * Price)	0	0	0*	0*	0	-0.001*	-0.001*	0.002*	0*	0*
	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)
CDD	0.002*	-0.008*	-0.008*	-0.001*	-0.001	0.014*	-0.001	-0.007*	0.001*	0.002*
	(0)	(0.001)	(0.001)	(0)	(0.001)	(0.001)	(0)	(0.001)	(0)	(0)
I(HAM * CDD)	0	0.005*	0.005*	-0.003*	-0.01*	-0.011*	0	0.006*	-0.004*	-0.001*
	(0)	(0.001)	(0.001)	(0)	(0.001)	(0.001)	(0.001)	(0.001)	(0)	(0)
I(HAM * underZDAM)	.	-0.013	0.074*	-0.011*	-0.043*	0.009	0.029*	-0.086*	0.103*	.
		(0.012)	(0.009)	(0.005)	(0.018)	(0.007)	(0.005)	(0.02)	(0.004)	
N	29035	18471	17651	33107	7165	19160	39570	52496	52782	30322
$RMSE$	0.049	0.254	0.232	0.168	0.24	0.22	0.21	0.297	0.088	0.044
R^2	0.104	0.138	0.115	0.142	0.225	0.191	0.477	0.143	0.147	0.03

* $p \leq 0.05$

Table C.4: P_B

	A	B	C	D	E	F	G	H	I	J
(Intercept)	-998.766*	68.42*	30.065*	58.159*	21.958	13.035*	36.682*	7.001*	10.291*	-9.886*
	(0.017)	(1.422)	(2.413)	(0.413)	(16.443)	(1.044)	(0.489)	(1.757)	(0.083)	(0.014)
HAM	0.085*	-5.666*	-10.103*	-4.095*	-14.525*	-6.283*	-8.236*	-23.933*	-4.202*	0.221*
	(0.039)	(1.421)	(2.042)	(0.454)	(2.946)	(1.609)	(0.432)	(2.186)	(0.142)	(0.019)
Li.shift.15	-0.001	-2.261*	-9.179*	0.759*	-9.632*	-3.143*	0.929*	-18.665*	-0.223*	-0.022*
	(0.012)	(0.734)	(1.216)	(0.325)	(1.196)	(1.198)	(0.343)	(1.358)	(0.062)	(0.008)
I(HAM * Li.shift.15)	0.006	2.881*	11.244*	-0.814	4.071	7.295*	0.337	16.231*	0.48*	-0.005
	(0.017)	(1.125)	(1.961)	(0.468)	(2.516)	(1.723)	(0.492)	(1.983)	(0.09)	(0.011)
I(HAM * qfirm2)	0*	0	0.002*	-0.008*	-0.002	-0.004*	-0.003*	-0.006*	0.002*	0*
	(0)	(0)	(0.001)	(0)	(0.001)	(0.001)	(0)	(0.001)	(0)	(0)
I(HAM * Price)	0	-0.058*	0.018	0.071*	0.371*	-0.221*	0.06*	0.254*	-0.027*	-0.001*
	(0)	(0.02)	(0.031)	(0.006)	(0.039)	(0.023)	(0.008)	(0.033)	(0.002)	(0)
CDD	0.023*	0.854*	2.275*	0.439*	0.834*	-0.598*	-0.018	-0.157	0.049*	0.012*
	(0.001)	(0.124)	(0.137)	(0.027)	(0.179)	(0.095)	(0.031)	(0.165)	(0.008)	(0.001)
NTHO	0.038*	-4.8*	-5.501*	7.464*	-0.16	57.713*	-3.387*	-16.32*	6.196*	-0.021*
	(0.008)	(0.692)	(1.08)	(0.208)	(1.39)	(1.31)	(0.245)	(1.412)	(0.068)	(0.007)
I(HAM * CDD)	0	-0.573*	-0.967*	-0.076*	-1.664*	0.671*	-0.255*	0.668*	-0.086*	-0.01*
	(0.001)	(0.156)	(0.178)	(0.032)	(0.229)	(0.125)	(0.037)	(0.202)	(0.01)	(0.001)
I(HAM * underZDAM)	.	8.997*	24.109*	0.073	29.596*	-1.99*	4.568*	-51.739*	1.259*	.
		(1.682)	(2.052)	(0.405)	(3.217)	(0.912)	(0.353)	(5.972)	(0.209)	
peak	0.042*	-6.216*	1.063	-0.26	-5.217*	-1.35*	1.974*	-0.552	0.13*	0.031*
	(0.007)	(0.706)	(1.003)	(0.184)	(1.377)	(0.509)	(0.2)	(1.031)	(0.049)	(0.006)
wknd	0.023*	-0.22	-0.008	0.806*	-3.148*	-0.021	0.855*	4.532*	0.123*	0.042*
N	29035	18471	17651	33107	7165	19160	39570	52496	52782	30322
$RMSE$	0.465	35.921	50.063	12.416	42.832	28.368	15.015	90.382	4.333	0.394
R^2	0.091	0.338	0.152	0.464	0.086	0.243	0.383	0.094	0.764	0.041

* $p \leq 0.05$

Table C.5: P_S

	A	B	C	D	E	F	G	H	I	J
(Intercept)	-968.767*	135.395*	76.012*	102.304*	121.77*	19.097*	53.731*	287.534*	492.385*	-4.006*
	(2.199)	(2.848)	(3.205)	(2.014)	(39.42)	(2.602)	(1.242)	(6.512)	(3.5)	(0.144)
HAM	-0.439	-5.65*	7.095*	15.241*	-43.828*	15.012*	-10.683*	-114.02*	-229.761*	0.916*
	(5.115)	(2.845)	(2.741)	(2.213)	(7.096)	(4.011)	(1.097)	(8.077)	(5.953)	(0.195)
Li.shift.15	-1.935	-7.84*	-32.254*	-4.935*	-16.391*	-2.178	1.19	14.511*	0.302	-0.406*
	(1.506)	(1.47)	(1.605)	(1.581)	(2.868)	(2.984)	(0.873)	(5.016)	(2.611)	(0.081)
I(HAM * Li.shift.15)	1.279	7.361*	39.804*	5.905*	5.565	0.571	-0.964	15.408*	21.702*	0.218
	(2.16)	(2.253)	(2.609)	(2.281)	(6.037)	(4.3)	(1.25)	(7.324)	(3.777)	(0.117)
I(HAM * qfirm2)	-0.005	-0.013*	-0.016*	-0.01*	-0.015*	-0.045*	0.001	-0.03*	0.008	0*
	(0.008)	(0.001)	(0.001)	(0.002)	(0.002)	(0.003)	(0.001)	(0.002)	(0.005)	(0)
I(HAM * Price)	0.052	0.047	-0.016	-0.392*	0.746*	0.243*	0.158*	1.737*	1.104*	-0.008*
	(0.028)	(0.039)	(0.042)	(0.031)	(0.095)	(0.058)	(0.019)	(0.121)	(0.067)	(0.002)
CDD	2.662*	1.692*	1.627*	-0.609*	0.777	0.379	-0.056	3.296*	0.924*	0.156*
	(0.134)	(0.248)	(0.181)	(0.13)	(0.43)	(0.237)	(0.078)	(0.61)	(0.331)	(0.009)
NTHO	2.576*	6.406*	-18.456*	38.038*	9.475*	145.649*	13.026*	-81.014*	57.08*	-0.007
	(1.022)	(1.386)	(1.43)	(1.012)	(3.369)	(3.262)	(0.624)	(5.216)	(2.852)	(0.069)
I(HAM * CDD)	-0.121	-1.748*	1.152*	0.071	1.336*	1.266*	-0.186*	7.044*	-5.187*	-0.114*
	(0.162)	(0.312)	(0.236)	(0.158)	(0.55)	(0.313)	(0.094)	(0.746)	(0.399)	(0.011)
I(HAM * underZDAM)	.	8.107*	-3.488	-6.963*	22.556*	-22.218*	3.523*	-181.324*	52.044*	.
		(3.367)	(2.722)	(1.974)	(7.889)	(2.276)	(0.897)	(22.059)	(8.766)	
peak	5.068*	-22.59*	-14.397*	7.767*	-29.436*	-5.781*	0.29	-5.656	2.214	0.37*
	(0.97)	(1.414)	(1.335)	(0.898)	(3.308)	(1.269)	(0.508)	(3.811)	(2.068)	(0.065)
wknd	3.545*	2.973*	5.048*	0.752	6.567*	1.16	1.901*	29.705*	-1.301	0.195*
	(0.79)	(1.187)	(1.113)	(0.738)	(2.683)	(1.157)	(0.429)	(3.257)	(1.771)	(0.053)
N	29035	18467	17338	33097	7127	19079	39570	52456	52782	30322
$RMSE$	60.695	71.923	66.03	60.483	102.682	70.595	38.164	333.815	182.062	4.147
R^2	0.059	0.365	0.362	0.361	0.141	0.156	0.187	0.114	0.363	0.038

* $p \leq 0.05$

APPENDIX D

BIDDERS USED IN THIS STUDY

Identifier	NYISO Masked Bidder ID
A	3807750
B	6227750
C	17427750
D	28207750
E	57427750
F	59477750
G	63537750
H	67716180
I	71257750
J	83807750