

# Do Supply Function Equilibrium Models Describe Behavior in Electricity Spot Markets: An Empirical Analysis of the ERCOT Market

Ramteen Sioshansi\*

ramteen@ieor.berkeley.edu

Department of Industrial Engineering and Operations Research  
University of California, Berkeley

February, 2005

## Abstract

We present an empirical analysis of a supply function equilibrium model in the Texas spot electricity market. We derive conditions for optimal bidding behavior in a spot market with *ex ante* bilaterally contracted sales. By using generation cost information, we are able to derive a set of *ex ante*- and *ex post*-optimal bid curves and use a nonparametric model of firm behavior to compare our supply functions to actual bids made in 2002. Our results show that with the exception of the largest generators, generating firms make bids with markups far in excess of what would constitute profit-maximizing behavior, most likely to exclude themselves from the market. We then analyze a variant of the econometric model to determine whether there is a systematic difference in bidding between on- and off-peak bid periods. Finally, we show that there is some indication of learning on the part some of the generators over the course of the year.

## 1 Introduction

The analysis of any competitive market is heavily dependent on a model of firm behavior. The interaction of firms determines the performance of the market, and industrial organization (IO) theory has a wide array of models of firm behavior. These models are often used by the theoretical economist to gain insights into observed behavior of firms. Recently, with the need for market-based mechanisms to replace central-coordination control mechanisms, economists have applied these models to theorize the performance of a proposed market. The results of these analyses and their accuracy in describing markets outcomes are highly dependent upon the assumed firm behavior being reflective of actual behavior.

In this paper, we present an empirical analysis of the supply-function equilibrium (SFE) model, developed by Klemperer and Meyer (1989), in the context of a spot electricity market. SFE models have appeared in the literature

---

\*The work described in this paper was supported by the US Department of Energy's Energy Information Administration (EIA) Research Fellows Program, conducted in conjunction with the American Statistical Association. The Research Program is designed to produce theoretical and empirical statistical and economic analyses that serve to improve the statistical programs of the EIA. Support for this research was also provided by NSF Grant EEC0119301 and by the Power Systems Engineering Research Center (PSERC). The opinions and conclusions expressed in this paper are those of the author and do not necessarily represent those of the EIA, NSF, or PSERC. Republication in whole or part must be cleared with the author.

to analyze electricity market designs due to their assumptions being an extremely good description of the underlying market. The literature has to a large extent, however, lacked any empirical evidence to suggest the SFE model is indeed an accurate description of firm behavior. Our work seeks to provide this analysis by comparing actual bids to theoretical optima. In addition to this attempt at empirical validation of the theory, our work can also act as a gauge of the extent to which firms exploit their potential market power. The rest of the paper is organized as follows. Section 2 provides a background of different modeling techniques used to study electricity markets, along with some empirical studies conducted to validate or refute these models. Section 3 describes the Electricity Reliability Council of Texas (ERCOT) markets and the balancing energy service (BES) spot market, which is the specific market considered in our analysis. Section 4 describes our supply function model of the BES market and the methodology for deriving optimal bid functions. Section 5 presents our econometric models comparing actual to optimal bid functions giving the results of the comparison. Section 6 concludes.

## 2 Models of Spot Electricity Markets

Our research builds on an existing body of work analyzing electricity markets using a variety of industrial organization and other types of models. Although SFE-type models are more theoretically-sound in their underlying assumptions of the market, other modeling techniques have also been applied widely in this area.

Borenstein, Bushnell, and Knittel (1997) use a Cournot-based approach to model spot market competition in the PJM area. The underlying Cournot model posits that firms use their quantity supplied as strategic variables, and the market price is determined by the demand function. This has the immediate drawback that the analysis is crucially dependent on demand being price elastic, with the price being undefined and the market unanalyzable without this assumption. In reality, spot electricity markets typically have extremely price-*inelastic* demand, owing to the fact that the majority of end consumers do not face the actual spot price of electricity, but rather a regulated retail rate. In order to overcome this obstacle Borenstein, Bushnell, and Knittel assume a constant elasticity demand function. Although they are able to make some inferences about the relationship between system load and spot prices, these results are highly dependent on their assumed demand function. For this reason, analyses based on Cournot-based models are somewhat dubious. Cardell, Hitt, and Hogan (1997) and Borenstein and Bushnell (1999) conduct similar Cournot-based analyses of other spot markets.

Wolfram (1999) and Kim and Knittel (2004) use a conjectural variations-type model to estimate price-cost markups using an econometric specification of firm behavior. This branch of IO, called new empirical industrial organization (NEIO), has become a popular econometric tool as it allows the empirical economist to estimate markups without needing underlying cost information. The model gives that each firm's Lerner index is inversely related to the elasticity of its residual demand function. By estimating this demand function and using the actual observed price, one can impute the underlying marginal cost each firm faces. Assuming the model is correct, this technique would be of particular use for industries in which cost data is difficult to estimate. Wolfram and Kim and Knittel conduct studies similar to ours to test the validity of the NEIO model. Using cost data, which is relatively easy to estimate for the electricity industry, they compare the marginal cost predicted by the NEIO model to the actual cost derived by their engineering calculations. Wolfram finds the NEIO model to provide a noisy estimate of the actual cost but cannot statistically reject the model, whereas Kim and Knittel find the model to provide poor estimates of cost especially with changes in fuel costs. Studies carried out by Genesove and Mullin (1994) for the sugar and Clay and Troesken (2003) for whiskey industries yield similar results. Finally, Wolak (2003) conducts a similar type of analysis; by estimating the residual demand function facing each supplier in the California market he uses the

elasticity of residual demand as an estimate of a firm’s potential market power, and uses this to gauge the extent to which generators exercised this power.

Green and McDaniel (1999a) (1999b) analyze the British spot market as a single-unit auction. As Riley and Samuelson (1981) did in their seminal paper on optimal auctions, they use the concept of an equilibrium bidding function to characterize the behavior of generators. The first-order necessary condition (FONC) of the bidders’ profit maximization problem gives a differential equation defining the equilibrium bid function. von der Fehr and Harbord (1993) and Wolfram (1998) expanded auction-type analyses by studying bidding in a multiunit auction setting, having the advantage of allowing firms greater exercise of market power by accounting for multiunit effects. The drawback to multiunit auction-type analyses is the inherent intractability of analyzing them with multiple bidders.

Green and Newbery (1992) is the seminal application of an SFE model to an electricity market. They use it to analyze market power in England and Wales following restructuring. Their model was greatly simplified by the fact that at the time there were only three generation owners in the markets, only two of which were assumed to be ‘strategic bidders.’<sup>1</sup> Their analysis showed that absent significant (by their estimates a socially-inefficient amount of) entry, the two incumbent firms would be able to exercise considerable market power and inflate prices well above marginal cost. Newbery (1998) expands the original work by allowing for an outside contract market as well as entry. He shows that if new capacity has the same operating cost as those of the incumbents, there will be entry when there is insufficient capacity. If, on the other hand, new generation has a lower marginal cost then incumbents can profitably invest to deter entry. Finally, Green (1996) uses a linear supply function model to test the effect of different policies to increase the level of competition in the England and Wales spot market.

Hortascu and Puller (2004) conduct an empirical analysis of an SFE-type model which is similar to ours. They base their analysis on the share-auction model, developed by Wilson (1979), where a firm’s contract price and position is considered to be private information. By assuming the optimal bid function is what they call *additively-separable and linear in the private information* (AS-LPI), their model essentially becomes a standard SFE. They compare actual bids to theoretical optima to test for strategic bidding behavior using mainly ‘pointwise’ tests of optimality—comparing profits and dispatch under actual and theoretically optimal bids. Our work takes a markedly different approach, which is to compare the entire length of the actual and optimal bid curves. Our method assumes the actual price-cost markups observed in the bids are a multiple of the optimal markups, wherein the multiplier captures the degree to which bidders are rational profit-maximizers.

### 3 The ERCOT Electricity Markets

ERCOT acts as the system operator for the NERC region by the same name, which covers most of southern and central Texas.<sup>2</sup> In this role, its primary responsibility is to ensure reliability of the system, which is achieved both through bilateral action on the part of market participants and a number of centrally-operated energy markets. The bulk of wholesale electricity is traded bilaterally between parties. Prior to each day, market participants submit resource and obligation schedules to ERCOT through Qualified Scheduling Entities (QSEs). The QSEs are meant to act as intermediaries between stakeholders and the system operator, and they also act as aggregators for smaller generators and utilities—by allowing multiple firms to submit schedules and bids through a single QSE. For example, in 2001 the same QSE submitted schedules and bids for both Reliant Energy and City Public Service of San Antonio.

---

<sup>1</sup>The third generator, Nuclear Electric plc, held all the nuclear assets in the market, and as such acted as a price taker.

<sup>2</sup>A small portion of western Texas is part of the WECC, northern Texas is part of SPP, and the region east of Houston is part of SERC.

Invariably, electricity generators and procurers would need a market through which to buy and sell excess energy, since load forecasts are never exactly correct. The BES is meant to serve as this spot market in which power-generating companies (PGCs)—through their QSEs—can submit bids to increment (inc) and decrement (dec) their generation. Up until mid-2002, QSEs were required to submit balanced day-ahead schedules. This balanced schedule requirement was intended to minimize the use of the BES as a market to procure baseload resources, and help ensure PGCs and load-serving entities (LSEs) use it as a true ancillary service market to only cover resource imbalances. Even after the balanced schedule requirement has been dropped, the BES is still used mainly as an ancillary service market, with typically only 3% of energy traded in the market. The market itself operates much like a commodity spot market. For each hour, PGCs submit price/quantity bids specifying the amount of energy they are willing to inc or dec at a given price, subject to a \$1000 price cap.<sup>3</sup> Absent transmission constraints, the market clears like a single power pool—ERCOT aggregates the bids into a supply curve, and for each 15-minute interval intersects the price-inelastic demand for balancing energy with the supply curve to determine the least-cost dispatch and a uniform market-clearing price for energy (MCPE). Participation in the BES market is voluntary, with the exception of a regulatory rule imposed by the Public Utility Commission of Texas (PUCT) that all QSEs are required to offer to decrement at least 15% of their scheduled energy at any price within the price cap. The PUCT’s rationale behind this requirement was to ensure decremental service is available due to a fear that QSEs would overschedule resources day-ahead.

Given the basic characteristics of the BES, an SFE-type model should be a theoretically sound representation. SFE assumes firms commit themselves to supply functions—which is the equivalent to submitting quantity/price bids. The market clearing mechanism intersects the aggregate supply of the firms with the market demand function, which need not be price-elastic. In reality, generators will have excellent information regarding their competitors. Operating costs are relatively easy to estimate using engineering techniques; the marginal generating cost of a fossil-fuel driven plant can be estimated from its heat rate, which is a measure of its thermal efficiency. There are a number of firms in the business of compiling and selling this type of cost information. Given that we as academicians were able to estimate these costs, it is no leap of the imagination to assume generators can as well. As for the actual operating status of a rival’s plants, generating firms will see a brief fluctuation in the power grid’s voltage and frequency if a large generator is taken offline. Moreover, there are firms which monitor the operational status of plants and sell this information on a real-time basis. Thus, a PGC should be able to very-well predict which of its rival’s plants are operating at any given time. Finally, generators interact in the BES market on an hourly basis everyday. This repeated interaction essentially makes this an infinite-horizon game. The SFE model assumes firms play Nash equilibrium strategies, which is often an unrealistic assumption in single-shot games due to perceived or real limited rationality of opponents, difficulty in predicting their behavior, and other cognitive and behavioral limitations of the players. In the case of the BES, we predict generators should be able to converge towards a Nash outcome through the repeated interaction and its associated learning effects.<sup>4</sup>

## 4 A Supply Function Model of the ERCOT BES

Based on the inherent characteristics of the ERCOT BES market it is a common belief that an SFE-type model should well describe the bidding behavior of the firms involved. The specific model we use is a SFE which, like

---

<sup>3</sup>Note that negative bids are allowed, primarily for decremental offers, with a minimum price cap of -\$1000.

<sup>4</sup>It should be noted that the repeated interaction does also allow for a multitude of cooperative or collusive equilibria in which suppliers raise the MCP above what would result from repeated stage-game Nash bidding. Based on our analysis of the bidding behavior of the large suppliers, which will be discussed later, we do not believe this to be the case in the BES.

the share-auction model used by Hortascu and Puller, takes into account the contracted supply position of each generating firm. Our derivation shows that contractual obligations affect optimal bidding only through the quantity contracted and not the contract price.

## 4.1 Derivation of Supply Function Model

To derive generator  $i$ 's optimal bid curve, we solve its profit-maximization problem. We define the notation  $s_j(p)$  to be firm  $j$ 's supply function—specifying quantity supplied at each price,  $c_j(q)$  to denote firm  $j$ 's cost function,  $Q_j^{DA}$  to be the quantity firm  $j$  has contractually obligated itself to supply at the contracted price  $p_j^C$ ,<sup>5</sup> and  $l$  to be the estimated system load. Firm  $i$ 's objective is to maximize its profits:

$$\begin{aligned} \max_p \Pi_i(p) &= p \cdot (l - \sum_{j \neq i} (s_j(p) + Q_j^{DA})) - c_i(l - \sum_{j \neq i} (s_j(p) + Q_j^{DA})) - (p - p_i^C)Q_i^{DA} \\ &= p \cdot RD_i(p) - c_i(RD_i(p)) - (p - p_i^C)Q_i^{DA}, \end{aligned} \quad (1)$$

where  $RD_i(p) = l - \sum_{j \neq i} (s_j(p) + Q_j^{DA})$  is firm  $i$ 's residual demand function. Note that we have specified forward contracts to settle as contracts for differences based on the prevailing MCPE in the BES market. Firm  $i$  sells all its generation through the BES market and reimburses (or is reimbursed by) its contract counterparties for the difference between the *ex post* realization of the BES MCPE and the contracted price. Differentiating equation (1) and setting the result equal to zero gives the FONC for firm  $i$ 's profit-maximization problem:

$$p - c'_i(RD_i(p)) = -\frac{RD_i(p) - Q_i^{DA}}{RD'_i(p)}. \quad (2)$$

The FONC in (2) is a differential equation characterizing firm  $i$ 's optimal bid function given its residual demand, which has a unique solution when a boundary condition is given. Our specification of the profit function as a contract for differences implicitly defines the boundary. If  $RD_i(p) = Q_i^{DA}$  (firm  $i$  has zero dispatch in the BES), then  $p = c'_i(RD_i(p))$ . Furthermore, assuming rival firms' supply functions are non-decreasing, we will have  $RD'_i(p) < 0$ . This then gives us that if  $RD_i(p) > Q_i^{DA}$  [ $RD_i(p) < Q_i^{DA}$ ] *i.e.* if firm  $i$  is dispatched to inc[dec] in the market then we have  $p > c'_i(RD_i(p))$  [ $p < c'_i(RD_i(p))$ ]. This says a firm will have a positive markup over marginal cost to increment generation and a negative markup to decrement. When a PGC is dispatched to inc generation, it is paid the MCPE and incurs the marginal generating cost of increasing output. Symmetrically, if a PGC is dispatched to dec, it foregoes the cost of generation but must pay ERCOT the MCPE (it essentially 'buys' its scheduled generation back from ERCOT). Thus, the markup and markdown rule implied by equation (2) makes intuitive sense.

The FONC of each PGC's profit-maximization problem will yield an equation like (2). A Nash equilibrium will be a set of bid functions simultaneously solving the FONC of all firms. This set of bid functions will have the Nash property that no PGC would have a profitable unilateral deviation.

## 4.2 Assumptions and Data

Derivation of optimal bid curves requires data on generation costs of the firms. Implicit in our derivation is that firms decide their bidding at a firm-wide level—as opposed to generation plants or units making individual bidding

<sup>5</sup>Because only the contract position and not the price affects the profit-maximizing behavior of a firm in the BES market, we assume a single contract price for notational ease. One could reformulate the problem with multiple contract prices, although the result would remain the same.

Table 1: Individually-Identified Generating Firms

PGC	% Gen. Cap.	PGC	% Gen. Cap.
TXU	22	BP Energy	< 1
Reliant Energy	17	Bryan Texas Utilities	< 1
Calpine	8	City of Garland	< 1
Central Power and Light	6	Rio Nogales Power Project	< 1
City of San Antonio Public Service	6	Tenaska Gateway Partners	< 1
City of Austin	4	Cogeneration Lyondell	< 1
Lower Colorado River Authority	3	Bastrop Energy Partners	< 1
West Texas Utilities	2	Mirant Wichita Falls Management	< 1
Midlothian Energy	2	South Texas Electric Cooperative	< 1
Guadalupe Power Partners	2	Brownsville Public Utility Board	< 1
Lamar Power Partners	2	AES Deepwater	< 1
Brazos Electric Power Cooperative	1	Gregory Power Partners	< 1
Sweeny Cogeneration General	< 1	Extex Laporte	< 1
Hays Energy	< 1	Denton Municipal Electric	< 1
Tractable Power	< 1		

decisions. Our analysis is confounded by an identification problem due to the QSE relationships between firms. A number of PGCs interact with ERCOT through a QSE which is used by other PGCs. In most cases, however, the schedules of individual PGCs can be identified because their generation assets and bids are located within a congestion zone which no other PGC sharing the same QSE also uses. Thus, although two PGCs may use a single QSE, if their assets are in different zones, then the QSE schedules and bids from the two firms can be distinguished. In some cases, however, multiple PGCs sharing congestion zones bid through a single QSE—in these cases individual bids cannot be distinguished. We assume that if a single PGC represents more than 70% of the actual electricity generated within a congestion zone for its bidding QSE, then those bids and schedules are for that single firm. As Table 1 shows, we are able to include the major PGCs and the vast majority of the bidding assets in ERCOT. Optimal bids for firms which cannot be identified are not derived, but their *actual* bids are still used in deriving the residual demand function of each firm, which is used in deriving their optimal bid curve.

To derive each firm’s cost function, we assume the plants are dispatched in economic merit order. Thus, a firm generating 5,000MW will generate its 5,000 cheapest megawatts available. PGCs dispatching resources out of merit order due to operational or other constraints is not captured in our analysis. Because of their significant ramping constraints, we assume nuclear units are not bid strategically and are instead run at 100% of available capacity. Because of the difficulty in estimating resource availability, we exclude hydroelectric, wind, and solar plants from the generation portfolios. We feel justified in making this simplifying assumption since renewables only constitute about 5% of Texas’s generation capacity.

For fossil fuel-driven plants, we assume each unit has a constant marginal cost. The fuel cost is the product of its heat rate and fuel price. We impute an average heat rate for each month using heat produced and net generation for each plant as reported in EIA Form 906. For months in which that data is unavailable, the tested heat rate is used instead. We realize there is some endogeneity from using the average heat rate, as it is affected by bidding behavior through the actual dispatch of a given unit, but we believe this to be minimal. Fuel prices for natural gas is

estimated using the Henry Hub spot price plus \$0.10/mmBTU for transportation. Although it is common practice for PGCs to contract for fuel and pay a price different to the spot price, it nonetheless represents the opportunity cost of burning the fuel. The cost of other fuels are estimated using the heat content-weighted average of fuel procured as reported in EIA Form 423. In addition to fuel costs, generators are also subject to emission fees from both the US Environmental Protection Agency (EPA) and the Texas Commission on Environmental Quality (TCEQ). The TCEQ charges each polluting plant the greater of a fixed fee to administer its monitoring program and a charge based on actual emissions of pollutants. For plants paying the fixed fee, we assume no variable emission cost. For plants subject to the variable emission-based charges, we estimate the cost per megawatt by dividing the total charge for the year by the plant's net generation for the year. The EPA charges for SO<sub>2</sub> as part of its acid rain program. The program is administered through an emissions trading program, whereby a polluter must obtain emission credits for each ton of SO<sub>2</sub> emitted. Using TCEQ data, we are able to estimate the average SO<sub>2</sub> output per megawatt and multiply that by the cost of an emission permit as reported by Cantor-Fitzgerald Environmental Trading Brokerage. Finally, we estimate a variable operations and maintenance cost for each plant based on its generating technology.

In determining a firm's cost of providing inc and dec service, we assume all units which had not experienced an outage (as recorded in ERCOT's outage scheduler) were available to ramp generation. Thus, we ignore ramping constraints and any intertemporal constraints on a unit's on or off time. Taking account of these constraints would require detailed operational data not available to us.

### 4.3 Derivation of Bid Curves

For the purposes of comparison, we derive two sets of bid curves for each generator. The first is an *ex post*-optimal bid curve, which is the optimal reaction of each PGC to the actual bids of its rivals. The second is an *ex ante*-optimal set of bid curves which simultaneously solve equation (2) of all PGCs. Testing of the *ex ante*-optimal curves are meant to show the degree to which the industry as a whole bids theoretically optimal supply functions. Assuming the SFE model is correct, PGCs should bid supply functions simultaneously solving the FONC of all PGCs. The reason for testing the *ex post*-optimal curves is to allow our model to be more robust to some firms not bidding theoretical optima. Observation of the bids shows some firms, especially smaller municipalities and cooperatives, are reluctant to deviate from their scheduled delivery by participating in the BES. These firms will typically make offers with substantial markups and markdowns to minimize the odds of being dispatched unless there is high demand for BES resources. Because the *ex post* bid curves are the optimal reaction to the actual bids of each PGC's rivals, it captures the degree to which a firm is able to anticipate the bidding of its rivals and optimally react (even when rivals are not Nash players).

One complication which arises in the bid curve analysis is the format of bids into the BES. The equations governing the optimal bidding behavior of the firms assumes continuous and differentiable supply functions. Bids into the BES, however, are price/quantity pairs defining a step function. ERCOT limits each QSE to bidding 40 steps for each of the inc and dec side of its supply function (giving a total of 80 steps), posing two problems. First, in deriving each firm's bid function we would need to 'flatten' our optimal bid curve into a step function to make it conform to the actual bid curve to which it is being compared. In doing this, we assume the bid quantities to be fixed, based on those actually used by the firm. For instance, in the hour ending 3:00am on 4 August, 2002 Tenaska Gateway Partners' bid curve consisted of 10 steps—5 for inc and 5 for dec service. The inc bids had steps at 625, 626, 650, 651, and 768 megawatts. In deriving optimal bid functions we assume the PGC uses the same bid quantities. Secondly, in constructing each firm's residual demand curve, the step function format of the bids will give a step residual demand function. Since it would be overly-zealous to assume PGCs estimate the exact location of the steps *ex ante*, we

smooth-out the residual demand curve using a kernel function as seen, for instance, in Wolak (2003). We estimate the derivative of the residual demand function using a finite difference method, as direct differentiation of the kernel function proved highly volatile with respect to the choice of the smoothing parameter.

Our period of study is 2002, with all bid periods (24 per day) included. However, assuming the BES clears as a simple power pool requires there to be no binding transmission constraints. Thus, any hour with a congested transmission line would have to be removed from our sample, since the BES would clear with multiple MCPs for each congestion zone. In accounting for this, we removed any day in which there was *any* interzonal congestion. The rationale for removing days with *any* congestion from the sample is that any anticipation of congestion on the part of PGCs could likely lead to substantially different bidding patterns on the part of any PGCs with locational market power. We felt that excluding days with any interzonal congestion (even in a few of the hours) would control for such distortion to some extent. After excluding congested days, our sample was reduced to 102 days, giving a total of 2448 bidding periods.

## 5 Comparison of Actual to Optimal Bid Curves

In comparing the actual to optimal bid curves, our objective is to study the nature of the entire length of the bid curve as opposed to using ‘pointwise’ tests of optimality as done in Hortascu and Puller’s study of the BES. Qualitatively comparing the actual and theoretical bid curves shows that the supply function equilibrium model is a relatively poor representation of the bidding behavior of most firms. We find that almost all firms offer dec service with substantial markdowns from marginal cost—generally much more than can be explained by the model. Furthermore, most firms overbid their inc service, with the exception of the larger power producers. Firms whose bidding best matches our theoretical bid curves are TXU, Reliant Energy, and City of San Antonio Public Service. As an example, Figure 1 shows the actual and optimal bids for City of San Antonio. Note that the inc bids (offer quantities greater than zero) match quite closely, whereas the dec bids differ substantially with the bids in the middle of the curve being marked down more than the model predicts and the markdown being less than optimal for extreme decs.

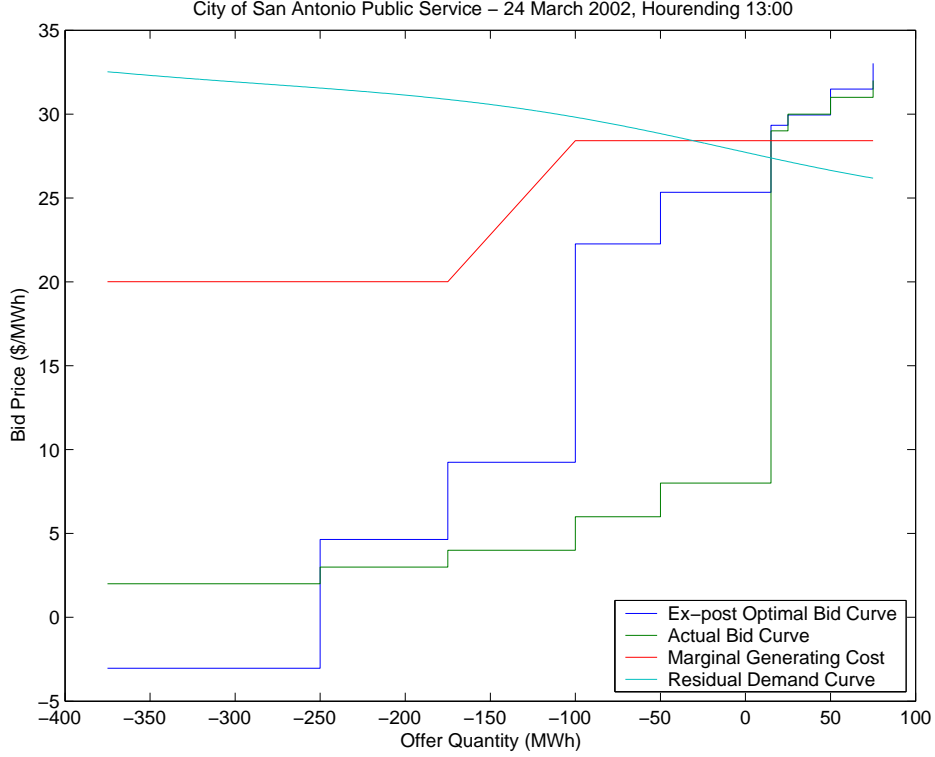
In order to compare the bids more rigorously, we estimate an econometric model of firm behavior. Our model posits that generators, in making their bids, choose markups to be some multiple of the theoretically optimal markup. Using the notation  $MU_t(q)$  for the actual observed and  $MU_t^*(q)$  as the optimal markup in bidding period  $t$  (both being functions of the offer quantity), our model is:

$$MU_t(q) = \phi \cdot MU_t^*(q),$$

where the multiplier,  $\phi$  can be thought of as a measure of conduct. A value of  $\phi$  close to zero gives zero markup or perfectly competitive bidding. Higher values of  $\phi$  would be indicative of more rational profit-maximizing behavior, with  $\phi = 1$  being perfect rationality. Values of  $\phi > 1$  would be indicative of firms trying to exclude themselves from the market, overaggressively bidding towards the price cap, collusion, or some other behavior which is inconsistent with our static SFE model.

One possible estimation approach would be to assume the  $\phi$  parameter fixed along the supply curve, in which case the model could be estimated by standard parametric techniques such as least squares. We believe this specification would be overly restrictive on firm behavior, by assuming constant ‘conduct’ in bidding throughout their offer curves. Qualitative analysis of the data shows that some firms opt to ‘hockey-stick’ their bids by bidding reasonable markups in the middle of their supply stacks, and bidding towards the price cap at the two extremes. In view of such anecdotal

Figure 1: Actual and Optimal Bids Example



evidence against a fixed multiplier, we opt for a model with a variable conduct multiplier

$$MU_t(q) = \phi(q) \cdot MU_t^*(q), \quad (3)$$

where  $\phi(q)$  is an unspecified smooth function of the offer quantity  $q$ . In order to estimate this model, we divide equation (3) through by the optimal markup,  $MU_t^*(q)$  to yield a standard nonparametric model:

$$\frac{MU_t(q)}{MU_t^*(q)} = \phi(q) + \epsilon_t(q), \quad (4)$$

where the error term,  $\epsilon_t(q)$  with  $E[\epsilon_t(q)] = 0$  and  $\text{Var}(\epsilon_t(q)) < +\infty$ , allows for misestimation of rivals' bids and miscalculation of an optimal reaction. We estimate the model in Equation (4) using the kernel-based method set out by Nadaraya (1964) and Watson (1964).

In order to make bids between different periods comparable, we estimate the model using two different normalizations of the offer quantities,  $q$ . In the first we normalize the offer quantities,  $q$ , to be the fraction of the total offer a firm makes in each given bid period (a bids' location within a firm's supply stack), meaning  $q$  is restricted to  $[-1, 1]$ . For example, in Figure 1, San Antonio made 4 inc and 5 dec bids for that hour. Its inc quantities were for 15, 10, 25, and 25MW, giving a total offer of 75MW. Those bid points would correspond to  $q = \{1/5, 1/3, 2/3, 1\}$ . Symmetrically, the dec bids would correspond to values of  $q \in [-1, 0)$ . In the second specification, we normalize the offer quantities to be the percentage of total available capacity bid by the PGC (a bids' location within a firm's resource stack), meaning we now have  $q \in [0, 1]$ . We make these normalizations because firms may offer different absolute quantities in different bid periods, yet our model attempts to capture how the markup multiplier  $\phi(q)$  varies

along a firm’s supply curve. The first specification will look for the extent to which conduct differs within the *supply* stack, whereas the second will capture whether the location within the *resource* stack has an effect. Moreover, our initial estimates using absolute quantities yielded an even weaker fit of the model with significantly higher estimator variances.

By using the cross section of data on all bids, we are able to estimate the model in Equation (4) for all PGCs bidding into the BES market. As discussed above, the purpose of this analysis is to gauge the extent to which the industry as a whole bids according to a supply function equilibrium model. Figure 2 below shows the estimated  $\hat{\phi}(q)$  for the two normalizations, along with a pointwise 95% confidence interval. The confidence interval is derived by using the asymptotic normality of the kernel estimator. If we use the notation  $n$  to denote the sample size,  $h$  for the window width used in the kernel estimator,  $f(q)$  for the density of  $q$ ,  $\sigma^2(q) = \text{Var}(\epsilon(q))$  for the variance of the residuals, and  $K(\cdot)$  for the kernel function, then we have (under certain regularity conditions<sup>6</sup>) that:

$$\sqrt{nh}(\hat{\phi}(q) - \text{E}[\phi(q)]) \xrightarrow{d} \mathcal{N}\left(0, \frac{\sigma^2(q) \int K(\psi)^2 d\psi}{f(q)}\right) \sim \mathcal{N}(0, s^2(q)).$$

Letting  $\hat{f}(q)$  denote a kernel estimator for the density of  $q$  and  $\hat{\sigma}^2(q)$  for the sample variance of the residuals from the kernel regression, we can estimate the asymptotic distribution as:

$$\mathcal{N}\left(0, \frac{\hat{\sigma}^2(q) \int K(\psi)^2 d\psi}{\hat{f}(q)}\right) \sim \mathcal{N}(0, \hat{s}^2(q)).$$

Furthermore, because our optimal window width choice used in the kernel estimator is  $h = o(n^{-1/4})$ , we have that  $h \rightarrow 0$  as  $n \rightarrow +\infty$ , thus the random variables  $\hat{\phi}(q_1) - \text{E}[\phi(q_1)]$  and  $\hat{\phi}(q_2) - \text{E}[\phi(q_2)]$  are independent for  $q_1 \neq q_2$ . Table 2 summarizes the estimated values  $\hat{\phi}(q)$  under our two normalizations ( $B$  for quantities normalized by the total quantity bid and  $C$  for quantities normalized by total generating capacity), and gives values for upper and lower bounds of an estimated 95% confidence interval.

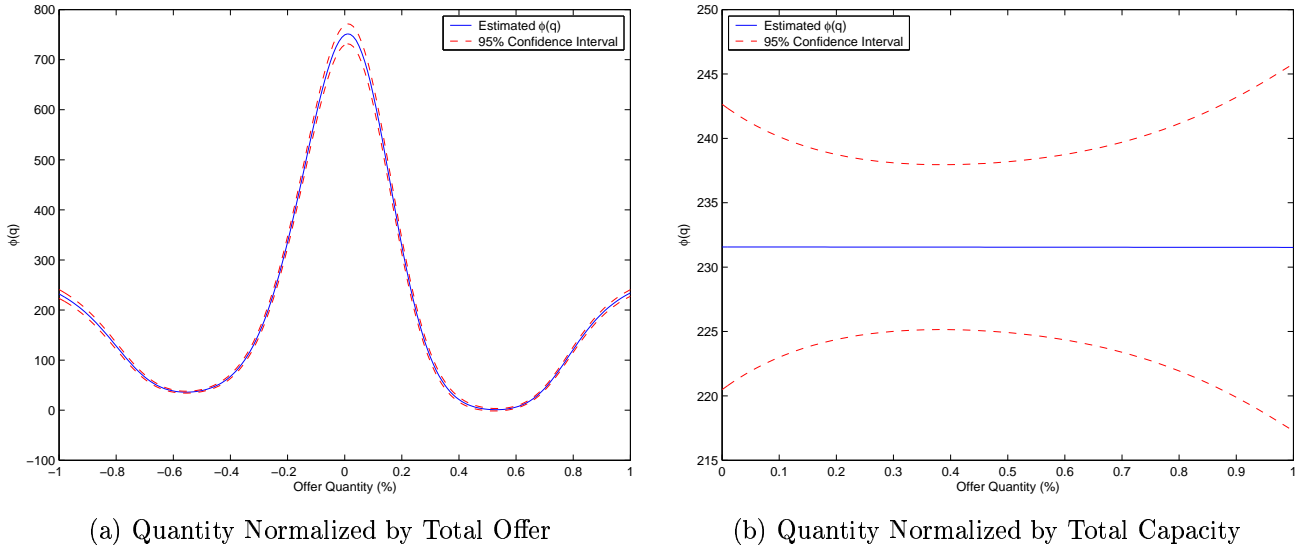
Our sample consists of a total of 391,875 bid points for all PGCs over the entire sample period. We note that the bid quantity normalization gives a better fit of the data, in that the variances are smaller (as demonstrated by the tighter confidence interval). In both cases, however, the estimated  $\hat{\phi}(q)$  shows SFE to be a very poor model of aggregate firm behavior, as the actual bids are on average one or two orders of magnitude greater than the theoretical optima.

Table 2: Estimated Industry Conduct Curve with *Ex Ante*-Optimal Bid Curves

$q$	-1	-0.8	-0.6	-0.4	-0.2	0	0.2	0.4	0.6	0.8	1
$\hat{\phi}_B(q)$	232.13	128.2	38.311	67.388	335.66	749.59	328.04	21.276	6.1736	121.07	234.06
$\hat{U}_B(q)$	241.02	134.99	40.537	71.51	347.09	769.33	343.06	26.159	8.4773	126.45	240.66
$\hat{L}_B(q)$	223.25	121.41	36.086	63.266	324.24	729.86	313.01	16.394	3.8698	115.68	227.45
$\hat{\phi}_C(q)$						231.57	231.56	231.55	231.55	231.54	231.53
$\hat{U}_C(q)$						242.65	238.74	237.96	238.74	241.14	245.8
$\hat{L}_C(q)$						220.49	224.37	225.15	224.35	221.94	217.27

<sup>6</sup>We exclude a discussion of the technical requirements for this Central Limit Theorem to hold, and refer the interested reader to any standard nonparametric econometric text, for example Pagan and Ullah (1999).

Figure 2: Estimated Industry Conduct Curve with *Ex Ante*-Optimal Bid Curves



### 5.1 Estimating Ex Post-Optimal Bid Curves

The purpose of comparing the *ex post*-optimal bid curves to true bids is to determine the extent to which individual PGCs bid optimally, even though the firms taken together do not act as rational profit-maximizers in our SFE model. In achieving this *ex post*-optimal bidding, a PGC would have to correctly guess the conduct of each of its rivals, and properly choose its bid curve to maximize its own expected profits in light of this estimate. In general, this could prove to be complicated as a firm would have to guess the  $\phi(q)$  of each rival and take account of that in making its own bidding decision. Due to the repeated nature of the interaction, though, we surmise that over time a purely profit-driven firm could anticipate its rivals' bidding behavior and adjust its bidding patterns to that behavior. As Figure 1 shows, City of San Antonio has been able to make such an adjustment to some extent. As with the analysis of the *ex ante* bid curves, we compare the *ex post* bid curves using the same nonparametric model of Equation (4). Our analysis differs in that we compare the curves of each PGC individually (as opposed to using the bids of all PGCs in aggregate). Again, the distinction is that we now wish to capture individual firm behavior, as opposed to modeling the behavior of the industry as a whole.

Figures 3 through 8 show the estimated  $\hat{\phi}(q)$  for the major PGCs participating in the BES, along with the same pointwise 95% confidence interval. In addition, Table 7 in Appendix A gives summary statistics for the estimated conduct curve of all PGCs.

Our estimates show that with the exception of TXU, Reliant, and City of San Antonio, most bidders' behavior is not consistent with the predictions of an SFE model, which is largely consistent with anecdotal evidence based on observation of bids. We posit that most smaller power producers, cooperatives, and cogenerators prefer to generate according to their day-ahead schedule. To help ensure this they overbid their generation into the balancing market with markups and markdowns significantly higher (in some extreme cases up to three orders of magnitude greater) than can be explained by profit-maximizing behavior. Such behavior would act to keep them out of the balancing market, except when load is high enough to give them a high rent for providing balancing resources. This conjectured behavior is further supported by the inc and dec patterns of the various PGCs. Table 3 shows that many small PGCs

Table 3: Percentage of Bidding Periods with Only DEC Bids Submitted

<b>PGC</b>	<b>% DEC Bid Only</b>	<b>PGC</b>	<b>% DEC Bid Only</b>
Brazos Electric Power Cooperative	97.3	Calpine	16.1
Mirant Wichita Falls Management	86.8	City of Garland	15.4
Hays Energy	84.3	City of San Antonio Public Service	9.1
Midlothian Energy	71.6	BP Energy	7.6
Bryan Texas Utilities	71.4	Guadalupe Power Partners	7.5
Bastrop Energy Partners	53.5	Central Power and Light	7
Lamar Power Partners	41.7	Cogeneration Lyondell	2.3
Gregory Power Partners	39.8	Denton Municipal Electric	2.1
Rio Nogales Power Project	39.4	AES Deepwater	0.9
Tractable Power	37.5	City of Austin	0.7
Brownsville Public Utility Board	33.3	Lower Colorado River Authority	0.4
South Texas Electric Cooperative	32	Reliant Energy	0.2
Sweeny Cogeneration General	26.4	Extex Laporte	0.1
West Texas Utilities	17.2	TXU	0
Tenaska Gateway Partners	17.1		

Table 4: Percentage of Bidding Periods with Only a Single DEC Bid at -\$1000

<b>PGC</b>	<b>% -\$1000 DEC Bid Only</b>
Bastrop Energy Partners	24.5
Brownsville Public Utility Board	23.7
Lamar Power Partners	16
Sweeny Cogeneration General	9.3

often opt to exclude themselves from the BES by submitting only dec bids, which they are required to, without any inc bids. Furthermore, as Table 4 shows, four of the small generators submitted only a single dec bid at the price cap of -\$1000 in a number of bid periods. These observed patterns of bidding are indicative of many of the small PGCs participating in the BES only in so far as they are required to by the PUCT's dec offer requirement.

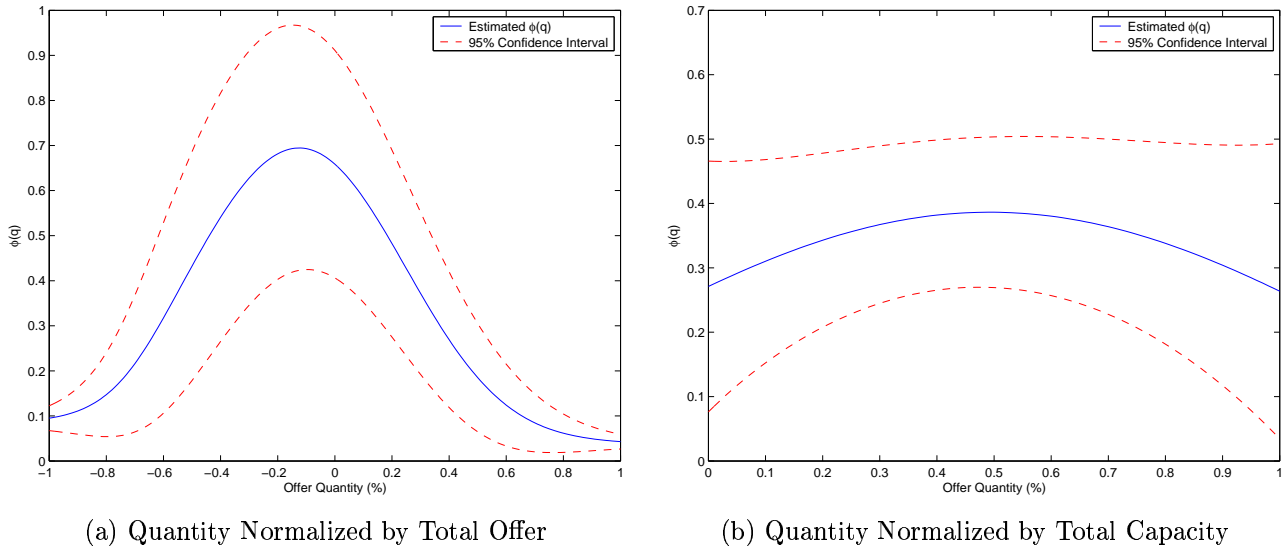
With TXU, we see that on average their markups are at most half of the theoretical optimum. As the majority holder of generation assets (22% of nameplate capacity during 2002) in Texas, TXU is often a pivotal supplier in the BES and as such should be able to exercise significant market power by being the price setter, which is surprisingly absent. One possible explanation for this observed restraint is that TXU Energy (a subsidiary of TXU Corporation) is one of the largest LSEs in Texas with approximately 2.9 million customers. To the extent that TXU Energy would have to purchase BES resources to balance its schedule but receive a fixed regulated rate for its retail sales, TXU may have a disincentive to act to inflate the wholesale price of electricity. One way to capture this phenomenon would be to estimate an econometric model of behavior which accounts for a PGCs load imbalance. This is one of our intended areas of future work.

The most surprising result that we find is the bidding behavior of Calpine. Calpine, which is an independent power producer, has been consistently increasing its share of asset holdings in Texas by purchasing from incumbent utilities and investing in new generation. Surprisingly, our results show Calpine to be bidding at least 10 times higher

than our model predicts to be optimal, which would act to exclude it from the BES market.

The results of our *ex post* analysis are fairly consistent with Hortascu and Puller’s findings. One of their measures of rational bidding is to compare a firm’s profits under optimal bidding to that under their actual bids, and calculate the percent of potential profits a firm foregoes with its actual bids. Their results show that amongst the largest PGCs, Reliant and TXU perform best realizing 83% and 45% of their potential profits, respectively. Moreover, they find that Calpine’s behavior yields them only 22% of potential profits. This shows that our findings of Calpine’s seemingly irrational bidding behavior is fairly consistent with other analysis done in these regards.

Figure 3: TXU Conduct Curve Estimates



## 5.2 Semiparametric Models of Behavior

As a final point of comparison, we are interested to see the extent to which exogenous factors affect bidding behavior. In order to test for such effects, we estimate a semiparametric version of the model in Equation (4):

$$\frac{MU_t(q)}{MU_t^*(q)} = \beta^\top \mathbf{X}_t + \phi(q) + \epsilon_t(q), \quad (5)$$

where  $\mathbf{X}$  is a vector of regressors linearly independent of  $q$ , and we assume  $E[\epsilon|\mathbf{X}, q] = 0$ . In our model, we conduct two tests for the five largest PGCs (TXU, Reliant, Calpine, Central Power and Light, and City of San Antonio) first for differences in bidding behavior during on-peak, off-peak, and weekends bid periods. Second, we look to see if there is any systematic difference in bidding which develops over time.

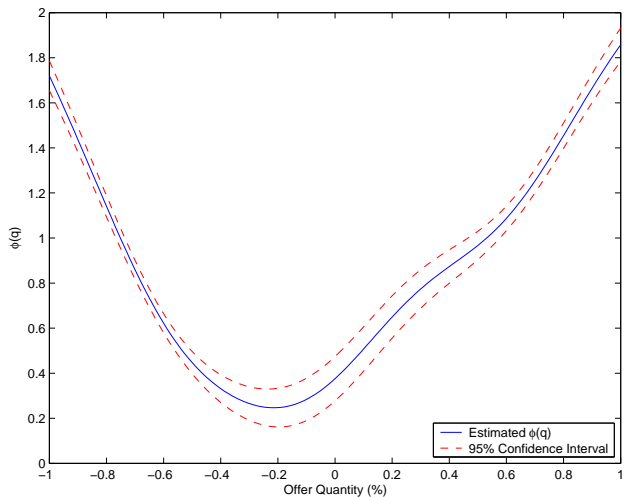
We estimate this model using the technique developed by Speckman (1998). Taking conditional expectations of Equation (5) and noting that by the tower property of expectations,  $E[\epsilon_t(q)|q] = E[E[\epsilon_t(q)|q, x]|q] = 0$  we get:

$$E\left[\frac{MU_t(q)}{MU_t^*(q)}|q\right] = \beta^\top E[\mathbf{X}_t|q] + \phi(q). \quad (6)$$

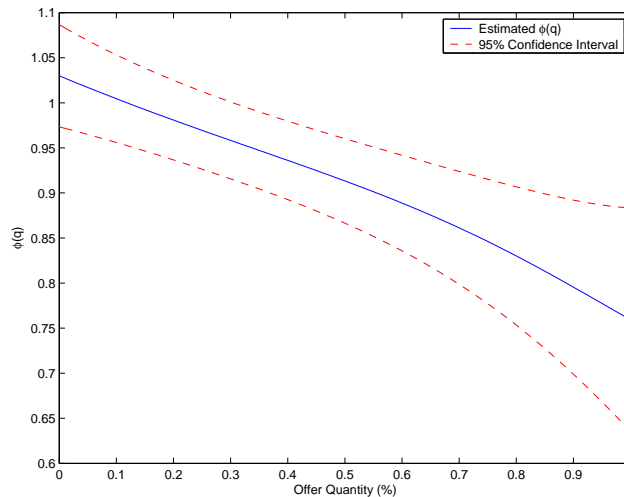
Subtracting Equation (6) from (5) gives:

$$\frac{MU_t(q)}{MU_t^*(q)} - E\left[\frac{MU_t(q)}{MU_t^*(q)}|q\right] = \beta^\top (\mathbf{X}_t - E[\mathbf{X}_t|q]) + \epsilon_t(q), \quad (7)$$

Figure 4: Reliant Energy Conduct Curve Estimates

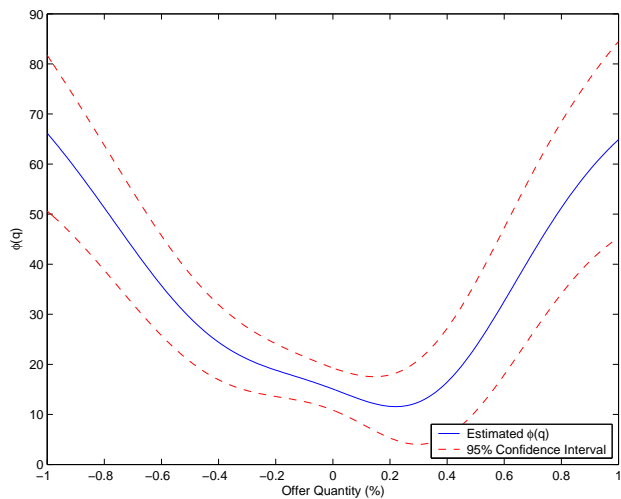


(a) Quantity Normalized by Total Offer

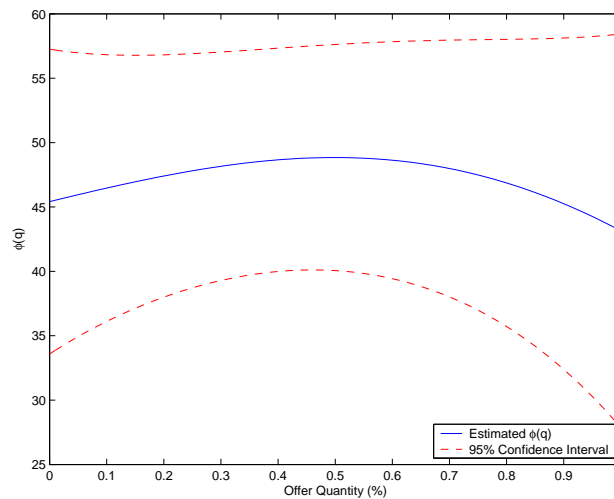


(b) Quantity Normalized by Total Capacity

Figure 5: Calpine Conduct Curve Estimates

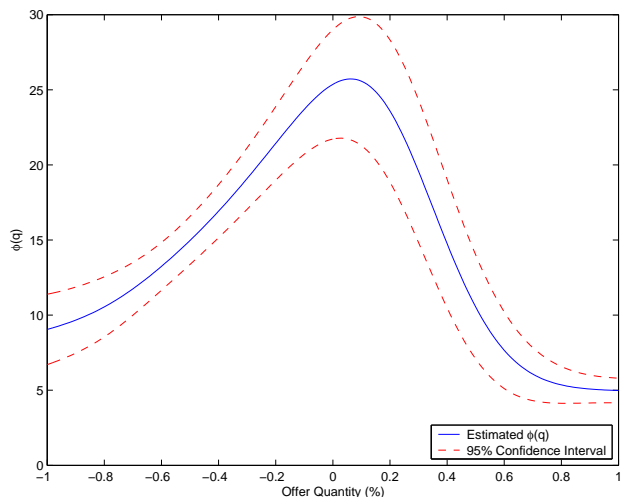


(a) Quantity Normalized by Total Offer

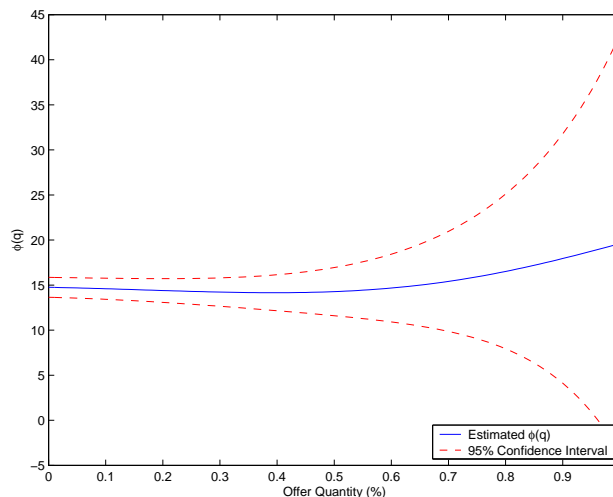


(b) Quantity Normalized by Total Capacity

Figure 6: Central Power and Light Conduct Curve Estimates

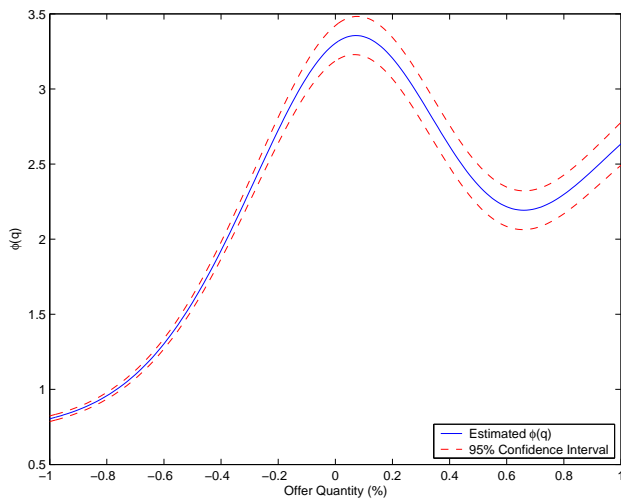


(a) Quantity Normalized by Total Offer

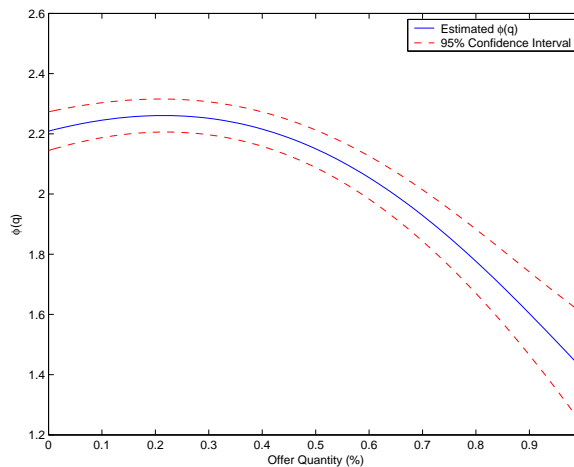


(b) Quantity Normalized by Total Capacity

Figure 7: City of San Antonio Public Service Conduct Curve Estimates

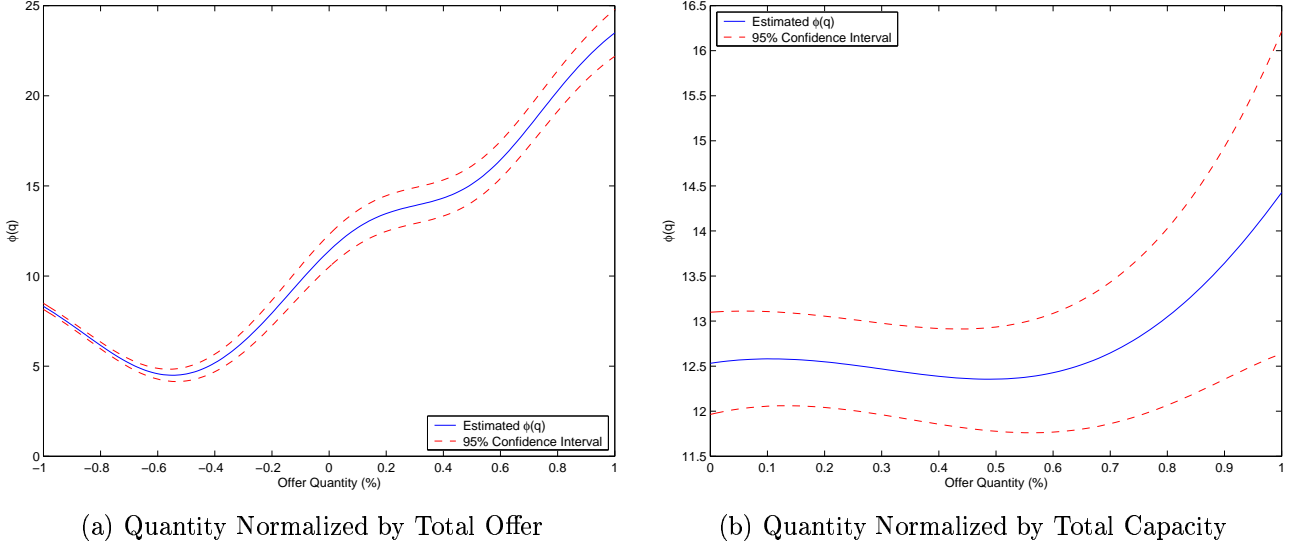


(a) Quantity Normalized by Total Offer



(b) Quantity Normalized by Total Capacity

Figure 8: City of Austin Conduct Curve Estimates



which is simply a linear parametric regression model in  $\beta$ . Our technique of estimation is to first estimate the two conditional expectations using a kernel estimator. We define:

$$\mathbf{X}_t = g_X(q) + \eta_t(q),$$

and

$$\frac{MU_t(q)}{MU_t^*(q)} = g_M(q) + \theta_t(q),$$

and estimate  $g_X(q)$  and  $g_M(q)$  using the Nadaraya-Watson kernel. Plugging our estimates into Equation (7) gives:

$$\frac{MU_t(q)}{MU_t^*(q)} - g_M(q) = \beta^\top (\mathbf{X}_t - g_x(q)) + \epsilon_t(q),$$

which is now a parametric linear model. Using standard least squares techniques we can find an estimate of the parameter,  $\hat{\beta}$ . Finally, plugging the conditional expectation and parameter estimates into Equation (6) gives:

$$\hat{\phi}(q) = g_M(q) - \hat{\beta}(q)^\top g_X(q).$$

For our first test, we define the set of additional regressors as:

$$\mathbf{X} = [x_t^W, x_t^{OP}]^\top,$$

where  $x_t^W = 1$  if time period  $t$  is on a weekend (0 otherwise) and  $x_t^{OP} = 1$  if time period  $t$  is an off-peak weekday (we define on-peak to be between 8am and 5pm). Our interest in estimating this model is to determine whether the parametric coefficients are significantly nonzero. If so, this is evidence indicating that bidding behavior is affected by the bid period.

In the second, we divide the year into four quarters by defining the variables:

$$\mathbf{X} = [x_t^1, x_t^2, x_t^3]^\top,$$

where  $x_t^i = 1$  is observation  $t$  occurs in quarter  $i$ , and is zero otherwise. In this case, we are interested to see if a firms' markup multiplier differ systematically over time.

In order to conduct these tests, we utilize the asymptotic normality of the estimator  $\hat{\beta}$ . Letting  $n$  denote the sample size,  $\sigma^2 = \text{Var}(\epsilon_t(q))$  the variance of the residuals, and  $V = \text{E}[\eta\eta^\top]$  we have:

$$\sqrt{n}(\hat{\beta} - \beta) \xrightarrow{d} \mathcal{N}(0, \sigma^2 V^{-1}).$$

If we use the sample average to estimate this expectation:

$$\hat{V} = \frac{1}{n} \eta \eta^\top = \frac{1}{n} (\mathbf{X} - g_X)(\mathbf{X} - g_X)^\top,$$

and estimate the variance by the sample variance  $\hat{\sigma}^2 = \frac{1}{n} \|\epsilon\|_2^2$ , then we can estimate this asymptotic distribution as

$$\mathcal{N}(0, \hat{\sigma}^2 \hat{V}).$$

The hypothesis we wish to test is  $H_0 : \beta = 0$  versus the alternative  $H_1 : \beta \neq 0$ . Under the null hypothesis we have:

$$\frac{\sqrt{n}}{\sigma} \hat{V}^{1/2} \hat{\beta} = \hat{\zeta} \xrightarrow{d} \mathcal{N}(0, I),$$

where  $I$  is the identity matrix. Because  $\hat{\zeta}$  is multivariate normally-distributed with zero covariances, each element of  $\hat{\zeta}$  is independently distributed. Thus, the statistic  $T = \|\hat{\zeta}\|_2^2$  will have a  $\chi_d^2$  distribution, where  $d$  is the number of variates in  $\mathbf{X}$ . Because the asymptotic normality condition assumes homoskedastic residuals, we conduct our test using the total quantity bid normalization (as opposed to the total capacity normalization) because the variances are more constant for the former. This is reflected in the more uniform confidence bands in the figures, and is consistent with our variance estimates.

Figure 9 shows the bid curves of the five PGCs, and Table 5 summarizes the estimated values and the  $p$ -values from the associated  $\chi^2$  distribution. We see that in the two statistically significant (for a size 0.95 test) cases of Reliant and City of San Antonio, weekend markups are on average lower than on weekdays. The effect of off-peak versus on-peak bidding, on the other hand, is mixed with Reliant's off-peak  $\phi(q)$  being about 0.25 higher than on-peak and San Antonio's being about 0.2 lower. For the case of TXU, which is nearly significant with a  $p$ -value of approximately 0.7, weekend and off-peak bids are both lower than on-peak weekday bidding.

Table 5: Semiparametric Estimates of On Peak/Off Peak/Weekend Bidding

PGC	$\hat{\beta}^W$	$\hat{\beta}^{OP}$	$p$ -value
TXU	-0.24072	-0.31237	0.06891
Reliant Energy	-0.2031	0.23348	0
Calpine	21.703	-6.1095	0.19307
Central Power and Light	4.1448	0.61184	0.1756
City of San Antonio Public Service	-0.72889	-0.18443	0

Finally, we conduct our test for systematic differences in firm bidding over the course of the study year. Figure 10 and Table 6 show the results of our estimates for the five large PGCs. With the exception of TXU, we see that there is a significant difference in firm bidding over the course of the year. With Reliant, Central Power and Light, and San Antonio, we find that markups tend to trend upward during the course of the year. One explanation for this could be seasonal differences in load, which would be caused by seasonal air conditioning and heating loads in the

summer and winter. A second possible explanation is some learning effects from participation in the market. One piece of evidence in support of the learning explanation is a tendency for PGCs to use more bid points during the course of the year. Hortascu and Puller note in their study that from September 2001 to July 2002 TXU, Reliant, and Calpine increased the average number of bid points from 7 to over 10. Although a small difference, it does reflect more sophistication in their bidding strategies. With Calpine’s bids, we note that its markups in the first three months, are significantly different from the last nine. This suggests one possible explanation of the behavior observed in our nonparametric analysis of Calpine’s bids is that Calpine may have taken some time to learn how to bid into the BES to maximize its profits. This explanation would be consistent with the fact that the BES had only begun operation in late 2001.

Table 6: Semiparametric Estimates of Quarterly Bidding

PGC	$\hat{\beta}^1$	$\hat{\beta}^2$	$\hat{\beta}^3$	$p$ -value
TXU	0.44587	-0.18277	-0.10296	0.25121
Reliant Energy	-0.88595	-1.0877	-0.69752	0
Calpine	371.82	-0.49797	-4.09	0
Central Power and Light	-7.3307	22.939	-9.09	0
City of San Antonio Public Service	-2.2681	-2.7371	-2.7017	0

## 6 Conclusion

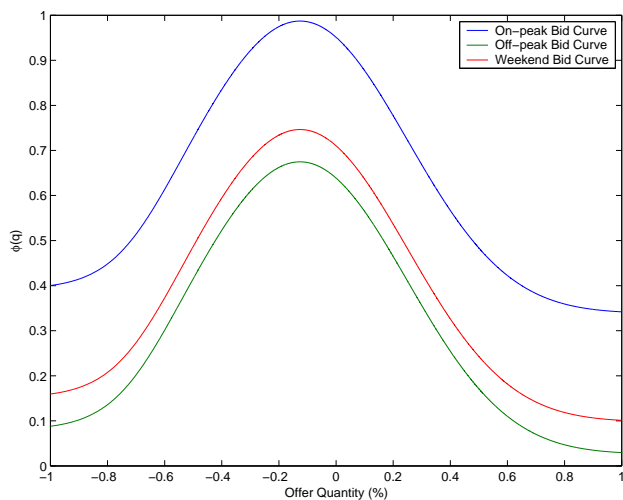
The results of our analysis show that most bidders participating in the ERCOT BES do not act in accordance with an SFE model. This is characterized by them making bids with markups and markdowns which are far in excess of that implied by our theoretically profit-maximizing supply curves. Even when comparing the bids of individual PGCs to their *ex post*-optimal supply curves, we find that most generators do not follow SFE. With smaller power producers, municipalities, cooperatives, and cogenerators, that is often explained as an unwillingness to deviate from their day-ahead schedules, which is also reflected in their patterns submitting only dec bids in many bid periods. This leads them to bid balancing services with extremely high markups and markdowns to ensure they are only dispatched in rare high-load instances.

Amongst the large PGCs, only TXU, Reliant, and San Antonio’s behavior matched our theoretical optima systematically. Moreover, our findings (especially with regards to TXU, Reliant, and Calpine’s behavior) are consistent with other work done analyzing the ERCOT BES market. TXU’s markups were found to be at most 70% of optimal. We believe the native load served by TXU Energy—to the extent that the LSE subsidiary would have to purchase balancing resources—to be a potential cause of this underbidding. One area of future work is to expand our model to take account of a PGCs imbalance position and determine whether this affects bidding patterns. Calpine, the other large PGC, was found to be bidding very inconsistently with the SFE model. Our analysis of bidding behavior over the course of the year shows that Calpine’s markups were an order of magnitude greater in the first quarter of 2002. One possible explanation for Calpine’s behavior is that it has been slow to adjust its bids to maximize profits. We hope to explore this further by including year 2003 data in our analysis.

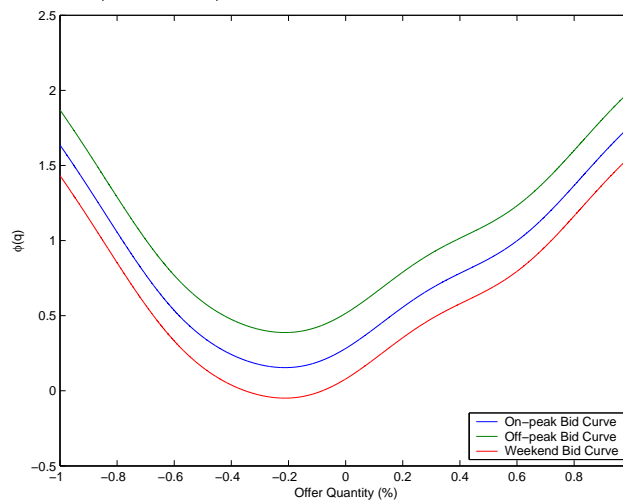
In spite of its theoretical attractiveness, our study shows the inherent weakness of SFE in describing spot market behavior. Its saving grace, however, is that the behavior of some of the large PGCs does coincide with our optimal benchmarks. To the extent that these firms lead the market, SFE-based analysis may still prove a fruitful tool for

analyzing market outcomes.

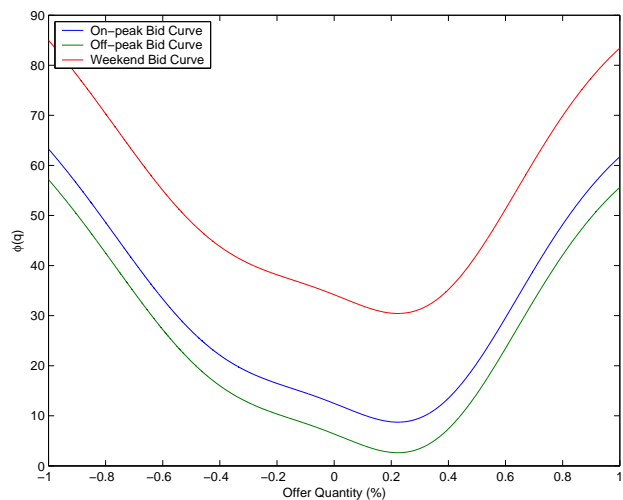
Figure 9: Semiparametric Curves of On Peak/Off Peak/Weekend Bidding



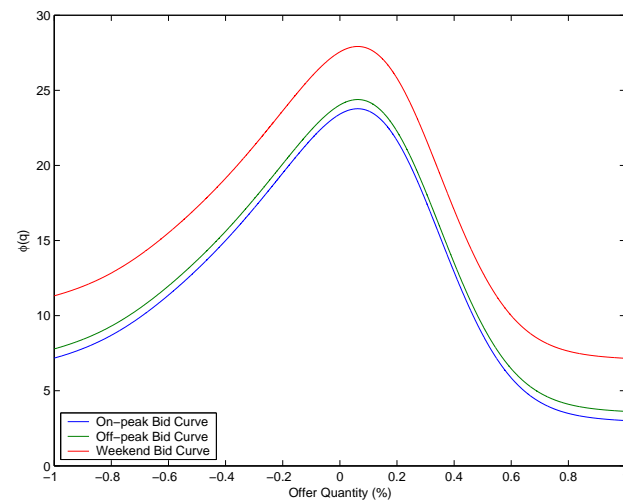
(a) TXU Bid Curve



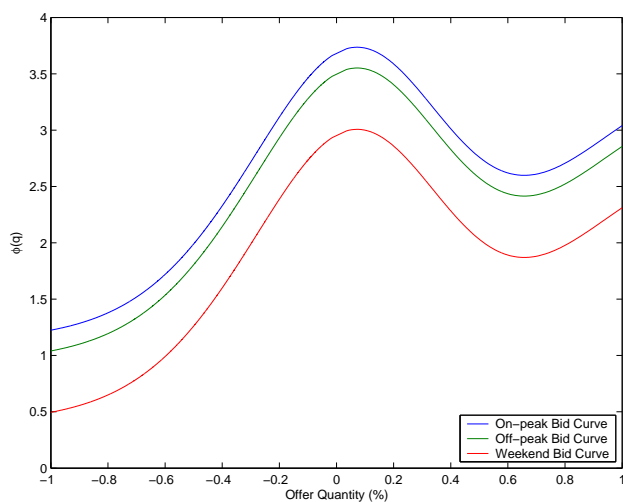
(b) Reliant Bid Curve



(c) Calpine Bid Curve

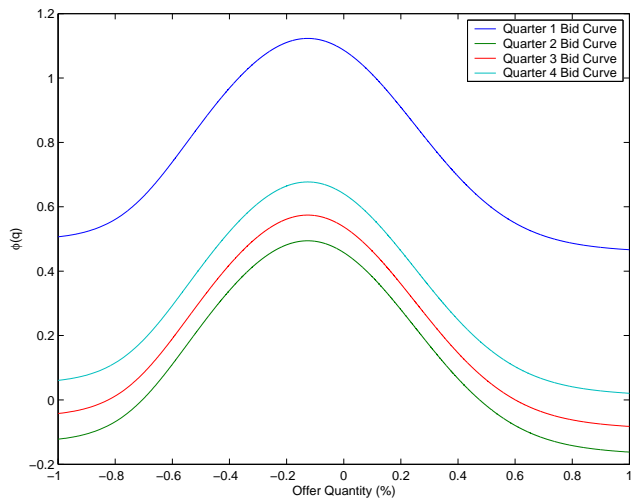


(d) Cental Power and Light Bid Curve

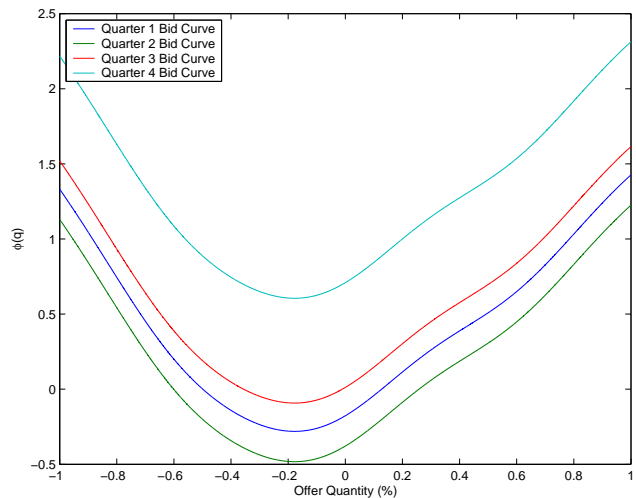


(e) City of San Antonio Public Service

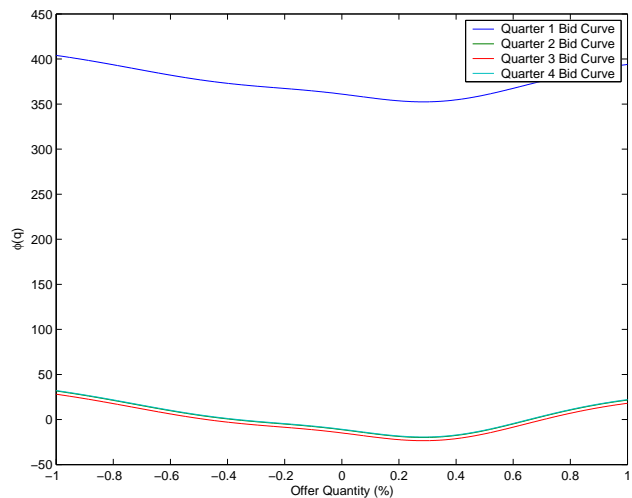
Figure 10: Semiparametric Curves of Quarterly Bidding



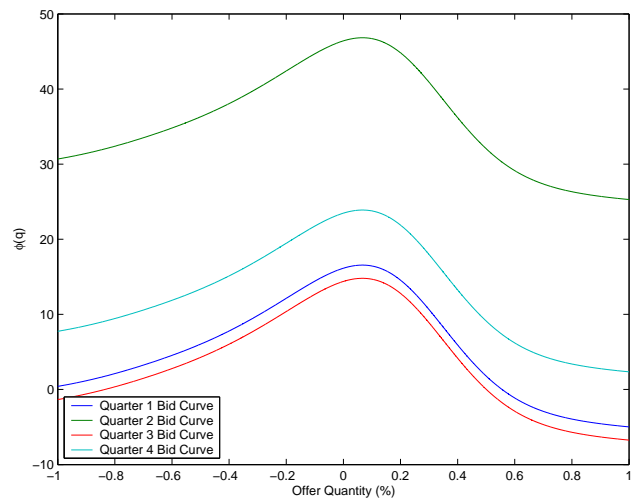
(a) TXU Bid Curve



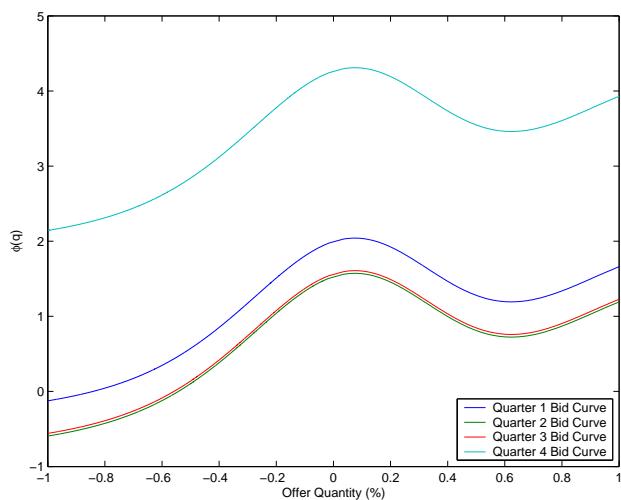
(b) Reliant Bid Curve



(c) Calpine Bid Curve



(d) Central Power and Light Bid Curve



(e) City of San Antonio Public Service

## References

- BORENSTEIN, S., AND J. BUSHNELL (1999): "An Empirical Analysis of the Potential for Market Power in California's Electricity Industry," *Journal of Industrial Economics*, 47, 285–323.
- BORENSTEIN, S., J. BUSHNELL, AND C. KNITTEL (1997): "A Cournot-Nash Equilibrium Analysis of the New Jersey Electricity Market," Discussion Paper EA97060396, New Jersey Board of Public Utility, Review of the General Public Utilities' Restructuring Petition.
- CARDELL, J. B., C. C. HITT, AND W. W. HOGAN (1997): "Market Power and Strategic Interaction in Electricity Networks," *Resources and Energy Economics*, 19, 109–137.
- CLAY, K., AND W. TROESKEN (2003): "Further Tests of Static Oligopoly Models: Whiskey, 1882-1898," *The Journal of Industrial Economics*, 51, 151–166.
- GENESOVE, D., AND W. MULLIN (1994): "Testing Static Oligopoly Models: Conduct and Cost in the Sugar Industry," *The RAND Journal of Economics*, 29, 355–377.
- GREEN, R. (1996): "Increasing Competition in the British Electricity Spot Market," *The Journal of Industrial Economics*, 44, 205–216.
- GREEN, R., AND T. MCDANIEL (1999a): "Expected Revenues in the Balancing Market: Equivalence Between Pay-as-Bid and SMP," .
- (1999b): "Modeling Reta: A Model of Forward Trading and the Balancing Mechanism," .
- GREEN, R., AND D. NEWBERY (1992): "Competition in the British Electricity Spot Market," *The Journal of Political Economy*, 100, 929–953.
- HORTASCU, A., AND S. L. PULLER (2004): "Testing Strategic Models of Firm Behavior in Restructured Electricity Markets: A Case Study of ERCOT," UCEI CSEM Working Paper 125.
- KIM, D.-W., AND C. KNITTEL (2004): "Biases in Static Oligopoly Models?: Evidence from the California Electricity Market," UCEI CSEM Working Paper 131.
- KLEMPERER, P. D., AND M. A. MEYER (1989): "Supply Function Equilibria in Oligopoly Under Uncertainty," *Econometrica*, 56, 1243–1277.
- NADARAYA, E. A. (1964): "On Estimating Regression," *Theory of Probability and Its Applications*, 9, 141–142.
- NEWBERY, D. (1998): "Competition, Contracts, and Entry in the Electricity Spot Market," *The RAND Journal of Economics*, 29, 726–749.
- PAGAN, A., AND A. ULLAH (1999): *Nonparametric Econometrics*. Cambridge University Press, The Edinburgh Building, Cambridge CB2 2RU, UK.
- RILEY, J. G., AND W. F. SAMUELSON (1981): "Optimal Auctions," *The American Economic Review*, 71, 381–392.
- SPECKMAN, P. E. (1998): "Kernel Smoothing in Partial Linear Models," *Journal of the Royal Statistical Society. Series B (Methodological)*, 50, 413–436.

- VON DER FEHR, N.-H. M., AND D. HARBORD (1993): "Spot Market Competition in the UK Electricity Industry," *The Economic Journal*, 103, 531–546.
- WATSON, G. S. (1964): "Smooth Regression Analysis," *Sankhya—The Indian Journal of Statistics, Series A*, 26, 359–372.
- WILSON, R. (1979): "Auctions of Shares," *Quarterly Journal of Economics*, 93, 675–689.
- WOLAK, F. A. (2003): "Measuring Unilateral Market Power in Wholesale Electricity Markets: The California Market 1998 to 2000," *American Economic Review*, 93, 426–430.
- WOLFRAM, C. (1998): "Strategic Bidding in a Multiunit Auction: An Empirical Analysis of Bids to Supply Electricity in England and Wales," *The RAND Journal of Economics*, 29, 703–725.
- (1999): "Measuring Duopoly Power in the British Electricity Spot Market," *American Economic Review*, 89, 805–826.

# A Tables

$q$	-1	-0.8	-0.6	-0.4	-0.2	0	0.2	0.4	0.6	0.8	1
	TXU				$n = 24394$		$h = 0.265$				
$\hat{\phi}_B(q)$	0.095	0.147	0.317	0.541	0.682	0.659	0.482	0.269	0.124	0.062	0.043
$\hat{\phi}_C(q)$						0.271	0.343	0.382	0.380	0.338	0.264
	Reliant Energy				$n = 27148$		$h = 0.260$				
$\hat{\phi}_B(q)$	1.720	1.141	0.622	0.331	0.247	0.376	0.650	0.873	1.087	1.455	1.858
$\hat{\phi}_C(q)$						1.030	0.981	0.936	0.889	0.830	0.759
	Calpine				$n = 10125$		$h = 0.316$				
$\hat{\phi}_B(q)$	66.164	51.256	35.73	24.414	18.848	15.068	11.602	16.449	32.596	51.261	64.887
$\hat{\phi}_C(q)$						45.417	47.406	48.662	48.632	46.867	43.147
	Central Power and Light				$n = 27389$		$h = 0.259$				
$\hat{\phi}_B(q)$	9.049	10.55	13.244	16.921	21.433	25.362	23.59	14.757	7.659	5.354	4.981
$\hat{\phi}_C(q)$						14.753	14.395	14.152	14.67	16.513	19.6
	City of San Antonio Public Service				$n = 16816$		$h = 0.286$				
$\hat{\phi}_B(q)$	0.805	0.958	1.303	1.924	2.726	3.304	3.205	2.619	2.216	2.298	2.635
$\hat{\phi}_C(q)$						2.209	2.260	2.216	2.054	1.776	1.418
	City of Austin				$n = 19326$		$h = 0.278$				
$\hat{\phi}_B(q)$	8.315	6.151	4.578	5.178	7.946	11.4	13.465	14.328	16.443	20.264	23.489
$\hat{\phi}_C(q)$						12.531	12.548	12.387	12.427	13.047	14.126
	Lower Colorado River Authority				$n = 14881$		$h = 0.293$				
$\hat{\phi}_B(q)$	6.000	5.401	4.856	4.752	5.028	5.186	4.969	5.212	6.737	9.055	10.962
$\hat{\phi}_C(q)$						6.370	6.501	6.551	6.523	6.439	6.345
	West Texas Utilities				$n = 26098$		$h = 0.262$				
$\hat{\phi}_B(q)$	15.041	20.822	30.486	37.454	40.108	36.405	23.08	8.441	2.255	1.590	2.231
$\hat{\phi}_C(q)$						21.591	22.572	23.281	23.232	21.976	19.336
	Midlothian Energy				$n = 3916$		$h = 0.382$				
$\hat{\phi}_B(q)$	166.76	434.06	1048	1850.2	2400.5	2628.9	2646.2	2439.9	1852.9	966.66	337.81
$\hat{\phi}_C(q)$						1714.7	1555.2	1382	1201.8	1023.4	857.76
	Guadalupe Power Partners				$n = 36407$		$h = 0.245$				
$\hat{\phi}_B(q)$	130.9	105.83	158.89	409.88	779.75	961.1	768.95	380.02	142.23	145.21	224.22
$\hat{\phi}_C(q)$						1445.1	971.25	517.18	231.37	122.15	87.179

$q$	-1	-0.8	-0.6	-0.4	-0.2	0	0.2	0.4	0.6	0.8	1
	Lamar Power Partners				$n = 5006$	$h = 0.364$					
$\hat{\phi}_B(q)$	1741.8	1569.8	1257.2	795.47	348.29	100.13	18.273	-1.955	-8.671	-12.564	-15.14
$\hat{\phi}_C(q)$						2290.5	1344.2	731.91	385.17	206.99	118.36
	Brazos Electric Power Cooperative				$n = 8545$	$h = 0.327$					
$\hat{\phi}_B(q)$	189.09	146.13	104.43	79.296	72.263	74.336	78.289	79.748	78.224	89.968	121.49
$\hat{\phi}_C(q)$						127.61	125.29	123.03	120.85	118.76	116.8
	Sweeny Cogeneration General				$n = 21287$	$h = 0.273$					
$\hat{\phi}_B(q)$	97.833	96.537	107.49	127.57	132.09	87.767	-13.368	-73.439	-76.492	-64.724	-54.421
$\hat{\phi}_C(q)$						78.117	60.799	47.184	36.42	27.835	20.911
	Hays Energy				$n = 2340$	$h = 0.424$					
$\hat{\phi}_B(q)$	473.75	1079.3	2222.1	3590	4551.1	4972.7	5035.8	4806.7	4152.1	2939.5	1556.7
$\hat{\phi}_C(q)$						3125.7	2871.5	2610.9	2348.7	2087.7	1830.9
	Tractable Power				$n = 3526$	$h = 0.390$					
$\hat{\phi}_B(q)$	730.54	1447	2748.6	4144.6	4896.6	4818.7	4087.7	2960.9	1773.9	867.56	366.12
$\hat{\phi}_C(q)$						2719.8	2805.1	2824.4	2776.5	2663.2	2488.7
	BP Energy				$n = 21830$	$h = 0.271$					
$\hat{\phi}_B(q)$	228.86	257.34	607.69	1376.3	1906.5	1819.6	1295.2	677.4	280.38	207.87	299.61
$\hat{\phi}_C(q)$						1571.8	2418.1	2734.7	2718.7	2489	2160.3
	Bryan Texas Utilities				$n = 11788$	$h = 0.307$					
$\hat{\phi}_B(q)$	39.794	40.493	42.693	45.114	45.264	40.325	26.744	7.6671	-5.1046	-12.883	-19.209
$\hat{\phi}_C(q)$						42.483	39.235	34.564	29.301	24.051	19.196
	City of Garland				$n = 11379$	$h = 0.309$					
$\hat{\phi}_B(q)$	22.62	25.562	30.593	35.535	34.616	19.699	-6.657	-22.482	-22.928	-19.103	-16.68
$\hat{\phi}_C(q)$						16.431	14.566	12.318	10.025	7.984	6.375
	Rio Nogales Power Project				$n = 2947$	$h = 0.405$					
$\hat{\phi}_B(q)$	221.44	259.82	309.84	356.83	375.44	339.48	245.17	133.96	56.345	20.016	7.014
$\hat{\phi}_C(q)$						212.33	206.56	198.53	188.17	175.37	159.74
	Tenaska Gateway Partners				$n = 34115$	$h = 0.248$					
$\hat{\phi}_B(q)$	21.364	13.956	9.1736	7.2595	5.846	2.854	-1.332	-3.630	-3.253	-2.498	-2.446
$\hat{\phi}_C(q)$						47.046	38.66	24.256	13.575	8.383	5.553

$q$	-1	-0.8	-0.6	-0.4	-0.2	0	0.2	0.4	0.6	0.8	1
	Cogeneration Lyondell				$n = 9747$		$h = 0.319$				
$\hat{\phi}_B(q)$	77.44	70.93	66.15	69.935	79.975	83.608	85.267	135.82	257.97	405.13	516.05
$\hat{\phi}_C(q)$						257.68	238.27	213.8	189.2	171.67	165.92
	Bastrop Energy Partners				$n = 2263$		$h = 0.427$				
$\hat{\phi}_B(q)$	3122.5	2903.7	2482.1	1806.9	1031.9	444.74	138.25	18.22	-19.139	-29.76	-33.217
$\hat{\phi}_C(q)$						1858.4	1995.8	2093.6	2146	2146.3	2084.3
	Mirant Wichita Falls Management				$n = 1107$		$h = 0.492$				
$\hat{\phi}_B(q)$	618.34	543.96	473.52	413.65	366.78	330.55	299.45	267.14	229.93	191	159
$\hat{\phi}_C(q)$						449.69	444.37	439.02	433.62	428.2	422.73
	South Texas Electric Cooperative				$n = 7518$		$h = 0.336$				
$\hat{\phi}_B(q)$	116.82	123.33	135.46	150.8	162.64	160.92	119.88	24.544	-26.728	-36.483	-38.268
$\hat{\phi}_C(q)$						163.12	122.03	99.289	87.815	80.645	74.416
	Brownsville Public Utility Board				$n = 18748$		$h = 0.280$				
$\hat{\phi}_B(q)$	944.51	558.7	231.84	64.9	15.04	4.754	1.653	-0.736	-3.716	-8.269	-13.139
$\hat{\phi}_C(q)$						540.5	344.67	170.01	67.674	21.663	3.331
	AES Deepwater				$n = 4873$		$h = 0.366$				
$\hat{\phi}_B(q)$	48.884	48.888	48.953	50.237	74.468	316.22	560.05	584.72	586.03	586.1	586.1
$\hat{\phi}_C(q)$						262.44	257.02	269.01	289.93	314.59	340.79
	Gregory Power Partners				$n = 7874$		$h = 0.333$				
$\hat{\phi}_B(q)$	65.085	64.216	60.875	51.888	36.333	18.797	7.025	4.035	6.646	10.59	13.545
$\hat{\phi}_C(q)$						80.371	68.438	54.891	41.199	28.844	18.961
	Extex Laporte				$n = 2516$		$h = 0.418$				
$\hat{\phi}_B(q)$	138.89	38.527	3.580	-4.761	-6.031	-5.571	-4.650	-3.620	-2.676	-1.975	-1.576
$\hat{\phi}_C(q)$						-6.750	-6.608	-6.026	-4.995	-3.599	-2.051
	Denton Municipal Electric				$n = 7966$		$h = 0.332$				
$\hat{\phi}_B(q)$	73.718	63.485	59.744	67.827	88.434	139.16	386.77	1536	3517.6	4654.3	5079.4
$\hat{\phi}_C(q)$						524.11	830.16	119.7	1569	1905.2	2104.1

Table 7: Firm Conduct Estimates for *Ex Post*-Optimal Bid Curves