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AN EMPIRICAL ANALYSIS OF THE IMPACT OF HEDGE CONTRACTS ON BIDDING BEHAVIOR IN A COMPETITIVE ELECTRICITY MARKET*

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A major concern in the design of wholesale electricity markets is the potential for the exercise of market power by generating unit owners. To better understand the determinants of generating unit owner market power and how it is exercised, this paper derives a model of bidding behavior in a competitive electricity market which incorporates various sources of uncertainty and the impact of the electricity generator's position in the financial hedge contract market on its expected profit-maximizing bidding behavior. The model is first used to characterize the profit-maximizing market price that a generator would like set by its bidding strategy for several hedge contract and spot sales combinations. This model is applied to bid and contract data obtained from the first three months of operation of the National Electricity Market (NEM1) in Australia. This analysis illustrates the sensitivity of expected profit-maximizing bidding strategies to the amount of financial hedge contracts held by the generating unit owner. It also provides strong evidence for the effectiveness of financial hedge contracts as a means to mitigate market power during the initial stages of operation of a wholesale electricity market. [L 94]

1. INTRODUCTION

This paper derives a model of bidding behavior in a competitive electricity market which incorporates the impact of the electricity generator's position in the hedge contract market on its expected profit-maximizing bidding behavior.[1] The

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[1]Hedge contracts are usually signed between a generating company and an electricity retailer. A hedge contract guarantees the price at which a fixed quantity of electricity will be sold. They are purely financial obligations. If the market price exceeds the contract price, then the contract seller pays to the buyer the difference between these two prices times the contract quantity. If the market price is less than the contract price the buyer pays the absolute value of

model is first used to characterize the profit-maximizing market price that a generator would like set by its bidding strategy for several hedge contract and spot sales combinations. This model is applied to bid and contract data obtained from the first three months of operation of the National Electricity Market (NEM1) in Australia to answer several questions about the bidding behavior of a major participant in this market.

Questions addressed by this analysis include: How close does this generator's current bidding strategy come to earning the highest profits possible given its hedge contract position and the bidding strategies of the remaining market participants? Are there changes in this generator's hedge contract position that could increase its expected profits, assuming the bidding strategies of the remaining participants do not change? If more profitable hedge contract position exists, why haven't generators competing in this market moved to this more profitable level of contracting? The answers to these questions will shed light on the structure of optimal bidding and hedge contracting strategies in a competitive electricity market.

A major concern of regulators and governments re-structuring their electricity supply industries and forming competitive markets for electricity generation is the exercise of market power. In this context, market power is the ability of a generating company to raise the market price by its bidding behavior and to profit from this price increase. A first step in determining whether a generator possesses market power is an accurate model of the optimal bidding behavior for a generator competing in this market. Using such a model, I show that a firm's hedge contract position can exert a dramatic effect on its optimal bidding strategy, and its short-term desire to raise the market price. In fact, for sufficiently high hedge contract levels, a generator should attempt to reduce market prices below its own marginal cost of production by its optimal short-term bidding strategy.

These results also have implications for monitoring the exercise of market power. Even given knowledge of a firm's bidding behavior in a competitive electricity market, without knowledge of a generator's hedge contract position, it is difficult, if not impossible, to determine if the firm is able to exercise market power. For a specific bid function, there is often a hedge contract position that can rationalize that bid function as expected profit-maximizing. This result implies that the strategic value of actual bid functions to other competitors is significantly reduced because a key ingredient necessary to determine a firm's profits from a given bidding strategy is unknown. Unfortunately, the monitoring value of actual bid functions to a regulator is also significantly reduced for the same reason.

Our empirical analysis of the bidding behavior of one of the major participants in NEM1 helps to explain several features of the pattern of prices in this market.

this same price difference times the contract quantity to the seller.

Specifically, since this market was formed, prices have fallen precipitously. Before re-structuring the average price of a megawatt-hour (MWH) of electricity was roughly 35 Australian dollars ($AU). With the formation of separate markets in the states of New South Wales and Victoria, prices in each market settled at an average value of roughly 25 $AU/MWH. With the interconnection of these two markets and the formation of NEM1 in May of 1997, average prices in the integrated market fell even further to around 15 $AU/MWH. My analysis finds that despite the fact that the marginal cost of generation for many of the large fossil fuel generating facilities is roughly 15 $AU/MWH, because of the large quantity of hedge contracts held by the major firms competing in this market, the short-run (conditional on their current hedge contract prices and quantities) profit-maximizing market price for these generators is very close to the actual market price set. Using my model of optimal bidding behavior, I then provide a rationale for why generators competing in this market sold hedge contracts in such large quantities that these low-prices became short-run optimal. I then present two counterfactual scenarios which show that reductions in the generator's contract position can significantly increase both the mean and standard deviation of the variable profits it earns from a profit-maximizing bidding strategy based a reduced quantity of hedge contracts.

The remainder of the paper proceeds as follows. The next section presents my model of optimal bidding behavior with hedge contracts for a generic competitive electricity market. In this section, I define a *best-response bidding strategy* as the set of daily bid prices and quantities that maximize expected daily variable profits given the strategies of other firms participating in the market. I also define the *best-response price* as the market-clearing price that maximizes the realized profits of the firm given the bidding strategies of its competitors, the realized value of the stochastic shock to the price-setting process, and its current hedge contract position. Section 3 then presents a graphical analysis of several scenarios which illustrate the relationship between the best-response price for a firm and the quantity of hedge contracts sold by the firm relative to its sales into the electricity spot market. Given this model of bidding behavior, Section 4 provides background on the market structure, market rules and regulatory oversight in NEM1 and describes the data necessary to implement this model empirically. Section 5 provides evidence for the validity of my model of the price-setting process in NEM1. Section 6 uses the results of Section 5 to derive best-response prices for a major firm participating in this market. Section 7 uses the results of the previous sections to explain the current pattern of prices in this market. This section also discusses the rationale for the high levels of hedge contracts in this market. The final section describes my related research in progress and the implication of these results for the design of competitive electricity markets.

2. A MODEL OF BEST-RESPONSE BIDDING AND BEST-RESPONSE PRICING

A competitive electricity market is an extremely complicated non-cooperative game with a very high-dimensional strategy space. A firm owning a single generating set competing in a market with half-hourly prices must, at a minimum, decide how to set the daily price for the unit and the quantity bid for 48 half-hours during the day.[2] In all existing electricity markets firms have much more flexibility in how they bid their generating facilities. For instance, in NEM1 firms are allowed to bid daily prices and half-hourly quantities for 10 bid increments per generating set (genset). For a single genset, this amounts to a 490-dimensional strategy space (10 prices and 480 half-hourly quantities). Bid prices can range from -9999.99 $AU to 5000.00 $AU, which is the maximum possible market price. Each of the quantity increments must be greater than or equal to zero and their sum is less than or equal to the capacity of the generating set. Most of the participants in this market own multiple gensets, so the dimension of the strategy space for these firms is even larger.

A generator's optimal bidding strategy will depend on the bidding strategies of all of its competitors. I assume that a firm selects its bidding strategy conditional on the strategies selected by its competitors to maximize its expected profits for the day. In the terminology of game theory, each generator would like to play its best response to its competitors' strategies for that day, given its costs of generation and hedge contract portfolio. If the strategies played by all participants satisfy this condition, then each strategy is that firm's Nash Equilibrium strategy.

Let $S(i)$ represent the daily bidding strategy of firm i, in the present context the set of 10 daily prices and half-hourly capacity bids for each generation set that firm i owns. Let $\pi_i[(S(1), S(2), ..., S(K))]$ equal the expected daily profit of firm i when there are K firms competing in the market and they bid according to the strategies $S(1)$, $S(2)$, ..., $S(K)$, respectively. The firm maximizes *expected* daily profits because there is uncertainty in the price-setting process that is unknown at the time each firm selects its bidding strategy for the following day. The expected profit function specifies the expected revenue received by firm i for the day when each firm's bids are described by the strategies $S(1)$, $S(2)$, ..., $S(K)$, minus the expected costs of generation, taking into account any expected revenues–positive or negative–from hedge contracts.

In order compute the expected profit function associated with any strategy the firm might play, I must have an accurate model of the process that translates the bids generators submit into the actual market prices they are paid for the electricity

[2]Electricity generating plants are usually divided into multiple generating sets or units. For example a 2 gigawatt (GW) plant will usually be divided into four 500 megawatt (MW) generating sets.

for all possible realizations of uncertainty about the price-setting process. The construction of a model of the price-setting process in NEM1 that is able to replicate actual market prices with reasonable accuracy is a necessary first step to compute best-response bidding strategies or perform any comparative analysis of the expected profitability of alternative bidding strategies. Without the ability to replicate actual market prices using actual generator bid functions, it is impossible to compare with any degree of confidence market outcomes under current or historical bidding strategies with what they would be under any alternative bidding strategies. A major part of the empirical half of the paper is devoted to demonstrating that my model of the price-setting process accurately reflects the actual price-setting process.

Given an expression for $\pi_i[(S(1), S(2), ..., S(K))]$, firm i's expected profit function for all possible strategies played by all firms, a strategy which maximize firm i's expected profits given the strategies played by its competitors, or best-response strategies, can be represented as the solution to the following optimization problem:

$$\max_{S(i)} \ \pi_i(S(i), S(\text{-}i)) \tag{1}$$

where $S(\text{-}i) = (S(1), S(2), ..., S(i\text{-}1), S(i+1), \ldots, S(K))$ is the vector of strategies of all other firms. Computing firm i's best-response strategy involves maximizing $\pi_i[S(i), S(\text{-}i)]$ with respect to all of the daily prices and half-hourly availability declarations for all generating units owned by firm i.

In NEM1, each day d is divided into the half-hour load periods i beginning with 4:00 am to 4:30 am and ending with 3:30 am to 4:00 am the following day. Let Firm A denote the generator whose bidding strategy is being computed. Define

- Q_{id} : Total market demand in load period i of day d
- $SO_{id}(p)$: Amount of capacity bid by all other firms besides Firm A into the market in load period i of day d as a function of market price p
- $DR_{id}(p) = Q_{id} - SO_{id}(p)$: Residual demand faced by Firm A in load period i of day d, specifying the demand faced by Firm A as a function of the market price p
- QC_{id} : Contract quantity for load period i of day d for Firm A
- PC_{id} : Quantity-weighted average (over all hedge contracts signed for that load period and day) contract price for load period i of day d for Firm A.
- $\pi_{id}(p)$: Variable profits to Firm A at price p, in load period i of day d
- MC : Marginal cost of producing a MWH by Firm A
- $SA_{id}(p)$: Bid function of Firm A for load period i of day d giving the amount it is willing to supply as a function of the price p

The market clearing price p is determined by solving for the smallest price such that the equation $SA_{id}(p) = DR_{id}(p)$ holds. The magnitudes QC_{id} and PC_{id} are usually set far in advance of the actual day-ahead bidding process. Generators sign hedge contracts with electricity suppliers or large consumers for a pattern of prices throughout the day, week, or month, for an entire fiscal year. There is some short-term activity in the hedge contract market for electricity purchasers requiring price certainty for a larger or smaller than planned quantity of electricity a some point during the year.

In terms of the above notation, I can define the variable profits[3] (profits excluding fixed costs) to Firm A for load period i during the day d at price p as:

$$\pi_{id}(p) = DR_{id}(p)(p - MC) - (p - PC_{id})QC_{id}. \tag{2}$$

The first term is the variable profits from selling electricity in the spot market. The second term, if $p > PC_{id}$, is the total payments made to purchasers of hedge contracts if the pool price, p, exceeds the contract price during that half-hour. If $p < PC_{id}$, the second term is the total payments made by purchasers of hedge contracts to Firm A. Once the market-clearing price is determined for the period, equation (2) can be used to compute the profits for load period i in day d.

Writing Firm A's profits in this manner shows that unless its bidding strategy can effect the market-clearing price p, Firm A's profits are unaffected by its bidding strategy for a given hedge contract quantity and price. The goal of Firm A's best-response bidding strategy will therefore be to find the daily bid function which results in market-clearing prices that make the expectation of the sum in equation (2) over all load periods in the day as large as possible.

To see this result more clearly, make the following extensions to the basic model. Suppose that there are stochastic demand shocks to the price-setting process each period, and that Firm A knows the distribution of these shocks. This could be due to the fact that it does not exactly know how its competitors will bid–SO(p) has a stochastic element to it–or it does not know the market demand used in the price-setting process when it submits its bids–Q is known up to an additive error. Let ε_i equal this shock to Firm A's residual demand function in load period i (i = 1,...,48). Re-write Firm A's residual demand in load period i accounting for this demand shock as $DR_i(p, \varepsilon_i)$. Define

$$\Theta = (p_1,\dots, p_{JK}, q_{1,1},\dots,q_{1,JK}, q_{2,1},\dots,q_{2,JK}, \dots, \quad q_{48,1},\dots,q_{48,JK})$$

[3]For the remainder of the paper, I use variable profits and profits interchangeably with the understanding that I am always referring to variable profits.

as the vector of daily bid prices and quantities submitted by Firm A. The rules of the NEM1 market require that a single price, p_k, is set for each of the $k=1,...,J\times K$ bid increments owned by firm A for the entire day. There are K increments for each of the J gensets owned by firm A. However, the quantity, q_{ik}, made available to produce electricity in load period i from each of the $k=1,...,J\times K$ bid increments can vary across the 48 load periods throughout the day. In NEM1, the value of K is 10, so the dimension of Θ is $10J + 48\times 10J$. Firm A owns a number of gensets so the dimension of Θ is more than several thousand. Let $SA_i(p, \Theta)$ equal Firm A's bid function in load period i as parameterized by Θ. Note that by the rules of the market, bid increments are dispatched based on the order of their bid prices, from lowest to highest. This means that $SA_i(p, \Theta)$ must be non-decreasing in p.

Let $p_i(\varepsilon_i, \Theta)$, denote the market-clearing price for load period i given the residual demand shock realization, ε_i, and daily bid vector Θ. It is defined as the solution in p to the equation $DR_i(p, \varepsilon_i) = SA_i(p, \Theta)$. Let $f(\varepsilon)$ denote the probability density function of $\varepsilon = (\varepsilon_1, \varepsilon_2,..., \varepsilon_{48})'$. Firm A's best-reply bidding strategy is the solution to the following optimization problem:

$$max_{\Theta}\int_0^{\infty}\cdots\int_0^{\infty}\sum_{i=1}^{48}\left[DR_i(p_i(e_i,\Theta))(p_i(e_i,\Theta))\text{-}MC)\text{-}(p_i(e_i,\Theta)\text{-}PC_i)QC_i\right]f(e)de_1...de_{48} \quad (3)$$

subject to $b_U \geq R\Theta \geq b_L$.

Define Θ^* as the expected profit-maximizing value of Θ. Besides the extremely large dimension of Θ, there are several other reasons to expect this problem to be extremely difficult to solve. First, in general, the residual demand function faced by Firm A is a non-decreasing, discontinuous step function, because the aggregate supply curve of all participants besides Firm A is a non-decreasing step function. Second, to compute the value of the objective function requires integrating with respect to a 48-dimensional random vector ε. Most important, the dimension of Θ for Firm A is greater than 2,000. A 2,000 dimensional nonlinear program exceeds the memory and computational limits of most large workstations. Finally, several sets of linear inequality constraints represented by the matrix R and vectors of upper and lower bounds b_U and b_L must be imposed on the elements of Θ. Specifically, none of the q_{ik} can be negative and the sum of the q_{ik} relevant to a given genset cannot be greater than the capacity of the genset. The prices for each bid increment cannot be smaller than -9999.99 \$AU, or larger than 5,000.00 \$AU. Although none of these problems are insurmountable, clearly this is an extremely complicated nonlinear programming problem that will tax the capability of even the most powerful workstation.

At this point it is useful to compare the optimal bidding strategy problem given in (3) to the problem of computing an optimal supply function with demand uncertainty discussed in Klemperer and Meyer (1989) and applied to the electricity supply industry in England and Wales by Green and Newbery (1992). Re-write equation (2) with the residual demand function for load period i that includes the shock for period i as:

$$\pi_{id}(p,\varepsilon_i) = DR_{id}(p,\ \varepsilon_{i},)(p - MC) - (p - PC_{id})QC_{id}. \tag{4}$$

Solving for the value of p that maximizes (4) yields $p_i{*}(\varepsilon_i)$, which is the profit-maximizing market clearing price given that Firm A's competitors bid to yield the residual demand curve, $DR_{id}(p,\ \varepsilon_{i},)$, with demand shock realization, ε_i, for the hedge contract position, QC_{id} and PC_{id}. Because this price maximizes the *ex post* realized profits of Firm A, for the remainder of the paper, I will refer to it as the *best-response price* for the residual demand curve $DR_{id}(p,\ \varepsilon_{i},)$ with demand shock realization ε_i for the hedge contract position QC_{id} and PC_{id}. Substituting this value of p into the residual demand curve yields $DR_{id}(p_i{*}(\varepsilon_i),\ \varepsilon_{i},)$. This price and quantity combination yields Firm A the maximum profit that it can earn given the bidding behavior of its competitors and the demand shock realization, ε_i. Klemperer and Meyer (1989) impose sufficient restrictions on the underlying economic environment–the demand function, cost functions and distribution of demand shocks–so that by tracing out the price/quantity pair $(p_i{*}(\varepsilon_i),\ DR_{id}\ (p_i{*}(\varepsilon_i),\ \varepsilon_{i},))$ for all values of ε_i yields a strictly increasing supply curve, $SA_i(p)$, for Firm A for load period i. For each demand shock realization this supply curve yields the best-response price for Firm A given the bidding strategies of Firm A's competitors and its hedge contract position. Green (1999) solves this supply function equilibrium problem with contract cover for the case of linear supply functions.

Because the market rules and market structure in NEM1 constrain the feasible set of price and quantity pairs that Firm A can bid in a given load period, it will be unable to achieve $p_i{*}(\varepsilon_i)$ for all realizations of ε_i using its allowed bidding strategy. As noted above, the allowed bidding strategy constrains Firm A to bid ten bid increments per genset, but more importantly, the prices of these ten bid increments must be the same for all 48 load periods throughout the day. This can severely limit the ability of Firm A to achieve $p_i{*}(\varepsilon_i)$. Determining the types of restrictions to put on the set feasible bidding strategies to yield the lowest possible market prices from firms competing using strategies from these restricted strategy sets is a important area for future research.

In the empirical half of the paper, I examine the extent to which Firm A's current bidding strategy falls short of the obtaining best-response pricing profits. I find that the variable profits from best-response pricing–setting $p_i{*}(\varepsilon_i)$ for demand shock realization ε_i assuming current hedge contract prices and quantities–for Firm A range from 11 to 17 percent higher than the variable profits from Firm A's current bidding strategies, depending on the marginal cost of generation assumed. How much of this profit difference is due to deviations from best-response bidding by Firm A and how much is due to the constraints on Firm A's best-response bid functions because on the market rules governing the price-setting process, is a topic I am currently investigating.

Best-response prices must yield the highest expected profits, followed by best-response bidding, because the former is based on the realization of ε_i as shown in (4), whereas the latter depends on the distribution of ε as shown in (3). The generator's actual expected profits can only be less than or equal to the best-response bidding expected profits. Recall that by definition, the best-response price, $p_i^*(\varepsilon_i)$, yields the maximum profits possible given the bidding strategies of Firm A's competitors and the value of the residual demand shock, ε_i. The best-response bidding strategy which solves (3) for the expected profit-maximizing vector of allowable daily bid prices and quantities, Θ^*, yields the highest level of expected profits for Firm A within the set of allowable bidding strategies. Therefore, by definition, this bidding strategy should lead to higher average profits than Firm A's current bidding strategy for the same set of competitors' bids and own hedge contract positions. The extent to which profits from a best-response bidding strategy lie below the maximum possible obtainable from best-response prices will not be addressed here. However, given the high-dimensional strategy space available to Firm A, it appears that a non-negligible portion of the difference between the best-response pricing variable profits and variable profits under Firm A's current bidding strategy can be attributed to the use of bidding strategies that are not best-response in the sense of not solving optimization problem (3).

The empirical half of the paper also demonstrates, using my model of the price-setting process and bids by other generators besides Firm A, that significant increases in Firm A's expected variable profits are possible if it unilaterally reduces its hedge contract position and manages to set best-response prices for its new hedge contract position. However, the downside of this reduction in contract quantity is a significantly more volatility across days in market prices and variable profits. In order to provide economic intuition for this and other results presented later, I now turn to a graphical analysis of the impact of a firm's hedge contract position on its best-response prices.

3. AN ECONOMIC ANALYSIS OF THE IMPACT OF CONTRACT QUANTITY ON BEST-RESPONSE PRICES

Before proceeding with this analysis, note that I can re-write equation (4), the realized period-level profits of Firm A, as:

$$\pi(p) = (DR(p) - QC)(p - MC) + (PC - MC)QC. \qquad (5)$$

Note that if QC is set equal to zero, then $\pi(p) = DR(p)(p - MC)$. For the remainder of the paper I will omit the subscripts on variables because my analysis is at the load period-level unless explicitly noted. For notational ease, I also omit ε_i from the residual demand function despite the fact that I deal only with the realized residual demand curve (including the realization of ε_i) faced by Firm A and best-response prices for the remainder of the paper.

Re-writing equation (3) in this manner isolates the impact of Firm A's hedge contract position on its optimal bidding behavior. Because contract prices and quantities, PC and QC, are set well in advance of the day-ahead bidding process and its marginal cost, MC, is known, for the purposes of Firm A's day-ahead bidding strategy, the second term in (5) is a fixed cost. Consequently, because its day-ahead bidding strategy has no impact on the second term of (5), Firm A's goal in setting its bid prices and quantities is to maximize the first term in (5). Define $DR_C(p) = DR(p) - Q_C$ as the net of contract cover residual demand faced by Firm A, recognizing that it can be both positive and negative. This means that Firm A can sell both more or less than its contract cover. The portion of its profits that are affected by its day-ahead bidding strategy can be written as $\pi^*(p) = DR_C(p)(p - MC)$. If it has nonzero contract cover, Firm A wishes to achieve a value of p that maximizes $\pi^*(p)$ by its bidding strategy.

To allow a graphical analysis, I assume Firm A faces a linear residual demand function for its output, so that $DR(p)$ takes the form given in Figure 1.[4] The line shifted to left parallel to $DR(p)$ is Firm A's residual demand less its contract cover Q_C. Associated with the both $DR(p)$ and $DR_C(p) = DR(p) - Q_C$ are marginal revenue functions, giving the increase in revenue to Firm A from selling one more unit of output. For the case of no contract cover this line is labeled MR_{NC}. The line labeled MR_C is the marginal revenue for contract cover level Q_C. Note that MR_C is a leftward shift of MR_{NC}. From standard microeconomic theory, the profit maximizing level of output for Firm A, given that it faces either residual demand curve and associated marginal revenue curve in Figure 1, is to produce at the point where that marginal revenue equals its marginal cost.

The intersection of Firm A's marginal cost with each marginal revenue function gives the best-response quantities with and without contract cover. Let S_{NC} denote the best-response quantity produced by Firm A with no contract cover. This is the quantity at the intersection of MR_{NC} with MC. Let $S_C - Q_C$ denote the value of net output (output less contract quantity) at the point where MR_C intersects MC. The two best-response prices are given on the vertical axis. They are the prices that solve the equation $DR(p) = S_I$, for $I = C$ and NC. The

[4]The mathematics underlying my analysis is unchanged by more complicated residual demand functions allowed by the rules of the market. Recall that $DR(p) = Q - SO(p)$. The rules of market require $SO(p)$ to be an increasing function and the structure of available generating technologies implies that $SO(p)$ increases an increasing rate, which implies $DR(p)$ decreases at a decreasing rate.

best-response price with no contract cover is P_{NC}. The best-response price with contract cover is P_C. Note that the best-response price with contract cover is below the best-response price without contract cover. This is a general phenomenon. In this case, Firm A is producing more electricity than its contract quantity so that $DR_C(P_C) = DR(P_C) - Q_C = S_C - Q_C > 0$. Because Firm A has a net long position in electricity, its profit maximizing price given the realization of its residual demand curve is greater than its marginal cost of generation, *MC*.

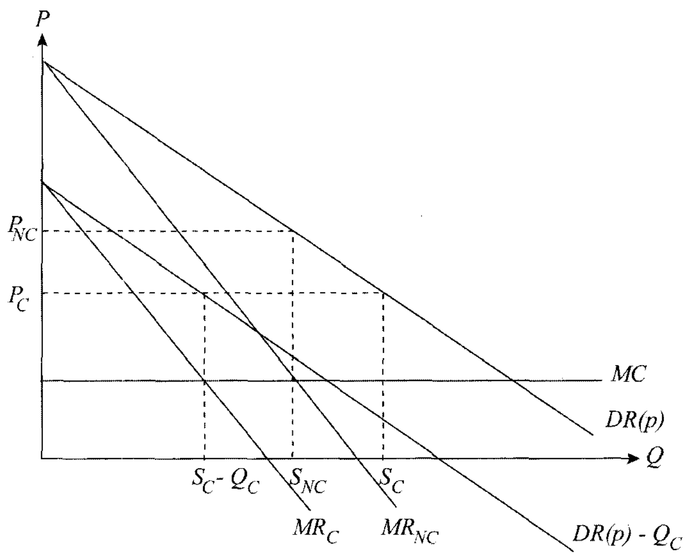

Figure 1. Best-Response Prices with Generation Greater than Contract Quantity

If Firm A sells less electricity than its contract quantity, then its best-response price will be less than its marginal cost. To see this consider the case given in Figure 2. The same curves are drawn as given in Figure 1. The only difference, is that $DR(p) - Q_C$ crosses the vertical (price) axis at a value of p that is less than Firm A's marginal cost. This implies that at a market price equal to Firm A's marginal cost, the amount of output Firm A sells is less than its contract quantity. To compute the best-response prices without contract cover in this case I proceed in the same manner as described for Figure 1. For the case of contract cover, I must extend, MR_C, the marginal revenue curve for $DR_C(p) = DR(p) - Q_C$ past the vertical axis to the point where it crosses Firm A's marginal cost curve. This gives the profit-maximizing level of net output for Firm A given its contract quantity Q_C. The price such that $S_C = DR(p)$ or $S_C - Q_C = DR_C(p)$ is P_C, the best-response price with contract quantity Q_C. As shown in the diagram, this price is less than Firm A's marginal cost. The intuition for this result, is that if Firm A has a greater contract quantity than electricity sales, its realized profits are maximized at a price less than its marginal cost. This can be seen by inspection of equation (3). Because $DR_C(p) = DR(p) - Q_C$ is negative, the profit contribution of the first term will be positive only if the market price is less than Firm A's marginal cost.

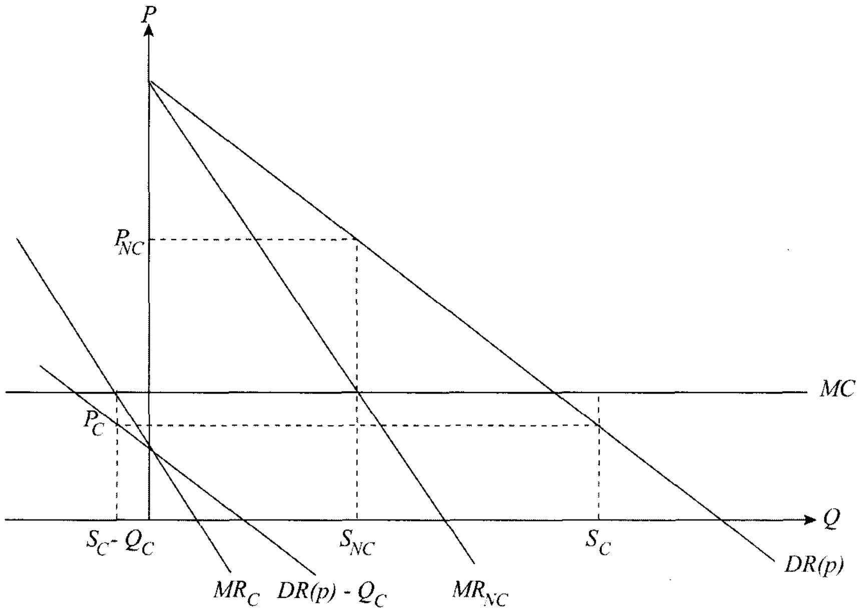

Figure 2. Best-Response Prices with Generation less than Contract Quantity

If Firm A becomes sufficiently over-contracted, its best-response price can even become zero, assuming negative market prices are not possible. If the market rules allow negative market clearing prices, then its best-response price would be negative. To see this logic, consider Figure 3, which repeats the curves drawn in Figure 2, but with $DR(p) - Q_C$ shifted further to the left. The value of Q_C relative to $DR(p)$ is so large that the price at which $DR(p) - Q_C$ crosses the vertical axis is less than negative one times Firm A's marginal cost. Repeating the analysis in Figure 3, yields a best-response price that is negative.

If negative market-clearing prices are not possible, then Firm A's best-response price in this case would be zero. In NEM1, the generators can pay to produce electricity in a load period, although the minimum price to consumers is zero. If the smallest price sufficient to satisfy total system demand is negative, then all generators producing during this half-hour pay this price to sell power into market, but electricity suppliers and large customers purchasing electricity from the market receive it for free. Because hedge contracts are tied to the market price and not the price generators must pay to produce, best-response pricing for Firm A under NEM1 rules for this hedge contract scenario is a market price equal to zero.

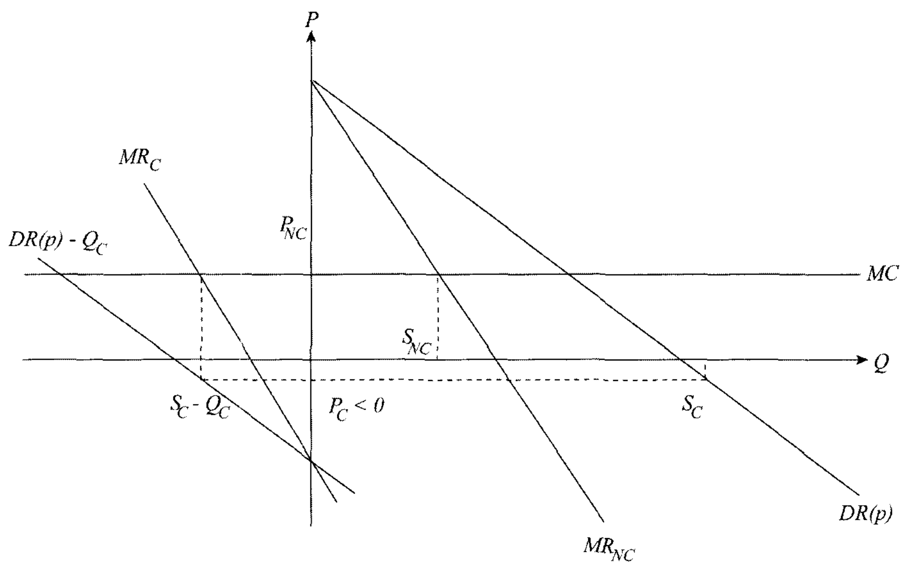

Figure 3. Best-Response Prices with Generation Significantly less than Contract Quantity

Given that the best-response price with contract cover is always lower than the best-response price, one might ask why Firm A should hold any contract cover. Clearly, the simple answer is that, Firm A always sells significantly more electricity under the best-response price with contract cover relative to what it sells at the best-response price without contract cover. In all of the figures $S_C > S_{NC}$, and in many cases by a substantial amount. Consequently, in choosing its contract quantity, Firm A should balance these two competing goals, higher market-clearing prices with less contract cover and higher sales with greater contract cover. The optimal contracting strategy assuming best-response pricing balances these two goals.

The fundamental determinant of the optimal amount of contract cover from the perspective of maximizing variable profits from bidding into the electricity market is the price elasticity of the residual demand that Firm A faces for its output. Recall the definition of the residual demand given earlier: $DR(p) = Q - SO(p)$. The only term in $DR(p)$ that depends on price is $SO(p)$, the amount supplied at price p by all other participants in the market besides Firm A. Therefore, the slope of the residual demand is minus one times the slope of the bid function of all other participants besides Firm A. The more aggressively these firms bid, the greater will be the surge in additional supply from these firms for a given increase in the market-clearing price.

The greater is the supply response from Firm A's competitors, the more elastic is the residual demand that Firm A faces. On the other hand, if these firms do not bid aggressively, there is a smaller surge in supply from these firms for a given increase in the market-clearing price. Very little supply response from Firm A's competitors implies a less elastic residual demand for Firm A's output. A less elastic demand implies a more steeply sloped residual demand function and therefore a greater divergence between the best-response-price without contract cover and best-response price with contract cover, and a smaller divergence between Firm A's production at these two prices. Conversely, a more price-elastic residual demand function implies a smaller divergence between these two prices and a greater divergence between Firm A's sales with and without contract cover.

Figure 4 illustrates a case where Firm A faces a very flat residual demand curve for its output. The divergence between the two best-response prices is very small, whereas Firm A sells significantly more output with contract cover than without contract cover. A firm faced with this sort of residual demand has a significantly greater incentive to sell contract cover for its output than a firm facing the steeper residual demand in Figure 1. If this firm sells more hedge contracts, then it will bid more aggressively into the electricity spot market in order sell more electricity than its forward financial obligation. This, in turn, will leave its competitor with a more elastic residual demand curve, which causes these competitors to want to sell more financial hedge contracts. Consequently, the incentives one firm has to sell financial contracts produces incentives for its competitors to sell more financial hedge contracts. As we show later in the paper, the amount of contract cover the firm finds optimal to sell also depends on its preferences towards risk.

Before analyzing the empirical implications of these results for the bidding and contracting behavior of Firm A, I provide an overview of the market structure of NEM1 and market rules governing its operation.

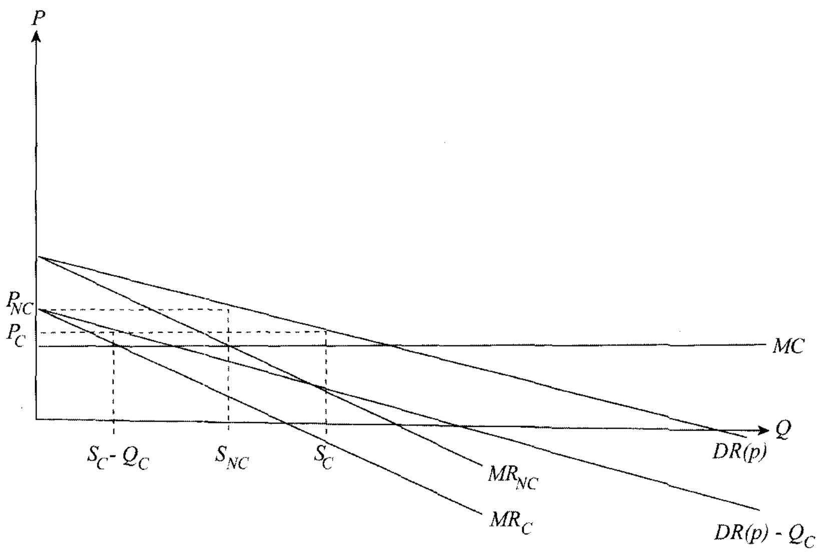

Figure 4. Divergence Between Best-Response Prices with Price Elastic Residual Demand

4. OVERVIEW OF NEM1

The Victoria Power Exchange (VPX) is the longest running wholesale electricity market in Australia. It was established under the Electricity Industry (Amendment) Act of 1994 and formally began operation on July 1, 1994. The New South Wales (NSW) SEM began operation May 10, 1996. NEM1 is the competitive electricity market established jointly by NSW and Victoria on May 4, 1997. It introduced unrestricted competition for generation dispatch across the two states, i.e., the cheapest available generation, after allowing for transmission losses and constraints, is called on regardless of where it is located, and all wholesale energy is traded through the integrated pool. The spot price in each state is determined with electricity flows in and between the state markets based on competitive bids or offers received in both markets.

The ultimate goal of this process is to establish a single interconnected electricity market across Queensland, NSW, Victoria and South Australia. The next step of this process began on December 12, 1998 when the Victoria and NSW markets were merged into a single national market. The Australian Capital Territory (ACT) is part of the NSW pool and South Australia trades through the Victorian pool. Queensland is not yet connected to the NSW grid, but this interconnection is planned to be in place by 2001. A link to Tasmania is also under consideration.

The formation of NEM1 started the harmonization of the rules governing the operation of the two markets in Victoria and NSW. The market structures of the two electricity supply industries in Victoria and NSW are similar in terms of the relative sizes of the generation firms and the mix of generation capacity by fuel type, although the NSW industry is a little less than twice the size (as measured by installed capacity) of the Victoria industry and the largest 3 generators in NSW control a larger fraction of the total generation capacity in their market than the three largest generators in Victoria control of their market.

A. Market Structure in NEM1

In 1994, restructuring and privatization of the State Electricity Commission of Victoria (SECV) took place at the power station level[5]. Each power station was formed into a separate entity to be sold. All former SECV generation capacity is now privately owned. Buyers have come from within Australia and abroad. For example, PowerGen, the second-largest United Kingdom generating company, owns a 49.9% share of Yallourn Energy, along with investors from Japan and Australia. Mission Energy, a U.S. company, owns 51% of the Loy Yang B station. Currently there are eight generating companies competing in Victoria. The supply and distribution sector was formed into five privatized companies which are owned by a combination of U.S. utilities and Australian companies.

The NSW SEM has four generators competing to supply power. All generating assets are still owned by the NSW government. There are seven corporatized state-owned electricity distribution and supply companies serving NSW and the Australian Capital Territory (ACT). The eventual goal is to privatize both the generation and supply companies, but the current very low electricity prices in NEM1 have delayed this process indefinitely.

In both Victoria and NSW, there is an accounting separation within the distribution companies between their electricity distribution business and their electricity supply business. All other retailers have open and non-discriminatory access to any of the other distribution company's wires. In NSW, the high-voltage transmission grid remains in government hands. In Victoria, the high-voltage transmission grid was initially owned by the government and called PowerNet Victoria. It was subsequently sold to the New Jersey-based US company GPU and renamed GPU-PowerNet. In NSW the transmission company is called TransGrid. Both the state markets operating under NEM1–SEM in NSW and VPX in Victoria–were state-owned corporatized entities separate from the bulk transmission entities.

[5]Wolak (1999) provides a more detailed discussion of the operating history of the VPX and compares its market structure, market rules and performance to the markets in England and Wales, Norway and Sweden and New Zealand.

Peak demand in Victoria runs approximately 7.2 GW. The maximum amount of generating capacity that can be supplied to the market is approximately 9.5 GW. Because of this small peak demand, and despite the divestiture of generation to the station level, three of the largest baseload generators have sufficient generating capacity to supply at least 20% of this peak demand. More than 80% of generating plant is coal-fired, although some of this capacity does have fuel switching capabilities. The remaining generating capacity is shared equally between gas turbines and hydroelectric power. The NSW market has a peak demand of approximately 10.7 GW and the maximum amount of generating capacity that can be supplied to the market is approximately 14 GW. There are two large generation companies each of which controls coal-fired capacity sufficient to supply more than 40% of NSW peak demand. The remaining large generator has hydroelectric, gas turbine and coal-fired plants. The Victoria peak demand tends to occur during the summer month of January, whereas peak demand in NSW tends to occurs in the winter month of July.

The full capability of the transmission link between the two states is nominally 1,100MW from Victoria to NSW, and 1,500MW in the opposite direction, although this varies considerably depending on temperature and systems conditions. If there are no constraints on the transfer between markets, then both states see the same market price at the common reference node. If a constraint limits the transfer capacity then prices in both markets diverge, with the importing market having a higher price than the exporting market.

There is a large joint two-state and federal government-owned hydroelectric participant, the Snowy Mountains Corporation, at the boarder of Victoria and NSW that sells into both markets. It owns 3.37 GW in capacity. Although all inter-pool energy flows are determined by competitive bids, for the first stage of NEM1 the existing Snowy arrangements in each of the two State markets have been retained. Snowy entitlements in the two markets receive different spot prices most of the time even though they are physically located at the same place on the network. To prevent possible arbitraging by the Snowy Hydro Trading Company between the two markets, it is required to submit a bid which will be proportioned between the markets in line with the size of the entitlements (~ 29% into Victoria and ~71% into NSW). Trading also takes place across the Victoria/South Australia border, with South Australia participating as a VicPool market participant in NEM1.

The market is mandatory in the sense that generators who operate generating units larger than 30MW must offer all electricity to be produced by those units into the market on a day-ahead basis. Generating facilities of less than 30MW in capacity that are embedded in the local distribution network do not need to be centrally dispatched or trade in the market; however they may elect to do so. Pool customers are retail suppliers and 'contestable' customers (large commercial or industrial customers who have half-hourly meters installed).

B. Market Rules in NEM1

With a few minor exceptions, NEM1 has standardized the price-setting process across the two markets. Generators are able to bid their units into the pool in 10 price increments which cannot be changed for the entire trading day—the 24 hour period beginning at 4 am and ending at 4 am the next day. The 10 quantity increments for each genset can be changed on a half-hourly basis. Demanders can also submit their willingness to reduce their demand on a half-hourly basis as function of price according these same rules. Nevertheless, there is very little demand side participation in the pool. A few pumped storage facilities and iron smelter facilities demand-side bid, but these sources total less than 500 MW of capacity across the two markets.

All electricity is traded through the pool at the market price and all generators are paid the market price for their energy, unless it is equal zero. For the reasons discussed earlier, generators may have to pay money to supply power during that half-hour periods with zero prices. The ex-ante Dispatch Price determined for each 5-minute dispatch cycle is the maximum of: (1) the highest-priced capacity band which is targeted by the economic dispatch system and (2) the Interpool transfer price. The spot price for the half hour is the average of the six ex-ante dispatch prices for each 5-minute cycle of the local dispatch process. As noted earlier if this average is negative the market price is set to zero. If demand exceeds supply for a 5-minute interval, then the price is set equal to the Value of Lost Load (VOLL), which is currently set equal to 5,000 $AU/MWH.

Power flows between the two state markets are determined at 5-minute intervals, taking into account the competitive bids and offers into each of the state-based markets. Power flows between the two markets may be constrained by technical interconnector line limits due to such factors as thermal and power system stability. The scheduling process takes into account these restrictions on flows between the two markets.

C. Regulatory Oversight of NEM1

Under NEM1, the Office of the Regulator General in Victoria was responsible oversight of the Victoria Electricity Supply Industry. It sets prices for both transmission and distribution services, using a price cap regulation plan. In NSW the Independent Pricing and Regulatory Tribunal oversaw the operation of the SEM. It was charged with setting prices for transmission and distribution services, using a price cap regulation plan. Australia Competition and Consumer Commission regulates the state transmission grids in the integrated national electricity market. Oversight of distribution companies remains with the two state regulatory bodies.

5. MODELING THE PRICE-SETTING IN THE NEM1

This section describes the results of my attempts to model the price-setting process in NEM1 using generator bid data and market demand data that I obtained for the period May 15, 1997 to August 24, 1997. An accurate model of the price-setting process is necessary to compute the profit function given in equation (5) for Firm A for any set of bids submitted by Firm A's competitors and level of market demand net of transfers in the state in which Firm A operates. The day-ahead generator bids in NEM1 consist of the following information for each generating unit: (1) the quantity or capacity band bid (in MW) for each half-hour, (2) available capacity in MW for each half-hour, (3) fixed loading quantity (in MW) for each half-hour, and (4) the 10 daily price bids in Australian cents/MWH.

There are nine quantity band bids which determine the nine quantity bid increments. The last, and most often, tenth half-hourly quantity band is determined by CAPIMM, the maximum amount of capacity available from the facility during that half-hour. Demand-side bids have a similar structure except that bidders tend not to use all 10 bid increments.[6]

The nine quantity bids and the CAPIMM quantity together with the ten price bids can be used to determine a supply curve for each generating unit for each half hour. Often the value of CAPIMM for a given half-hour is set to a number less than the sum of the nine capacity bands, or is set equal to zero.[7] In those instances, only those capacity bands or portions of bands less than CAPIMM are considered in the construction of the aggregate supply curve for that half-hour. If the dataset has a value for FIXED for a given generating facility for a given half-hour, that generation facility is assumed to run at that capacity for the half-hour and the FIXED capacity is subtracted from the aggregate demand and excluded from the aggregate supply bid function used to set the predicted market price. All of these adjustments to the price-setting process where verified by members of the NEM1 staff as reflecting what is actually done in the price-setting process.

The first approach to modeling the price-setting process uses the intersection of the half-hourly demands–net of demand-side bids, FIXED bids for all generators for that half-hour, and transfers between the markets–with the half-hourly aggregate supply curve to determine a predicted price of electricity for each half-hour. The second approach to modeling the price-setting process uses the intersection of the half-hourly supply curve with the 5-minute ahead demand forecasts net of these same half-hourly magnitudes to compute the 5-minute ahead

[6]The demand-side bidders usually draw power from the system at full capacity or shut down completely.

[7]Values of CAPIMM equal to zero are common. For example, treating the unit of observation as the generating unit and day pair, roughly 20% of the observations defined in this way have values of CAPIMM equal to zero. This percentage of values of CAPIMM equal to zero is uniform across the 48 load periods in the day, with a minimum over all load periods of 20.8 percent zeros and a maximum of 21.6 percent zeros.

prospective price. The six prospective 5-minute ahead prices for each half-hour are then averaged to compute a prediction of the half-hourly price. The latter process more closely follows the actual price-setting process, so it is hoped that the extra computational burden would be justified by the increased accuracy in replicating actual pool prices.

All bid prices for each generating unit are adjusted for loss factors obtained from NEM1 staff to convert all prices to the standard reference node for the purposes of constructing the aggregate supply function. Demand-side bidders, primarily pumped-storage facilities, were treated in the same manner as supply-side bidders in the construction of the aggregate supply curve, with the only difference being that if the market price is less than their bid price, the load will be in service and if it is greater than the bid price, the load will not be in service.

A. Simulations: Predicted Versus Actual Prices

The first two columns of Table 1 give the sample means and standard deviations at the load period level of the actual half-hourly pool price from the NSW market for the period May 15, 1997 to August 24, 1997. The second two columns give the sample means and standard deviations of the predicted prices obtained using the intersection of the average half-hourly demands with the half-hourly supply curves to determine the half-hourly market-clearing price. Before comparing the results of these calculations, it is important to note that the use of half-hourly demand to determine market-clearing prices introduces some degree of approximation into my results relative to the actual price-setting process. This approximation to the actual price-setting process should therefore work best in those instances in which electricity demand of over the half-hour period is stable, meaning that the half-hourly demand figure is representative of all of the five-minute ahead demand figures in that half-hour period. Conversely, the load periods when my approximation technique should work poorly are those where the 5-minute ahead demand forecasts in a half-hour period differ significantly from one another, due to an increasing or decreasing system demand during that half-hour. For the purposes of this table and all subsequent tables, Period 1 corresponds to the half-hour beginning at 4:00 am and Period 48 corresponds to the half-hour beginning at 3:30 am the following day.

Comparing the mean prices in columns 1 and 3 of the Table 1, shows that my procedure does a good job of predicting the actual half-hourly prices for most of the load periods. The difference between the mean actual price and the mean predicted price is almost always less than one Australian dollar. The largest this difference ever gets is a little less than three dollars in load period 30, the period beginning at 6:30 pm. I expect the half-hourly average demand to be very unrepresentative of the 5-minute ahead demands for that half-hour. This is borne out by the extremely high standard deviation of actual prices during that period

Table 1. Means and Standard Deviations of Actual, Predicted, and Best Response Prices Assuming MC = $15/MWH Using Half-Hourly Demands to Set Prices for Full Sample of Bid Data

	Actual Price		Predicted Price		Best Response Price	
Period	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev
1	$8.51	$4.11	$8.07	$4.45	$12.25	$8.80
2	$8.02	$4.09	$7.95	$4.39	$11.84	$8.27
3	$8.64	$3.77	$8.83	$4.08	$12.15	$8.57
4	$9.95	$3.03	$10.05	$3.42	$13.87	$9.07
5	$11.93	$3.14	$11.90	$2.66	$18.91	$17.01
6	$13.61	$3.70	$13.70	$3.44	$26.77	$31.59
7	$13.53	$2.73	$15.06	$5.85	$31.10	$37.06
8	$17.96	$7.93	$17.16	$7.30	$39.27	$40.51
9	$18.73	$8.26	$17.66	$7.04	$39.22	$39.88
10	$17.29	$6.53	$15.85	$5.06	$35.83	$35.72
11	$18.79	$7.38	$17.79	$6.36	$46.19	$52.08
12	$18.13	$6.97	$17.23	$6.28	$44.85	$49.87
13	$17.34	$5.62	$15.77	$4.62	$33.65	$32.83
14	$16.62	$4.68	$15.18	$3.62	$33.22	$32.41
15	$15.87	$4.71	$15.31	$4.41	$31.28	$31.79
16	$15.86	$6.00	$15.44	$4.76	$30.08	$32.78
17	$14.88	$4.35	$14.56	$4.01	$29.74	$32.35
18	$14.58	$4.08	$14.47	$3.63	$28.26	$29.84
19	$15.04	$4.52	$14.59	$3.94	$28.62	$30.20
20	$14.74	$4.42	$14.13	$3.32	$27.06	$27.75
21	$14.41	$4.10	$14.12	$3.40	$27.40	$29.06
22	$14.02	$3.33	$13.89	$3.15	$26.13	$25.79
23	$13.86	$3.27	$13.93	$3.53	$25.38	$25.31
24	$14.02	$3.45	$14.16	$3.82	$23.96	$19.32
25	$14.35	$4.14	$14.25	$4.00	$22.82	$21.23
26	$15.23	$4.91	$16.05	$6.48	$24.50	$20.78
27	$17.87	$7.21	$18.93	$8.73	$32.95	$44.71
28	$24.30	$14.70	$23.06	$16.12	$49.64	$66.47
29	$22.56	$12.60	$20.31	$11.15	$47.84	$71.78
30	$22.04	$11.84	$18.09	$6.82	$38.38	$47.83
31	$19.47	$8.06	$16.81	$5.66	$32.46	$29.36
32	$18.36	$6.47	$16.88	$5.84	$33.57	$31.94
33	$18.42	$6.37	$17.55	$5.95	$36.17	$34.33
34	$17.48	$5.72	$16.16	$5.08	$31.90	$29.55
35	$15.03	$4.29	$14.29	$3.13	$30.63	$33.29
36	$13.71	$3.20	$13.50	$2.45	$25.32	$25.97
37	$14.38	$2.91	$14.48	$3.40	$33.44	$43.48
38	$13.56	$2.27	$13.35	$1.58	$25.16	$26.51
39	$16.24	$4.69	$14.48	$3.75	$32.77	$48.17
40	$14.39	$3.58	$13.73	$2.60	$30.44	$40.75
41	$14.08	$3.40	$14.09	$3.19	$32.92	$42.41
42	$13.50	$2.59	$13.45	$1.73	$28.79	$33.00
43	$15.27	$3.71	$13.36	$1.71	$29.32	$31.06
44	$13.58	$2.91	$13.06	$2.55	$24.53	$25.25
45	$12.28	$2.63	$12.36	$2.26	$22.55	$23.71
46	$11.14	$3.31	$11.52	$2.49	$19.55	$21.05
47	$10.01	$3.85	$9.69	$4.00	$15.97	$15.45
48	$8.97	$3.95	$8.85	$4.18	$13.50	$10.02

and those adjacent to it. My model of the price-setting process is also able to predict the standard deviation of the actual half-hourly prices as well. Comparing the numbers in columns two and four, I find relatively close agreement between period-level the standard deviations of prices. These results lead me to conclude that my model of the price-setting process which uses the average half-hourly demands satisfactorily replicates the actual price-setting process and can be used to perform meaningful counterfactual experiments such as my best-response price analysis.

To see if these results could be improved upon, I used the 5-minute-ahead demand data for the month of July 1997 in my simulation of the price-setting process. With this data, I first compute the intersection of the aggregate supply curve for the associated half-hour for each of the 5-minute demand forecasts in that half-hour. This gives 6 predicted 5-minute-ahead prices, which are then averaged to compute the predicted pool price for that half hour. If the average of the 5-minute ahead predicted prices in a half-hour are negative, then this price is set equal to zero as required by the pool rules.

Table 2 gives the sample means and standard deviations of the actual half-hourly price and the predicted half-hourly price using the five-minute-ahead data for a sample of 5-minute demands from July 2,1997 to July 30, 1997. The 5-minute ahead demand data yields similar results to the half-hourly demand data, but with larger average misses than the half-hourly demand data. There are a variety of reasons why these price predictions differ from the actual market prices. A one reason can be traced to how transfers between the two markets are handled in the computation of market-clearing prices. As noted above, in both the half-hourly demand and 5-minute ahead demand simulated price-setting processes I assume that the half-hourly transfer capacity, TRANSF, is either added or subtracted from the aggregate demand forecast. However, different transfers are taking place during each 5-minute interval. Unfortunately, I am unable to obtain access to the five-minute transfer data necessary to model the actual price-setting process more accurately. A final reason for the difference between the two prices is also the most difficult to deal with. Each generation owner submits a ramp rate for each facility for each half-hour during the day giving the maximum rate at which the amount of power supplied from that facility can charge. According to the NEM1 rules for the price-setting process, plants constrained at their ramp rate during a 5-minute interval cannot set the price for that 5-minute interval. This implies that the 5-minute ahead price is not just the price at the point where aggregate demand crosses the half-hourly aggregate supply function. In order to know which generators to skip over because their ramp rates cannot cover the increase in demand across a 5-minute interval, I need to know the current operating level of all generators. Although, the ramp rate for a generating unit is given in the bid database, I do not know the amount of capacity in use at each generating facility for each 5-minute interval. Fortunately, information on the capacity level of each generating facility is only required for a single 5-minute period,

Table 2. Means and Standard Deviations of Actual and Predicted Half-Hourly Prices Using Using 5-Minute Ahead Demand to Determine Predicted Price for Period 7/2/97 to 7/30/97

	Actual Price		Predicted Price	
Period	Mean	Std Dev	Mean	Std Dev
1	$11.33	$1.11	$16.45	$27.52
2	$11.05	$1.11	$16.16	$27.33
3	$11.28	$1.01	$15.94	$24.94
4	$11.61	$1.06	$16.11	$23.91
5	$12.12	$1.06	$16.35	$21.87
6	$13.40	$3.60	$17.28	$18.36
7	$13.07	$3.28	$15.93	$12.45
8	$14.72	$5.96	$14.96	$4.85
9	$14.21	$4.71	$14.42	$4.73
10	$13.09	$2.46	$13.62	$3.14
11	$13.52	$1.36	$13.58	$1.94
12	$13.87	$2.14	$13.67	$1.88
13	$14.15	$1.75	$13.85	$2.55
14	$14.78	$2.71	$16.47	$16.62
15	$12.79	$1.43	$16.10	$16.70
16	$12.69	$1.29	$16.65	$20.38
17	$12.61	$1.51	$15.69	$16.15
18	$12.61	$2.08	$15.97	$18.36
19	$12.70	$1.93	$16.64	$21.82
20	$12.30	$1.21	$16.26	$20.45
21	$12.29	$1.20	$16.50	$21.92
22	$12.64	$2.49	$16.17	$20.47
23	$12.22	$1.22	$16.30	$21.89
24	$12.26	$1.15	$16.71	$24.41
25	$12.32	$1.13	$15.32	$18.61
26	$12.84	$1.39	$13.53	$7.66
27	$16.24	$8.06	$13.38	$4.41
28	$20.47	$13.31	$15.28	$6.57
29	$17.21	$7.97	$16.79	$13.36
30	$22.93	$18.00	$17.17	$11.37
31	$19.83	$11.78	$17.22	$11.11
32	$17.19	$7.34	$15.68	$7.27
33	$18.62	$8.15	$16.21	$7.86
34	$17.23	$7.55	$15.81	$7.11
35	$14.44	$5.79	$14.82	$7.08
36	$13.20	$4.15	$12.82	$4.04
37	$14.25	$2.97	$12.77	$2.91
38	$13.20	$2.36	$13.28	$4.65
39	$18.18	$6.44	$14.27	$6.12
40	$14.91	$4.20	$13.54	$1.98
41	$13.57	$2.14	$16.68	$18.74
42	$13.46	$1.03	$17.40	$21.99
43	$16.34	$3.35	$18.37	$23.56
44	$14.66	$2.66	$19.32	$24.80
45	$13.89	$1.77	$18.16	$24.89
46	$12.80	$1.03	$17.70	$26.06
47	$12.39	$1.01	$17.39	$27.27
48	$11.63	$0.89	$16.81	$27.38

because once this initial level is known, all 5-minute ahead prices can be determined relative to that point. Incorporating this information into the process of simulating actual prices would enormously increase the computational complexity of my problem. Given the accuracy I am able to achieve in predicting actual prices using the half-hourly demands, I decided this increase in complexity was unnecessary at this time. I therefore employ the price-setting process which uses average half-hourly demands to perform my best-response price analysis.

6. SIMULATIONS OF BEST-RESPONSE PRICES

This section uses the best-response pricing framework described in Section 2 and the price-setting process described in the previous section to perform various simulations which estimate the potential profit increases possible from achieving best-response prices relative to Firm A's current bidding strategy. The first step is to compute Firm A's profits from any market-clearing price. In order to do so, several elements of Firm A's profit function must be specified. First, an estimate of the marginal cost of generating a MWH is required. From my conversations with staff at Firm A, numbers in the range of 7.5 \$AU/MWH and 15 \$AU/MWH were deemed reasonable, with 15 \$AU/MWH the most plausible. Second, knowledge of contract prices and quantities for each half-hour period is necessary to obtain an accurate estimate of the variable profits accruing to Firm A from following any particular bidding strategy. Quantity-weighted average contract price and quantity information for my sample period was provided by staff at Firm A. This completes the information necessary to compute an estimate of Firm A's profit function for any half-hour.

A. Computing Profits under Best-Response Pricing

The first step in my analysis is to compute a baseline level of profits to compare to my estimated profits from using best-response prices. To compute estimates of the actual profits accruing to Firm A from its current bidding strategy, I first set values for marginal cost, *MC*, and the contract prices and quantities, *PC* and *QC,* for each load period and day in my sample. I then take the actual pool price from the NSW market for each load period as the value of p. For the value of $DR(p)$ at the actual market clearing price, I take the final pre-dispatch values for each load period given in the bidding database (the variable *DISPTG*) for all Firm A units. The first column of Table 3 gives the mean of my estimates of the actual load period level profits for my sample period assuming that $MC = 15$ \$AU/MWH. These profit levels and all profit levels reported in the paper are multiplied by a positive scalar to preserve confidentiality but also to allow all profits levels and

Table 3. Load Period Level Profits Assuming Marginal Cost of Generation Equals $15/MWH

Period	Mean of Actual Profits	Mean of Predicted Profits	Best Response Profits/ Actual Profits	Best Response Profits/ Predicted Profits
1	$7,693	$6,830	1.14	1.28
2	$7,782	$6,938	1.14	1.28
3	$8,291	$7,724	1.10	1.19
4	$8,587	$8,367	1.13	1.16
5	$9,305	$9,451	1.26	1.24
6	$11,059	$11,313	1.38	1.35
7	$24,542	$25,260	1.24	1.20
8	$26,972	$27,173	1.25	1.24
9	$28,052	$27,982	1.21	1.21
10	$28,010	$27,643	1.18	1.19
11	$27,693	$27,477	1.24	1.25
12	$27,501	$27,229	1.21	1.23
13	$28,558	$27,890	1.16	1.18
14	$28,250	$27,677	1.14	1.17
15	$27,843	$27,407	1.15	1.17
16	$32,750	$32,360	1.13	1.14
17	$27,986	$27,768	1.12	1.13
18	$26,782	$26,623	1.13	1.13
19	$26,734	$26,494	1.13	1.14
20	$26,197	$25,949	1.12	1.13
21	$25,643	$25,372	1.12	1.14
22	$25,029	$24,965	1.11	1.11
23	$24,875	$24,851	1.10	1.11
24	$25,467	$25,496	1.10	1.10
25	$27,486	$27,471	1.08	1.08
26	$27,425	$27,613	1.09	1.08
27	$28,597	$28,978	1.12	1.11
28	$30,431	$30,183	1.16	1.17
29	$30,405	$29,788	1.14	1.16
30	$30,500	$29,511	1.11	1.14
31	$29,754	$29,027	1.10	1.13
32	$29,241	$28,650	1.12	1.14
33	$28,429	$28,066	1.15	1.17
34	$27,383	$26,895	1.15	1.17
35	$29,316	$28,761	1.18	1.21
36	$29,035	$28,765	1.10	1.11
37	$13,197	$13,099	1.40	1.41
38	$12,992	$12,640	1.26	1.29
39	$13,530	$13,000	1.32	1.38
40	$12,779	$12,483	1.36	1.39
41	$12,277	$12,070	1.43	1.46
42	$11,300	$11,071	1.44	1.47
43	$10,847	$10,225	1.38	1.46
44	$9,585	$9,341	1.35	1.39
45	$8,482	$8,310	1.39	1.42
46	$8,165	$7,833	1.29	1.34
47	$7,963	$7,356	1.20	1.29
48	$7,696	$7,010	1.15	1.26

ratios to be comparable across tables. Only the absolute magnitude of profits is unknown. The first column of Tables 4 and 5 gives the mean of my estimates of the actual load period level profits for my sample period assuming that $MC = 10$ \$AU/MWH and $MC = 7.5$ \$AU/MWH, respectively. These numbers represent my best guess of the mean values of load period-level variable profits given the information at my disposal for these three values of Firm A's marginal cost of generation.

My simulation of the actual price-setting process for a given bid function forms the basis of my best-response calculations. To give a flavor for what my price predictions imply about variable profit levels relative to those computed based on actual market prices and pre-dispatch levels, in the second column of Tables 3-5, I present my average load-period-level predictions of Firm A's variable profits, employing my price-setting process that uses the half-hourly demands. For each load period, I solve for the smallest value of p such that $SA(p) = DR(p)$, i.e., the amount Firm A is willing to supply (according to its actual bids) is equal to the residual demand that it faces for its output. Call this price p^*. To compute Firm A's variable profits, I set p in equation (5) equal to p^* and the amount supplied by Firm A equal to $DR(p^*)$. This provides all of the information necessary to compute an estimate of Firm A's variable profits for my model of the price-determination process. The means of these load-period-level predicted profits are reported in the second column of Tables 3-5 for the marginal cost scenarios I consider. Despite the fact that I am using the half-hourly demands in my model of the price-setting process, I find close agreement between the actual profits and predicted profits for all load periods across all three tables. These results provide further support for the validity of my model of the price-setting process.

B. Computing Best-Response Prices

We now proceed to the final step of my analysis, a comparison of the profits from best-response prices to those obtained from the actual bidding strategy. Throughout this entire discussion I am assuming that all other firms in the market do not change their strategies in response to a change in Firm A's bidding strategy. My best-response price framework can be easily expanded to deal with changes in the bidding strategies of other firms, or uncertainty in their bidding strategies. In addition, as noted earlier, a full-blown computation of the actual best-response bidding strategy giving the optimal daily values of the ten bid prices for each generating unit and ten half-hourly capacity declarations for each generating unit will not be pursued here. Instead, the goal of my analysis is to show the maximum potential profits obtainable from pursuit of such a strategy and to characterize its general features. As discussed in Section 2, these maximum potential profits from best-response prices may not be obtainable because of the constraints placed on Firm A's bid functions by the market rules.

Table 4. Load Period Level Profits Assuming Marginal Cost of Generation Equals $10/MWH

Period	Mean of Actual Profits	Mean of Predicted Profits	Best Response/ Actual Profits	Best Response/ Predicted Profits
1	$12,315	$11,778	1.06	1.10
2	$12,393	$11,844	1.05	1.10
3	$12,994	$12,616	1.04	1.07
4	$13,594	$13,482	1.06	1.07
5	$15,227	$15,293	1.13	1.13
6	$17,624	$17,822	1.22	1.21
7	$31,509	$32,275	1.17	1.15
8	$34,444	$34,711	1.18	1.17
9	$35,857	$35,862	1.15	1.15
10	$35,894	$35,669	1.12	1.13
11	$35,804	$35,691	1.17	1.17
12	$35,636	$35,450	1.15	1.15
13	$36,692	$36,117	1.11	1.12
14	$36,352	$35,834	1.10	1.11
15	$35,876	$35,501	1.10	1.11
16	$40,678	$40,364	1.09	1.10
17	$35,698	$35,584	1.08	1.09
18	$34,382	$34,325	1.09	1.09
19	$34,321	$34,239	1.09	1.09
20	$33,668	$33,537	1.08	1.09
21	$33,031	$32,849	1.08	1.09
22	$32,297	$32,298	1.07	1.07
23	$32,078	$32,158	1.07	1.06
24	$32,777	$32,892	1.06	1.06
25	$34,851	$34,933	1.05	1.05
26	$35,146	$35,480	1.06	1.05
27	$36,769	$37,306	1.09	1.07
28	$38,829	$38,727	1.11	1.12
29	$38,761	$38,256	1.10	1.11
30	$38,801	$37,915	1.07	1.10
31	$38,044	$37,415	1.07	1.09
32	$37,540	$37,052	1.08	1.09
33	$36,771	$36,492	1.11	1.11
34	$35,576	$35,172	1.10	1.11
35	$37,100	$36,619	1.13	1.15
36	$36,125	$35,935	1.07	1.07
37	$20,644	$20,677	1.24	1.24
38	$20,040	$19,724	1.16	1.18
39	$20,866	$20,435	1.19	1.22
40	$19,867	$19,593	1.22	1.23
41	$19,285	$19,101	1.26	1.27
42	$18,077	$17,833	1.26	1.27
43	$17,661	$17,091	1.21	1.25
44	$15,947	$15,679	1.19	1.21
45	$14,443	$14,262	1.20	1.22
46	$13,681	$13,329	1.15	1.18
47	$13,031	$12,604	1.09	1.13
48	$12,485	$12,043	1.06	1.10

Table 5. Load Period Level Profits Assuming Marginal Cost of Generation Equals $7.50/MWH

Period	Mean of Actual Profits	Mean of Predicted Profits	Best Response Profits/ Actual Profits	Best Response Profits/ Predicted Profits
1	$14,626	$14,252	1.05	1.08
2	$14,698	$14,297	1.04	1.07
3	$15,346	$15,062	1.04	1.06
4	$16,097	$16,040	1.07	1.07
5	$18,188	$18,215	1.13	1.12
6	$20,907	$21,076	1.20	1.19
7	$34,992	$35,783	1.17	1.14
8	$38,179	$38,480	1.17	1.16
9	$39,760	$39,803	1.14	1.14
10	$39,836	$39,682	1.12	1.12
11	$39,859	$39,797	1.15	1.15
12	$39,703	$39,561	1.13	1.14
13	$40,759	$40,231	1.10	1.11
14	$40,403	$39,913	1.09	1.10
15	$39,892	$39,548	1.10	1.11
16	$44,642	$44,365	1.09	1.10
17	$39,553	$39,493	1.08	1.08
18	$38,182	$38,177	1.08	1.08
19	$38,114	$38,112	1.09	1.09
20	$37,403	$37,332	1.08	1.08
21	$36,726	$36,587	1.08	1.08
22	$35,931	$35,965	1.07	1.07
23	$35,679	$35,812	1.07	1.07
24	$36,432	$36,590	1.06	1.06
25	$38,533	$38,664	1.06	1.06
26	$39,007	$39,413	1.07	1.06
27	$40,855	$41,469	1.09	1.07
28	$43,029	$42,999	1.10	1.10
29	$42,939	$42,490	1.09	1.10
30	$42,951	$42,116	1.07	1.09
31	$42,189	$41,610	1.07	1.08
32	$41,689	$41,253	1.08	1.09
33	$40,942	$40,705	1.10	1.11
34	$39,672	$39,311	1.10	1.11
35	$40,992	$40,548	1.13	1.14
36	$39,670	$39,520	1.07	1.08
37	$24,368	$24,466	1.22	1.21
38	$23,563	$23,266	1.16	1.17
39	$24,534	$24,153	1.18	1.20
40	$23,411	$23,149	1.20	1.21
41	$22,789	$22,617	1.23	1.24
42	$21,466	$21,215	1.23	1.25
43	$21,068	$20,524	1.19	1.22
44	$19,128	$18,848	1.17	1.19
45	$17,423	$17,239	1.18	1.19
46	$16,439	$16,078	1.13	1.16
47	$15,565	$15,229	1.08	1.11
48	$14,880	$14,560	1.06	1.08

I compute how much actual profits, equation (5), could be increased if Firm A had obtained best-response prices over the sample period, taking its contract position as given. In these calculations, I assume that Firm A's contract quantity, *QC,* and contract price, *PC,* cannot be changed. Other calculations with my model reported below suggest that substantial increases in expected profits are possible from a change in *QC*.

The last two columns of Table 1 contain the sample mean and standard deviation of these optimal best-response prices at the load period level for my sample period May 15, 1997 to August 24, 1997, assuming the marginal cost of generation is 15 $AU/MWH. For all but load period 1, these prices are higher, sometimes significantly so, than either the actual market prices, or the predicted prices I calculated using Firm A's current bidding strategy.

The next step in the analysis estimates the increased profits that could be earned by Firm A if it were able to set these load period level best-response prices through its bidding behavior. The third column of Table 3 gives the ratio of the average of best-response profits to the average of actual profits for each load period, assuming a marginal cost of generation of $15/MWH. The last column gives the ratio of the average of best-response profits to the average of Firm A's predicted profits, calculated using my model of the price-determination process. These numbers provide my best estimate of an upper bound on the increase in profits obtainable by Firm A as a result of implementing a best-response bidding strategy. The last two columns of Tables 4 and 5 present the same set of calculations as those reported in Table 3 for the cases that the marginal cost of producing electricity by Firm A is 10 $AU/MWH and 7.50 $AU/MWH, respectively.

Several conclusions can be drawn from the results reported in these tables. First, for all three estimates of the marginal cost of producing electricity used, in all load periods there appear to exist opportunities for increasing profits by pursuing a best-response bidding strategy, relative to Firm A's current bidding strategy. These potential profit increases are largest for the case in which the marginal cost of generation is $15/MWH as opposed to $10/MWH and $7.50/MWH. The second conclusion is that there are considerable differences in the magnitude of these potential profit increases across load periods in the day. For example, the potential increases estimated range from as small as 4% in some load periods to as large as 44 % in other load periods. The ratio of the sample mean profits (over all load periods and days) from the best-response bidding strategy to the sample mean predicted profits (over all load periods and days) from the current bidding strategy yields a value of 1.17 for the case of the marginal cost of generation equal to 15 $AU/MWH, 1.12 for the case of a marginal cost of generation equal to 10 $AU/MWH and 1.11 for the case of a marginal cost of generation equal to 7.5 $AU/MWH. That is, my initial estimates predict an average improvement in profitability of 11% to 17% over the sample period from following a bidding strategy which yields these best-response prices.

Taken as a whole, these results suggest that increases in profits are available to Firm A from achieving best-response prices, assuming no change in its contract position. What is unknown is the extent to which Firm A can achieve these increased profits through its actual bidding strategy. Nevertheless, this result provides a justification for the computational effort necessary to solve for the best-response bidding strategy.

C. Best-Response Prices and Contract Quantities

As noted above, my modeling framework can be used to explore the impact of changes in Firm A's contract position on its best-response prices. I consider two simple cases. The first case assumes Firm A holds no contracts. The second case assumes that it uniformly cuts its contract position to half its present level, but maintains the same contract prices. I compute Firm A's best-response prices and profits under both of these scenarios. The first scenario implies that the second two terms in equation (2) are identically equal to zero. Under this assumption I have computed the best-response price, p^*, and the best-response profits for a marginal cost of generation of \$15/MWH. Table 6 gives the load period level mean and standard deviations of these profit levels for my sample period.

The first point to notice from these tables is the substantial increases in average variable profits in most load periods relative to the average variable profits under both the current bidding strategy with the current level of contract cover and under best-response pricing with the current level of contract cover. However, these mean variable profit increases are not without a downside. The second column of Table 5 shows that very large standard deviations in variable profits result from the no contract cover best-response prices. The presence of nonzero contract quantities considerably reduces the variability in load period level profits. According to my model, this is at a cost of a significant reduction in average load period level profits. These calculations suggest that, at a minimum, my modeling framework can be a powerful tool for determining the relevant trade-offs in terms of the means and variances in profits from pursuing different contracting and bidding strategies.

For comparison, Table 7 computes the average period-level profits assuming a marginal cost of 10 \$AU/MWH and current contracting levels and the average period-level profits that could be obtained if current contract levels were set to half their magnitude in all load periods and Firm A was then able to set best-response prices at these contract levels. I also compare these profits to those that could be obtained at current contracting levels at the best-response prices for current contract levels. The second to the last column of this table presents the ratio of the best-response pricing profits at half of current contract quantities over the actual profits at current prices, quantities and contract levels. The last column

Table 6. Load Period Mean and Standard Deviations of Best Response Profits with No Contract Cover, Assuming Marginal Cost of Generation Equals $15/MWH

Period	Mean of Profits	Std. Dev. of Profits
1	$10,163	$6,428
2	$9,462	$6,215
3	$10,265	$7,098
4	$12,301	$8,692
5	$20,531	$15,844
6	$40,826	$51,940
7	$102,792	$192,244
8	$238,717	$384,053
9	$306,815	$445,161
10	$294,159	$414,135
11	$450,623	$515,520
12	$404,370	$477,629
13	$297,995	$381,248
14	$221,979	$298,521
15	$169,244	$245,167
16	$142,133	$211,092
17	$110,686	$183,816
18	$99,016	$158,316
19	$102,442	$165,760
20	$84,395	$142,440
21	$73,758	$109,108
22	$61,662	$89,759
23	$53,386	$74,580
24	$62,644	$105,229
25	$77,835	$161,524
26	$168,533	$258,842
27	$513,946	$529,145
28	$876,724	$678,703
29	$801,871	$654,516
30	$555,336	$563,311
31	$361,541	$454,353
32	$245,595	$352,085
33	$193,060	$292,192
34	$125,104	$198,918
35	$63,095	$100,890
36	$40,354	$56,747
37	$60,068	$83,279
38	$39,194	$46,172
39	$58,067	$63,000
40	$43,779	$45,101
41	$40,479	$37,733
42	$32,680	$28,985
43	$32,552	$27,350
44	$25,724	$22,603
45	$22,759	$18,943
46	$19,308	$13,800
47	$15,142	$10,268
48	$12,342	$8,089

Table 7. Load Period Mean Actual, Predicted and Best Response (BR) Profits with Current Contract Quantity (CQ), BR Profits with One-Half Current CQ, Marginal Cost of Generation Equals $10/MWH

Period	Mean of Actual Profits	Mean of Predicted Profits	Mean of BR at Current CQ Profits	Mean of BR Profits at ½ CQ	BR ½ CQ/ Actual Profits	BR ½ CQ/ Predicted Profits	BR ½ CQ/ BR Current CQ
1	$5,661	$4,900	$12,998	$9,410	1.66	1.92	0.72
2	$5,486	$4,892	$13,033	$9,082	1.66	1.86	0.70
3	$6,066	$5,778	$13,546	$9,507	1.57	1.65	0.70
4	$6,921	$6,860	$14,471	$11,244	1.62	1.64	0.78
5	$8,858	$8,877	$17,255	$18,366	2.07	2.07	1.06
6	$11,315	$11,577	$21,478	$30,115	2.66	2.60	1.40
7	$18,404	$20,079	$37,015	$41,743	2.27	2.08	1.13
8	$23,671	$23,237	$40,706	$54,044	2.28	2.33	1.33
9	$25,105	$24,283	$41,317	$59,059	2.35	2.43	1.43
10	$23,896	$22,628	$40,339	$54,884	2.30	2.43	1.36
11	$25,207	$24,373	$41,857	$78,604	3.12	3.23	1.88
12	$24,597	$23,770	$40,867	$67,087	2.73	2.82	1.64
13	$24,475	$22,867	$40,554	$54,796	2.24	2.40	1.35
14	$23,697	$22,214	$39,857	$51,236	2.16	2.31	1.29
15	$22,772	$22,125	$39,565	$48,941	2.15	2.21	1.24
16	$25,145	$24,638	$44,480	$47,184	1.88	1.92	1.06
17	$21,734	$21,423	$38,684	$43,262	1.99	2.02	1.12
18	$20,800	$20,687	$37,318	$41,166	1.98	1.99	1.10
19	$21,154	$20,785	$37,320	$41,494	1.96	2.00	1.11
20	$20,556	$19,996	$36,405	$39,486	1.92	1.97	1.08
21	$19,941	$19,613	$35,764	$38,793	1.95	1.98	1.08
22	$19,185	$19,092	$34,648	$36,574	1.91	1.92	1.06
23	$18,929	$19,063	$34,231	$35,858	1.89	1.88	1.05
24	$19,454	$19,652	$34,821	$36,922	1.90	1.88	1.06
25	$20,785	$20,760	$36,750	$36,724	1.77	1.77	1.00
26	$21,736	$22,631	$37,359	$41,356	1.90	1.83	1.11
27	$24,948	$26,198	$40,026	$55,357	2.22	2.11	1.38
28	$31,382	$30,433	$43,246	$137,725	4.39	4.53	3.18
29	$29,841	$27,752	$42,610	$131,300	4.40	4.73	3.08
30	$29,562	$25,724	$41,643	$79,756	2.70	3.10	1.92
31	$27,011	$24,435	$40,601	$57,303	2.12	2.35	1.41
32	$25,800	$24,303	$40,556	$52,190	2.02	2.15	1.29
33	$25,516	$24,697	$40,647	$55,237	2.16	2.24	1.36
34	$24,019	$22,723	$39,212	$50,187	2.09	2.21	1.28
35	$22,507	$21,660	$42,078	$45,839	2.04	2.12	1.09
36	$20,699	$20,403	$38,627	$36,134	1.75	1.77	0.94
37	$13,627	$13,721	$25,543	$38,353	2.81	2.80	1.50
38	$12,562	$12,160	$23,182	$28,775	2.29	2.37	1.24
39	$15,205	$13,586	$24,932	$37,505	2.47	2.76	1.50
40	$13,190	$12,458	$24,156	$33,421	2.53	2.68	1.38
41	$12,644	$12,472	$24,214	$34,303	2.71	2.75	1.42
42	$11,513	$11,261	$22,724	$30,277	2.63	2.69	1.33
43	$12,626	$10,889	$21,325	$29,802	2.36	2.74	1.40
44	$10,443	$9,870	$18,996	$24,668	2.36	2.50	1.30
45	$8,778	$8,634	$17,387	$20,488	2.33	2.37	1.18
46	$7,749	$7,643	$15,730	$16,808	2.17	2.20	1.07
47	$6,793	$6,230	$14,267	$12,947	1.91	2.08	0.91
48	$5,967	$5,473	$13,286	$10,529	1.76	1.92	0.79

presents the ratio of best-response pricing profits at half of current contract quantities over the best-response pricing profits at current contract levels. Although the last column shows certain load periods where profits will fall because of reduced contract quantities, the increased average profits in other load periods more than compensate. The ratio of variable profits over all load periods for half of current contract quantities relative to variable profits over all load periods at current prices, quantities and contract levels is 2.34. The ratio of variable profits over all load periods with best-response pricing and one-half current contract levels in the numerator and variable profits over all load periods with best-response pricing and current contract levels in the denominator is 1.35. These results illustrate the significant potential increases in expected profits possible from reductions in the level of contract cover. The same downside mentioned above applies to these results as well. Period-level variable profits are significantly more volatile when the amount of contract cover is reduced. It is a worthwhile empirical question to determine whether a reduced level of contract cover combined with allowable best-response bidding would yield these same levels of profit increases.

Although I do not have information on the hedge contract position of other firms in the market there are several rules of thumb that can be used to estimate the hedge contract position of other major firms in this market. One such rule is to take the total capacity of all bids submitted below a given price as the contract quantity and the bid-quantity weighted price at which these bids are submitted as the contract price. I computed estimates of PC and QC for each load period for several of the other major participants in this market for values of this price bound at 20 $AU/MWH and 25 $AU/MWH. Using these values of PC and QC and similar estimates of the magnitude of the marginal cost of generation, I repeated my best-response pricing analysis. For these firms I found similar ratios of the average of best-response pricing profits to actual profits (assuming my estimated level of contract hedging and marginal costs of generation) to those obtained for Firm A. This result suggests that all major participants are employing bidding strategies which achieve close to best-response pricing profits.

7. WHY NEM1 FIRMS SELL SO MANY HEDGE CONTRACTS

Although the previous section shows that there appears to be some opportunities for increased profits to Firm A and other major participants from modifying the bidding strategies given their current contract positions, the difference between their current level of profits and the best-response pricing profits for these firms are not so large that one could claim that these firms are bidding in an irrational manner. Nevertheless, during this period extremely low market prices are being set, many below the presumed marginal cost of generation of these participants. As noted above it also is an open question whether a feasible bidding strategy can yield significantly higher profits than Firm A's current strategy, given it present hedge contract prices and quantities. The computations reported in Section 6 illustrate that reductions in the level of Firm A's contract cover can significantly increase the variable profits it can obtain from setting best-response prices. Similar results were achieved for this same analysis for the other major players in this market. However, as shown in Section 3, the extent to which reductions in contract cover will increase best-response pricing profits is determined by the elasticity of each firm's residual demand. For Firm A, this elasticity depends on the aggregate supply function of all generators besides Firm A. Similar logic applies to all other generators in the NEM1 market–the price elasticity of the residual demand that these generators face determines the extent to which best-response pricing by them will yield higher average prices from the electricity pool. The logic of the previous sections shows that the level of contract cover held by all generators rationalizes the very low prices since the beginning of NEM1.

From conversations with several market participants, there appears to be general agreement among the parties involved that the current low electricity prices in NEM1 are caused by the high levels of contract cover sold by the large generators serving this market. For the majority of days in the sample, Firm A sells less electricity than it has contract cover for. As Figures 2 and 3 show, the best-response price for a generator in this position is less than its marginal cost of production. Consequently, given the very high level of contracting of Firm A and its major competitors, it is rational for each of these firms to bid very aggressively into the pool in order to dispatch as much of their capacity as possible. This bidding strategy will yield very low pool prices, which are desired so long as the actual amount capacity dispatched is less than the firm's contract cover for that half-hour.

Given this set of circumstances, one question immediately arises: How did the major generators get themselves in a situation where aggressive bidding and low prices yield the maximum profits possible? Stated differently: Why did the generators sign contracts for such a large fraction of their capacity? A complete answer to this question involves some speculation, but the analysis of the previous section can contribute to an answer. Clearly, a major factor in the decision of the large generators to sign these contracts is excess generation capacity to serve both the VPX and NSW SEM. Even in the absence of contract cover being held by any participants, the large amount of capacity available to serve each state market relative to that state's demand in the vast majority of half-hours of the year implies that all generators face a significant probability all of their capacity will not be dispatched if they do not bid aggressively. If generators believe their competitors face these sorts of incentives, then they must in the language of Section 3 perceive themselves as facing very price-elastic residual demand functions for their output. Under these conditions, generators will find signing a contract that fixes the price for a certain quantity of electricity extremely attractive, so long as the contract price is higher than the generator's marginal cost of producing electricity. This follows from the analysis comparing the difference in best-response prices with a flat residual demand curve (aggressive bidding by competitors) given in Figure 4 to the steeper residual demand curve (less aggressive bidding by competitors) given in Figure 1.

Recall that a firm faces a virtually horizontal residual demand curve if its competitors bid very aggressively. This desire to sign contracts is particularly strong if the generator is risk averse, despite the fact that the expected value of the uncertain profit stream greatly exceeds the certain income stream. For a variety of reasons, one would expect a government-owned corporatized entity to be significantly more risk-averse than a privately-owned company. In fact, if a generator manages to sign contracts that exactly match the amount of electricity its manages to sell into the pool, that generator has a certain profit stream that is independent of the pool price of electricity. To see this result, re-write equation (2):

$$\pi(p) = DR(p)(p - MC) - (p - PC)QC \tag{6}$$

Setting $DR(p) = QC$ and solving for p, yields $\pi(p) = (PC - MC)QC$. At the market price that causes Firm A sell an amount equal to its contract quantity, its profits depend only on its contract price and quantity for that load period and its marginal cost of production. Its profits are completely insulated from fluctuations in the market clearing price. In fact, it can be shown that the best-response price subject to the constraint that Firm A produces its contract quantity is equal to its marginal cost. This appears to be the contracting strategy pursued by several major participants in this market.

This low-risk contracting and bidding strategy can have dire longer-term consequences if very low market prices are necessary for the generator to sell all of its contract quantity. These low prices cause purchasers of contracts to form expectations of very low future prices, which makes it difficult for the generator to sell future hedge contracts at prices above its marginal cost. If all generators decide to pursue this strategy, the results can be even more troublesome for the reasons discussed in Section 4. A very aggressive bidding strategy leaves a firm's competitors with very price-elastic residual demands. These very price elastic residual demands, by the logic of Figure 1 and Figure 4, increase the incentive for these other generators to sell more contract cover. Once these firms sell more contract cover, they will have an incentive to bid more aggressively into the electricity market, which leaves other generators with more price-elastic residual demands. Given these more price-elastic residual demands, the above process now repeats itself, leading to even more contracting and even lower prices.

The presence of excess generation capacity and risk-averse generating companies has contributed to the current low prices in NEM1. This statement seems to indicate that reducing the amount of excess capacity in the market can lead to higher prices. However, this capacity reduction strategy will only work if in response the generators to find it optimal to contract less, which in turn causes them to bid less aggressively. This less aggressive bidding will then lead to higher prices. Withdrawal of capacity from the market by Firm A can have these desired effects, but the bottom line is still that for all generators' best reply prices to be above their marginal costs, they must sell less contract cover than they produce in electricity. If Firm A were to reduce its capacity without changing its contract cover, so long as this capacity reduction did not prevent it from selling its best-response quantity in each load period, its optimal bidding strategy would be unaffected by this reduction in capacity and market prices should remain the same.

To understand this logic, consider the expression for the half-hourly profits earned by Firm A as a function of the market price. As shown earlier, half-hourly profits can be re-written as:

$$\pi(p) = (DR(p) - QC)(p - MC) + (PC - MC)QC. \tag{7}$$

The advantage of this expression for half-hourly profits is that the second term, $(PC - MC)QC$, is fixed from the perspective of the pool price setting process. This term is the profit that the generator earns from its contracts. Note that if the amount the generator sells to the pool at price p, $DR(p)$, is less than the contract cover, QC, the generator loses money on this process, unless the market price is below the generator's marginal cost of production. Consequently, if the residual demand faced by Firm A does not change, meaning that if other generators do not alter their bidding strategies, then reducing the amount of capacity Firm A holds will have no effect on its optimal bidding strategy, so long as Firm A is left with capacity greater than $DR(p)$ for all feasible values of p. Only changes in a firm's contract quantity will cause its best-response price to change. Therefore, any reduction in the amount of capacity bid into the market must be accompanied by a reduction in the amount of contract cover for this capacity reduction to have any direct effect on a firm's optimal bidding strategy.

How much of a reduction in contract cover is optimal depends on the risk tolerance of the firm. The combination of less aggressive bidding by Firm A and its competitors will lead to higher prices on average, and significantly higher average profits but significantly higher volatility in profits. Higher profit volatility will come about because a larger fraction of generation output will be sold at pool prices relative to contract prices.

A final reason for the large amount of hedge contracts held by Firm A is the relatively large amount of vesting contracts outstanding during this time period. Under the rules of the NSW and Victoria markets, generators in these markets were required to sell to retail suppliers of electricity hedge contracts in sufficient quantity to cover the forecast load of non-contestable, or captive, customers served by these retailers. Non-contestable customers are prohibited from choosing their retailer. They must purchase electricity from the incumbent local retailer. The prices of these vesting contracts are set by the state government at fairly generous levels relative to current prices in the wholesale market. Given the relatively small number of contestable customers in the NSW and Victoria market during the sample period, these vesting contracts were a very large fraction of the quantity of hedge contracts held by all generating companies.

8. MARKET DESIGN IMPLICATIONS AND DIRECTIONS FOR FUTURE RESEARCH

This analysis has yielded several results. First, a detailed analysis of the impact of the level of contracting on a firm's best response-prices was presented. Here I found that if a firm sells less electricity than it has contract cover, then its best-response prices are less than its marginal cost of production. If the amount of over-contracting is sufficiently great, then best-response prices can be negative (if market prices are allowed to be negative) or zero (if the market rules prohibit negative prices). I also showed that although the best-response price with some level of contract cover is below the best-response price with no contract cover, depending on the price-elasticity of the residual demand function that the firm faces, the quantity of electricity sold with contract cover can be significantly larger than that without contract cover. The price elasticity of the residual demand faced by a firm depends on the aggressiveness of its competitors' bids. In those instances when a firm faces a price-elastic residual demand, this difference in sales with and without contracting can be very large. If the firms faces a less price-elastic demand, this difference is smaller. In this sense, a firm has a greater incentive to sell contracts if it faces a price-elastic residual demand.

My model of the price-setting process in NEM1 which uses the actual bids submitted, inter-market transfers and average half-hourly market demand is able to replicate quite closely both the observed prices and variable profit levels actually achieved. Using this model of the price-setting process, I then computed best-response prices for Firm A and compared the profits it would achieve under these prices versus those obtained under their current bidding strategy. Depending on the assumptions made about Firm A's marginal cost of production, my predicted increase in profits from best-response pricing taken over all load periods in my sample ranged from 11 percent to 17 percent relative to their profits under current prices and contracting levels.

I also analyzed the impact of different contracting strategies on Firm A's best-response prices. I found that the case of zero hedge contracts yielded dramatically increased average prices and profits, but significantly greater volatility in both prices and profits across load periods. I then considered an intermediate case of one-half current contracting levels and current contract prices. Best-response pricing with this level of contracting yielded 134% higher variable profits than those at current prices and contracting levels. These results are indicative of the increased variable profits possible from reductions in contract quantities.

Using several rules of thumb to estimate the contract quantities of other major participants in the market, I repeated the best-response pricing profits to actual profits comparison and the reduced contract best-response pricing profits to current profits comparison. This analysis yielded similar quantitative increases in variable profits from best response-pricing at current contract levels to those obtained for Firm A. I also found variable profits increases from reduced contracting levels and best-response pricing relative current profit levels for these firms similar to those found for Firm A. Finally, I considered various strategies for achieving higher market prices. The results in Section 7 show that without a reduction in its contract quantity, a firm's best-response prices will not change. Consequently, its optimal bidding strategy would not change.

These results have several implications for the design of competitive electricity markets. Most re-structuring processes around world have imposed a large quantity of vesting contracts between electricity retailers and generators on these two classes of market participants. These are legally binding hedge contracts at prices and quantities set by the government regulator. This analysis shows that if the vesting contract quantity is a large enough fraction of each firm's expected sales into the market, this can cause firms to find it optimal to bid to achieve low prices. Consequently, if one is concerned about the exercise of market power in a re-structured electricity market, then effective price regulation can be imposed by forcing a large enough quantity of hedge contracts on the newly privatized generators. It is an open question what the optimal sequence is for reducing the levels of these vesting contracts over time and how the prices of the these contracts should change as their level is reduced.

The framework outlined here can be used to analyze a variety of issues in the design of competitive electricity markets. One extension currently underway is solution of the best-response bidding strategy given in (3) and a comparison of the expected profits levels that can be obtained from it to the those from best-response pricing and the current bidding strategy. Another extension is to formulate a Nash equilibrium in best-response bidding strategies in order to analyze the impact of changes in the constraints on bidding strategies on the market prices obtained.

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