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ABSTRACT

This paper presents several techniques for recovering cost function estimates for electricity generation from a model of optimal bidding behavior in a competitive electricity market. Two techniques are developed based on different models of the price-setting process in a competitive electricity market. The first assumes that the firm is able to choose the price that maximizes its realized profits given the bids of its competitors and the realization of market demand. This procedure is straightforward to apply, but does not impose all of the market rules on the assumed price-setting process. The second procedure uses the assumption that the firm bids to maximize its expected profits. This procedure is considerably more complex, but can yield more insights about the nature of the firm's variable costs, because it allows the researcher to recover generation unit-level variable cost functions. These techniques are applied to bid, market outcomes and financial hedge contract data obtained from the first three months of operation of the National Electricity Market (NEM1) in Australia. The empirical analysis illustrates the usefulness of these techniques in measuring actual market power and the ability to exercise market power possessed by generation unit owners in competitive electricity markets.

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1. Introduction

This paper presents several techniques for recovering cost function estimates for electricity generation from a model of optimal bidding behavior in a competitive electricity market. These procedures are applied to actual data from the Australian National Electricity Market (NEM1) to recover cost function estimates for a specific market participant. I find close agreement between the cost functions recovered from these procedures and those obtained from engineering estimates. The techniques developed in this paper for recovering cost function estimates are not limited to markets for electricity generation. They can used to recover cost-function estimates for a participant in any bid-based centralized market.

There are number of uses for the procedures developed in this paper. The primary use is to measure the extent of market power possessed by a market participant using only bid information and market-clearing prices and quantities.. A major research effort in empirical Industrial Organization is the measurement of market power. Bresnahan (1989) summarizes much of this research, although there has been an explosion of recent research on this general topic. The techniques presented in this paper are a logical extension of the techniques described by Bresnahan (1989) to bid-based markets.

A major challenge for designers of competitive electricity markets is devising market rules which limit the ability of generation unit owners to exercise market power. Market power is the ability of a firm owning generation assets to raise the market price by its bidding behavior and to profit from this price increase. Until the recent trend toward industry restructuring electricity was supplied by vertically-integrated geographic monopolies regulated by state public utilities commissions in U.S. or goverment-owned national or state monopolies in other countries around the world. All of the industry characteristics that led to this market structure make competitive markets for electricity generation ripe for the exercise of market power. Electricity is extremely costly to store, there are binding short-run capacity constraints on its production, and demand must equal supply throughout the electricity grid at every moment in time. In addition, because of the manner in which electricity was sold to final customers during the former vertically-integrated regime, the retail demand for electricity is very price inelastic on hour-ahead and even day-ahead time horizons. These features of the electricity production process and the insensitivity of retail demand to wholesale price fluctuations allow small defects in market design to enhance significantly the ability of generation unit owners to exercise market power.

For this same reason, seemingly innocuous changes in market rules can exert a large impact on market outcomes. Consequently, market design is an extremely important aspect of the ongoing industry restructuring process. All markets currently operating in the U.S. have in place an interactive process where independent regulatory bodies and the market monitoring unit within the Independent System Operator (ISO), the entity that operates the wholesale market and transmission grid, study all aspects of market performance in order to detect design flaws which enhance the ability of firms to exercise market power.[1] The next step in this market design process is to devise and implement market rule changes which eliminate these design flaws. Although economic theory plays a major role in the market design process, there are very few empirical methods with a firm foundation in economic theory for analyzing the vast volumes of bid and market outcomes data available to these market monitoring units. This paper develop these sorts of tools and illustrates their use in the market monitoring and design process.

The specific application I consider is estimation of forward market energy positions from spot market bid functions. In virtually all competitive wholesale electricity markets generators and loads

[1]For a comparative discussion of institutions and performance competitive electricity markets, see Wolak (1999).

engage in forward financial or hedge contracts which allow them to fix the price for a specified amount of energy delivered and consumed in real-time.[2] As noted in Wolak (2000), even with knowledge of a firm's bidding behavior in a competitive electricity market, it is difficult, if not impossible, to determine if the firm is able to exercise market power without knowing the generation unit owner's forward contract position. For a specific bid function and marginal cost function, there is a portfolio of forward financial contracts that can rationalize that bid function as expected profit-maximizing given that marginal cost function. Wolak (2000) also demonstrates the enormous influence a generation unit owner's financial contract position has on its incentive to bid to attempt to increase the market-clearing price in the spot electricity market. Consequently, a technique for estimating a market participant's hedge contract or forward market position from bids submitted to a spot market can allow a market monitor to determine more precisely when the generation unit owner is likely to possess significant market power.

The remainder of the paper proceeds as follows. The next section relates this research to the general literature in empirical Industrial Organization on measuring market power using data on market-clearing prices and quantities. This section discusses the gain in econometric identification of the underlying cost function that results from using bids in addition to market-clearing prices and quantities in the estimation process. Section 3 presents a model of optimal bidding behavior with hedge contracts for a generic competitive electricity market. This section defines 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*

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[2] Hedge contracts are usually signed between a generating company and an electricity retailer. This 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 this same price difference times the contract quantity to the seller.

price as the market-clearing price that maximizes the realized profits of the firm given the bids actually submitted by its competitors, the realized value of the stochastic shock to the price-setting process, and its current hedge contract position. Both of these concepts are used to derive estimates of the cost function for a bidder in a competitive electricity market using actual bid information and market outcomes.

Section 4 presents our estimation methodology based on the best-response price concept. Section 5 presents our methodology based on the best-response bidding strategy. Section 6 then describes the essential features of the Australian National Electricity Market and the dataset used in our empirical analysis. Section 7 presents the results of our empirical analysis. Section 8 describes how these techniques might be used in the market design process and discusses directions for future research.

2. Identifying Marginal Cost Functions from Bids and Market Prices and Quantities

Beginning with Rosse (1970), empirical Industrial Organization (IO) economists have devised estimation procedures to recover cost functions from data on market-clearing prices and quantities. Rosse used a sample of monopoly local newspapers and the assumption of profit-maximization to estimate the underlying marginal cost function of the monopolists. Porter (1983) employed a related approach in his study of price wars in the U.S. railroad industry during the 1880s. He assumes a firm-level, homogeneous product, quantity-setting conjectural variation oligopoly equilibrium. He aggregates the firm-level first-order conditions to produce an industry-wide cost function which he jointly estimates along with an industry-level demand function. Bresnahan (1981 and 1987) quantifies the extent of market power possessed by each vehicle model in the U.S. automobile industry using a discrete choice differentiated products model of individual demand with vertical product differentiation in the unobserved product quality dimension. Aggregating these discrete purchase decisions across U.S. households, yields an aggregate demand system for all automobile models. Bresnahan assumes Nash/Bertrand competition among the automobile makers facing this aggregate demand system to estimate the implied marginal cost of producing automobiles of each quality level. More recently Berry (1994), Berry, Levinsohn and Pakes (1995) and Goldberg (1995) have extended the techniques pioneered by Bresnahan to discrete choice oligopoly models with horizontal product differentiation.

The basic idea of all of the techniques described above can be illustrated using the following example which follows from the intuition given in Rosse (1970). Let $P(q,W,\theta,\epsilon)$ denote the inverse demand function facing a monopolist and $C(q,Z,\theta,\eta)$ its total cost function. The variables W and Z are demand and cost function shifters, respectively. θ is the vector of parameters to be estimated, and ϵ and η are unobserved, to the econometrician, stochastic shocks. These shocks are assumed to be observable to the monopolist. The profit function of the monopolist is:

$$\pi(q) = P(q,W,\theta,\epsilon)q - C(q,Z,\theta,\eta) \tag{2.1}$$

The first-order condition for profit-maximization are:

$$\pi'(q) = P'(q,W,\theta,\epsilon)q + P(q,W,\theta,\epsilon) - C'(q,Z,\theta,\eta) = 0. \tag{2.2}$$

The researcher is assumed to have only market-clearing price and quantity data and the values of the demand and supply shifters, W and Z, for a cross-section of monopolists selling the same homogenous product. The econometrician does not have information on production costs for any of the firms. The researcher could also have a time series of observations on the same information for a one or a small number of monopolists over time. This lack of cost data is the standard case faced by empirical researchers studying unregulated industries, such as automobiles, airlines, and personal computers, a few of the industries where these techniques have been applied. Industry associations or government regulators usually publicly disclose information on market-clearing prices and quantities, but little information on production costs.

In order for the econometrician to make any statement about the extent of market power exercised in this market, he must have an estimate of the marginal cost function, $C'(q,Z,\theta,\eta)$. This estimate is constructed in the following manner. The econometrician first specifies a functional form for the inverse demand function. Suppose he selects $P(q,W,\theta,\epsilon) = a + bq + cW + \epsilon$, where a, b, and c are elements of θ. The parameters of a, b, and c must be estimated by standard instrumental variables techniques to account for the fact that q and ϵ are correlated. This correlation occurs because the observed market clearing quantity is determined by solving the first-order condition for profit maximization given in (2.2). This implies that q^E, the equilibrium quantity, is a function of η and ϵ and the demand and supply shifters, W and Z, so that $q^E = f(W,Z,\eta,\epsilon)$. The market-clearing price is then determined by substituting q^E into the inverse demand function.

Given these estimates for the a, b, and c, the econometrician can then solve for the value of $C'(q,Z,\theta,\eta)$ implied by the first-order conditions for profit-maximization given in (2.2) using the observed market-clearing prices and quantities. Re-arranging (2.2) for the assumed parametric inverse demand function yields:

$$C'(q^E,Z,\theta,\eta) = P'(q^E,W,\theta,\epsilon)q + P(q^E,W,\theta,\epsilon) = bq^E + p^E \tag{2.3}$$

For each value of p^E and q^E, the market-clearing prices and quantities, compute an estimate of the marginal cost, $C'(q^E,Z,\theta,\eta)$, using (2.3). This estimate can then be used to compute an estimate of the amount of market power possessed by the firm in each market, by computing the Lerner index:

$$L = (p^E - C'(q^E,Z,\theta,\eta))/p^E \tag{2.4}$$

Note that in this case, estimates of only the parameters of the demand function are needed to compute an estimate of the Lerner index of market power.

Researchers often select a functional form for $C'(q^E,Z,\theta,\eta)$ and use the implied marginal costs derived from (2.3) to estimate the elements of θ contained in the cost function. An alternative approach, beginning with Rosse (1970), estimates the parameters of the inverse demand and cost function jointly using the assumption of profit-maximization to identify the marginal cost function from observed market-clearing prices and quantities.

The intuition embodied in this example is employed in all of the papers described above. Porter (1983) estimates the aggregate demand function facing the oligopoly that he studies. He makes assumptions on the functional form of costs for each individual firm and the nature of the strategic interaction among firms–cartel or perfect competition–to deliver two aggregate supply functions for the industry under these two behavioral assumptions. Then he jointly estimates these aggregate supply and demand equations as a switching regression model, using the assumption of profit-maximization to identify parameters of the underlying individual cost functions from time series data on market-clearing prices and quantities.

Bresnahan (1987) specifies a discrete-choice demand structure where each individual decides whether to purchase an automobile, and if so, which model. He aggregates this discrete choice demand structure across all consumers to derive a system of aggregate demand equations. Using various assumptions about the nature of strategic interaction–specifically, Nash/Bertrand competition or collusion among automobile producers–he estimates the parameters of this aggregate demand system along with the parameters of the marginal cost functions implied by the first-order conditions associated with profit-maximization. Bresnahan (1981) allows for a richer stochastic specification in the aggregate demand system, but follows the same basic procedure to recover estimates of the marginal cost function.

Berry, Levinsohn and Pakes (1995) allow for a multinomial logit discrete choice demand structure at the consumer level and assume unobservable stochastic consumer-level marginal utilities of product attributes. These marginal utilities are assumed to be independent non-identically normally distributed across of product attributes and independent identically distributed across consumers. Integrating individual-level purchase decisions with respect to these normal distributions yields the aggregate demand system for automobiles estimated by Berry, Levinsohn and Pakes (1995). They also propose a rich stochastic structure to handle the endogeneity of output prices in the aggregate demand system. They propose and implement an instrumental variables estimation technique which jointly estimates the demand system with the marginal cost function under the assumption of Nash/Bertrand competition among automobile producers. In contrast, Bresnahan (1981 and 1987) relied on maximum likelihood techniques.

Goldberg (1995) uses individual household-level data to estimate a general discrete-choice model for automobile purchases at the household-level. She then uses weights giving the representativeness of each these household in the population of U.S. households to produce a system of aggregate demand functions for automobiles based on the choice probabilities implied by her model of household-level automobile demand. Using the assumption of the Nash/Bertrand competition among automobile producers, she then computes implied marginal cost estimates similar to those given in (2.3), which she uses to estimate an marginal cost function for each automobile model.

The most important conclusion to draw from this line of research is that all marginal cost estimates are the direct result of the combination of the assumed functional form for the aggregate demand for the products under consideration and the assumed model of competition among firms. Similar to the example given above, the first-order conditions for profit-maximization and the demand function for each product determines the implied marginal cost for that product. Consequently, a major focus of this research has been on increasing the flexibility and credibility of the aggregate demand system used. However, because supply and demand functions are the econometrician's creation for describing the observed joint distribution of market-clearing prices and quantities across markets, a functional form for the demand curves faced by the oligopolists or the monopoly must be assumed in order to estimate any demand function.

Rosse (1970) and Porter (1983) explicitly make this functional form assumption for aggregate demand. Bresnahan (1981 and 1987) and Berry, Levinsohn and Pakes (1995) assume a functional form for the probabilities that determine individual purchase decisions. They derive the aggregate demand system actually estimated by summing these individual choice probabilities across consumers. Goldberg (1995) specifies a household-level choice model which she estimates using household-level data. The aggregate demand functions entering into her oligopoly model is an appropriately weighted sum of these estimated household-level demand systems across all U.S. households.

3. Models of Best-Response Bidding and Best-Response Pricing

This section shows how the techniques described above can be extended to estimate underlying marginal cost functions using data on bids and market-clearing prices and quantities from competitive electricity markets. Specifically, I demonstrate how the availability of bids allows the econometrician to identify the underlying firm-level cost function purely through an assumption about firm behavior. A functional form assumption for aggregate demand is no longer necessary. I consider two models of optimizing behavior by the firm to recover an estimate of the firm's marginal cost function. The first model makes the unrealistic but simplifying assumption that the firm is able to choose the market-clearing price which maximizes its profits given the bids submitted by its competitors. The second model is more realistic, but entails a significantly greater computation burden. It imposes all of the constraints implied by the market rules on the bids used by the firm to set the market clearing price. The firm is assumed to bid according to the rules of the competitive electricity market to maximize its expected profits. The second approach explicitly imposes the reality that the only way the firm is able to influence the market-clearing price is through the bids it submits.

A first step in describing both of these methodologies is a description of the payoff functions and strategy space for participants in a generic competitive electricity market. Specifically, I will describe the structure of bids and how these bids are translated into the payoffs that a market participant receives for supplying energy into the wholesale electricity market.

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 bid price for the unit and the quantity bid for 48 half-hours during the day.[3] In all existing electricity markets firms have much more flexibility in how they bid their generating facilities. For instance, in the Australian National Electricity Market (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 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. The England and Wales electricity market imposes

[3]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.

similar constraints on the bid functions submitted by market participants. Each genset is allowed to bid three daily price increments and 144 half-hourly quantity increments. Genset owners also submit start-up and no load costs as part of the day-ahead bidding process. Bidders in the California Independent System Operator's real-time electricity market bid 11 price and quantity increments, both of which can vary on an hourly basis.

In order to compute the profit function associated with any set of bids the firm might submit, 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 for all possible bids submitted by them and their competitors and all possible market demand realizations. 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 in the process of estimating cost functions from generator bidding behavior and market outcomes. One of the reasons the methodologies described in this paper may not yield accurate cost function estimates is because model of the price-setting process used does not accurately replicate the actual price-setting process. Wolak (2000) devotes significant attention to demonstrating that model of the price-setting process used accurately reflects the actual price-setting process.

In preparation for the empirical portion of the paper, I will describe the two procedures for the NEM1 in Australia, although the modifications to necessary to apply them to other competitive electricity markets is straightforward. In NEM1, each day of the market, 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

For the moment, I assume that MC, the firm's marginal cost, does not depend on the level of output it produces. For the general case of recovering marginal cost function estimates, I will relax this assumption.

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[4] (profits excluding fixed costs) earned by Firm A for load period i during day d at price p as:

$$\pi_{id}(p) = DR_{id}(p)(p - MC) - (p - PC_{id})QC_{id} \tag{3.1}$$

The first term is the variable profits from selling electricity in the spot market. The generator is assumed to be only a seller of hedge contracts, so the second term, if $p > PC_{id}$, is the total payments made to purchasers of hedge contracts during that half-hour by Firm A. 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 (3.1) can be used to compute the profits for load period i in day d.

Financial hedge contracts impose no requirement on the generator to deliver actual electricity. These contracts are merely a commitment between the seller (usually a generator) and the purchaser (usually a large load or load-serving entity) to make the payment flows described above contingent on the value of the market-clearing price relative to the contract price. However, as discussed in detail in Wolak (2000), a generator that has sold significant quantity of financial hedge contracts will find it optimal to bid more aggressively (to sell a larger quantity of energy in the spot market) than one that has sold little or no hedge contracts. This point can be illustrated by computing the first-order conditions for maximizing (3.1) with respect to p:

$$\pi_{id}'(p) = DR_{id}'(p)(p - MC) - (DR_{id}(p) - QC_{id}) = 0. \tag{3.2}$$

Because the residual demand curve is downward-sloping and the firm can only produce a non-negative quantity of electricity ($DR_{id}(p) \geq 0$), the price that solves (3.2) when $QC_{id} > 0$ is smaller than the price that solves (3.2) when $QC_{id} = 0$. This result implies that the firm produces a larger amount of energy when $QC_{id} > 0$ than it does when $QC_{id} = 0$. Figure 1 from Wolak (2000) gives a graphical

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

presentation of this logic. The first-order condition (3.2) shows that the contract price, PC_{id}, has no effect on the firm's profit-maximizing market-clearing price or output quantity. The level of the contract price simply determines the magnitude of the transfers which flow between the buyer and seller of the hedge contract. Wolak (2000) discusses the implications of this result for the design of financial contracts for mitigating market power in spot electricity markets.

This discussion demonstrates that another important input into my process for estimating the marginal cost function is the hourly hedge contract position of the firm. Conversely, if I have an accurate estimate of the generator's marginal cost function, then I can use the generator's bidding behavior and market clearing prices and quantities to recover estimates of the generator's hourly forward contract position.

Writing Firm A's profits in this manner illustrates two very important aspects of competitive electricity markets. First, unless a firm is able to move the market-clearing price by its bidding strategy, its profits are independent of its bidding strategy for a given hedge contract quantity and price. Given the market-clearing price, all of the terms in (3.1), the firm's actual variable profit function for load period i in day d, depend on factors unrelated to the bids it submits into the electricity market. Second, the difference between equation (3.1) and the usual oligopoly model profit function is that the residual demand function $DR_{id}(p)$ faced by Firm A is ex post directly observable given the bids submitted by all other market participants besides Firm A. As shown above, the residual demand curve faced by Firm A at each price, p, is simply the aggregate demand function less the aggregate bid curve of all market participants besides Firm A, $DR_{id}(p) = Q_{id} - SO_{id}(p)$.

In the standard oligopoly context, the residual demand faced by each market participant is not directly observable, because the aggregate demand function is not observable ex post. For example, in the Cournot duopoly model, the residual demand curve faced by one firm is simply the market demand, D(p), less the quantity made available by that firm's competitor, $DR(p) = D(p) - q_c$, where q_c is the quantity made available by the firm's competitor. Different from the case of a competitive electricity market, D(p) is not directly observable, so that an estimate of DR(p) cannot be constructed without first econometrically estimating D(p), the market aggregate demand function. In the case of a bid-based market such as electricity, even if load-serving entities could submit price responsive demands, as is currently possible in most competitive electricity markets, the residual demand curve facing any competitor in these markets can be directly computed using all of the bids submitted by all other market participants.

Because this residual demand function can be constructed by the econometrician using bid data, there is no need to make a functional form assumption for the demand curve the bidder faces in order to compute its implied marginal cost for any level of output. Given a model for the price-setting process in this market and a behavioral model for bidder behavior, implied marginal costs can be constructed for each observed level of output by Firm A.

This ex post observability of each generator's residual demand function has important implications for designing competitive electricity market. Because the price elasticity of the residual demand curve faced by a bidder determines the extent of market power that it is able to exercise, the goal of the market design process is to face all bidders with a perfectly price elastic residual demand functions. Under these circumstances, no generator possesses market power. However, the residual demand curve faced by one market participant depends on the bids submitted by all other market participants. Therefore aggressive bidding (very price-elastic bid supply functions) by a firm's competitors will leave it with a very elastic residual demand. This will cause the firm to bid very aggressively. This aggressive bidding will leave its competitors with elastic residual demand curves which will cause them to bid more aggressively. This sequence of self-reinforcing aggressive bidding also works in the opposite direction to reinforce less price-elastic bidding. Consequently, a very important aspect of the market design process is putting in place very strong incentives for aggressive spot market bidding. As discussed in Wolak (2000a) signing up generators for forward financial contracts is one way to accomplish this.

I now introduce our two models of optimal bidding behavior which form the basis for the two procedures for recovering marginal cost estimates from bid data. 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 uncertainty could be due to the fact that it does not exactly know the form of SO(p)–this function has a stochastic component to it–or it does not know the market demand used in the price-setting process when it submits its bids–Q is only known up to an additive error. Because I am not solving for an equilibrium bidding strategy, I do not need to be specific about the sources of uncertainty in the residual demand that Firm A faces. Regardless of the source of this uncertainty, Firm A will attempt to maximize profits conditional on the value of this uncertainty if the firm can observe it, or expected profits computing using the distribution of this uncertainty.

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 $DR_i(p,\epsilon_i)$. Define

$$\Theta = (p_{11},..., p_{JK}, q_{1,11},...,q_{11,JK}, q_{2,11},...,q_{2,JK}, ..., q_{48,11},...,q_{48,JK}) \qquad (3.2)$$

as the vector of daily bid prices and quantities submitted by Firm A. There are K increments for each of the J gensets owned by firm A. The rules of the NEM1 market require that a single price, p_{kj}, is set for each of the k=1,...,K bid increments for each of the j=1,...,J gensets owned by Firm A for the entire day. However, the quantity, q_{ikj} made available to produce electricity in load period i from each of the k=1,...,K bid increments for the j=1,...,J gensets owned by Firm A can vary across the i=1,...,48 load periods throughout the day. In NEM1, the value of K is 10, so the dimension of Θ is 10J + 48×10J. 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 $p_i(\epsilon_i, \Theta)$, 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 $DR_i(p,\epsilon_i) = SA_i(p,\Theta)$. Let $f(\epsilon)$ denote the probability density function of $\epsilon = (\epsilon_1, \epsilon_2,..., \epsilon_{48})'$. Define

$$E(\Pi(\Theta)) \quad \int_0^{\infty}...\int_0^{\infty} \sum_{i\;1}^{48} [DR_i(p_i(e_i,\Theta))(p_i(e_i,\Theta) \quad MC) \quad (p_i(e_i,\Theta) \quad PC_i)QC_i]f(e)de_1...de_{48} \tag{3.3}$$

as the expected profits to Firm A for the daily bid vector Θ.

Firm A's best-reply bidding strategy is the solution to the following optimization problem:

$$\max \; E(\Pi(\Theta)) \text{ subject to } b_U \geq R\Theta \geq b_L. \tag{3.4}$$

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. 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. Wolak (2000b) computes this optimal bidding strategy for one market participant in the Australian electricity and compares actual market outcomes to the those that would exist under this optimal bidding strategy.

At this point it is useful to compare the optimal bidding strategy problem given in (3.4) to 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 (3.1) with the residual demand function for load period i that includes the shock for period i as:

$$\pi_{id}(p, \epsilon_i,) = DR_{id}(p, \epsilon_i,)(p - MC) - (p - PC_{id})QC_{id}. \tag{3.5}$$

Solving for the value of p that maximizes (3.5) yields $p_i^*(\epsilon_i)$, which is the profit-maximizing market clearing price given that Firm A's competitors bid to yield the residual demand curve, $DR_{id}(p,\epsilon_i,)$, 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 $DR_{id}(p,\epsilon_i,)$ 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 $DR_{id}(p_i^*(\epsilon_i),\epsilon_i,)$. 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 tracing out the price/quantity pairs $(p_i^*(\epsilon_i), DR_{id}(p_i^*(\epsilon_i), \epsilon_{i,}))$ 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 (1996) 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 $p_i^*(\epsilon_i)$ 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 $p_i^*(\epsilon_i)$. Determining the types of restrictions to put on the set feasible bidding strategies to yield to lowest possible market prices from firms competing using strategies from these restricted strategy sets is a important area for future research.

Best-response prices must yield the highest profits, followed by best-response bidding, because the former is based on the realization of ϵ_i as shown in (3.5), whereas the latter depends on the distribution of ϵ as shown in (3.3). The expected value of the generator's actual profits can only be less than or equal to the expected value of the best-response bidding profits. Recall that by definition, the best-response price, $p_i^*(\epsilon_i)$, 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 (3.3) for the expected profit-maximizing vector of allowable daily bid prices and quantities, Θ^* , yields 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 contract hedge 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. Wolak (2000b) shows that a significant fraction of the difference between the actual variables profits earned by a firm in the Australian electricity market and the profits that it would earn from best-reply prices is due to the fact that the market rules constrain the ability of the firm to achieve $p_i^*(\epsilon_i)$ for every realization of ϵ_i using a bidding strategy that respects the NEM1 market rules. In addition, given the high-dimensional strategy space available to Firm A, Wolak (2000b) also shows 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 the optimization problem (3.4).

4. Recovering Cost Function Estimates from Best-Response Prices

This section describes a procedure for recovering marginal cost estimates based on our model of best-response pricing. This model can also be used to recover estimates of generator's forward hedge contract position. Doing this requires defining additional notation. Let C(q) denote the total variable cost associated with producing output level q. Rewrite the period-level profit function for Firm A in terms of this general variable cost function as:

$$\pi(p) = DR(p,\epsilon)p - C(DR(p,\epsilon)) - (p - PC)QC. \tag{4.1}$$

To compute the best-reply price associated with this realization of the residual demand function, $DR(p,\epsilon)$, differentiate (4.1) with respect to p and set the result equal to zero:

$$\pi'(p) = DR'(p,\epsilon)(p - C'(DR(p,\epsilon))) + (DR(p,\epsilon) - QC) = 0 \tag{4.2}$$

This first-order condition can be used to compute an estimate the marginal cost at the observed market-clearing price, p^E, by solving equation (4.2) for

$$C'(DR(p^E,\epsilon)) = p^E - (QC - DR(p^E,\epsilon))/DR'(p^E,\epsilon). \tag{4.3}$$

$DR(p^E,\epsilon)$ can be directly computed using the actual market demand and bid functions submitted by all other market participants besides Firm A. The market clearing price, p^E, is directly observed. I also assume that QC is observed. Computing $DR'(p^E,\epsilon)$ is the only complication associated with applying (4.3) to obtain an estimate of the marginal cost of Firm A at $DR(p^E,\epsilon)$.

For markets such as the California Power Exchange, where bidders submit piecewise linear functions starting at the point (0,0) in price-quantity space and ending at (2500,x) for any positive value of x they choose, the residual demand function facing any market participant is a piecewise linear function. Consequently, except at the points where two linear functions join, $DR'(p^E,\epsilon)$, is a well-defined concept. However, for most competitive electricity markets, bidders submit step-functions rather than piecewise linear functions. Consequently, strictly speaking $DR'(p^E,\epsilon)$ is everywhere equal to zero. However, because of the large number of bid increments permitted for each generating facility in the Australian market–ten per generating unit–and the close to 100 generating units in the Australian electricity market, the number of steps in the residual demand curve facing any market participant is very large. In addition, because of the competition among generators to supply additional energy from their units, there are usually a large number of small steps in the neighborhood of the market-clearing price. Nevertheless, some smoothness assumption on $DR(p,\epsilon)$ is still needed to compute a value for $DR'(p^E,\epsilon)$ to use in equation (4.3).

I experimented with a variety of techniques for computing $DR'(p^E,\epsilon)$, and found that the results obtained are largely invariant to the techniques I considered. One technique approximates $DR'(p^E,\epsilon)$ by $(DR(p^E+\delta,\epsilon) - DR(p^E,\epsilon))/\delta$, for values of δ ranging from 10 Australian cents to 1 Australian dollar. Another technique approximates the residual demand function by

$$DR(p) = Q_d - SO_h(p) \tag{4.4}$$

where the aggregate bid supply function of all other market participants besides Firm A is equal to

$$SO_h(p) \quad \sum_{n\ 1}^{N} \sum_{k\ 1}^{10} qo_{nk}\Phi((p\ po_{nk})/h). \tag{4.5}$$

qo_{ik} is the kth bid increment of genset n and p_{nk} is bid price for increment k of genset n, where N is the total number of gensets in the market excluding those owned by Firm A. The function $\Phi(t)$ is the standard normal cumulative distribution function and h is a user-selected smoothing parameter. This parameter smooths the corners on the aggregate supply bid function of all other market participants besides Firm A. Smaller values of h introduce less smoothing at the cost of a value for $DR'(p^E, \epsilon)$ that may be at one of the smoothed corners. This second technique was adopted because it is very easy to adjust the degree of smoothing in the resulting residual demand function. Using this technique results in

$$DR_h(p,\epsilon) \qquad \frac{1}{h}\sum_{n\ 1}^{N} \sum_{k\ 1}^{10} q_{nk}\phi((p\ p_{nk})/h), \tag{4.6}$$

where $\phi(t)$ is the standard normal density function. Using this method to compute $DR'(p^E,\epsilon)$, I can compute $C'(DR(p^E,\epsilon))$ using equation (4.4) for each market-clearing price.

There are variety of procedures to estimate the function C(q) given the C'(q) and q pairs implied by (4.3) applied to a sample of market-clearing prices and generators bids. In the empirical portion of the paper, I present a scatter plot of these (C'(q),q) pairs and one estimate of C(q).

The first-order condition for best-reply pricing can also be used to compute an estimate of the value of QC for that half-hour for an assumed value for C'(q) at that level of output. Re-writing (4.2) yields:

$$QC = (p^E - C'(DR(p^E,\epsilon)))DR'(p^E,\epsilon) + DR(p^E,\epsilon).$$

Different from the case of estimating the generator's marginal function, I expect QC to vary on a half-hourly basis both within and across days. Nevertheless, there are deterministic patterns in QC within the day and across days of the week. In the empirical portion of the paper I quantify the extent to which the half-hourly implied values of QC follow the same deterministic patterns within the day and across days of the week as the actual values of QC.

In concluding this section, it is important to emphasize that this procedure for estimating Firm A's marginal cost is only correct if the firm is somehow to able to obtain best-reply prices in all periods. As shown in Wolak (2000a and 2000b), this not possible because the market rules constrain the ability of generators to set best-reply prices for all realizations from the joint distribution of 48 residual demand functions that Firm A faces each day. Nevertheless, as Section 7 shows, the deviation of actual prices from best-reply prices for Firm A is not so great as to make these calculations uninformative about Firm A's marginal cost function or its half-hourly hedge contract holdings. Given that these calculations are relatively straightforward to perform, I believe that they can be very useful diagnostic tools for market power monitoring and analysis.

5. Recovering Cost Function Estimates from Best-Bidding Strategies

This section uses the assumption of best-reply bidding, or equivalently bidding to maximize expected profits subject to the market rules on feasible bid functions, to recover estimates of genset-level marginal cost functions for Firm A. Imposing all of the bidding rules on the process used to recover the firm's marginal cost function is likely to lead to more accurate estimates, than the method outlined in the previous section. However, this procedure involves significantly more computational effort and econometric complexity. Specifically, I derive a generalized method moments (GMM) estimation technique to recover genset-level cost functions for all of the units bid into the market by Firm A.

Deriving this estimation procedure requires additional notation. Let

$SA_{ij}(p,\Theta)$ = the amount bid by genset j at p price during load period i

$C_j(q,\beta_j)$ = the variable cost of producing output q from genset j

β_j = the vector of parameters of the cost function for genset j

$SA_i(p,\Theta) \quad \sum_{j\;1}^{J} SA_{ij}(p,\Theta)$ total amount bid by Firm A at price p during load period i

In terms of this notation, write the realized variable profit for Firm A during day d as:

$$\Pi_d(\Theta,\epsilon) \quad \sum_{i\;1}^{48} [DR_i(p_i(\epsilon_i,\Theta))p_i(\epsilon_i,\Theta) \quad \sum_{j\;1}^{J} C_j(SA_{ij}(p_i(\epsilon_i,\Theta),\Theta),\beta_j) \quad (p_i(\epsilon_i,\Theta) \quad PC_i)QC_i]$$

where ϵ is the vector of realizations of ϵ_i for i=1,...,48. As discussed above, $p_i(\epsilon_i, \Theta)$, the market-clearing price for load period i given the residual demand shock realization, ϵ_i, and daily bid vector Θ, is the solution in p to the equation $DR_i(p,\epsilon_i) = SA_i(p,\Theta)$. The best-reply bidding strategy maximizes the expected value of $\Pi_d(\Theta,\epsilon)$ with respect to Θ, subject to constraint that all bid quantity increments, q_{ikj}, must be greater than or equal to zero for all load periods, i, bid increments, k, and gensets, j, and that for each genset the sum of bid quantity increments during each load period is less than the capacity, $CAP_{j,}$, of genset j. As discussed earlier, there are also upper and lower bounds on the daily bid prices. However, Firm A's price bids for all bid increments, k, and gensets, j, and days, d, during my sample period are strictly below the upper bound and strictly above the lower bound.

This result allows me to use the first-order conditions for daily expected profit-maximization with respect to Firm A's choice of the daily bid price increments to derive a GMM estimator for the genset-level cost function parameters. For all days. d, the moment restrictions implied by these first-order conditions are:

$$E_{\epsilon}\left(\frac{\partial \Pi_d(\Theta_d,\epsilon)}{\partial p_{kj}}\right) \quad 0 \tag{5.1}$$

for all gensets, j, and bid increments, k. I index Θ by d to denote the fact that there are different values of Θ for each day during the sample period. Equation (5.1) defines the JxK moment restrictions that I will use to estimate the parameters of the genset-level cost functions. The sample analogue of this moment restriction is:

$$\begin{aligned}\frac{\partial \Pi_d(\Theta_d,\epsilon)}{\partial p_{kj}} \quad & \sum_{i\ 1}^{48} [(DR_i(p_i(\epsilon_i,\Theta),\epsilon_i)p_i(\epsilon_i,\Theta) \quad (DR_i(p_i(\epsilon_i,\Theta),\epsilon_i) \quad QC_i) \\ & \sum_{j\ 1}^{J} C_j(SA_{ij}(p_i(\epsilon_i,\Theta)),\beta_j)\left(\frac{\partial SA_{ij}}{\partial p_i}\right)\frac{\partial p_i}{\partial p_{kj}} \quad \sum_{j\ 1}^{J} C_j(SA_{ij}(p_i(\epsilon_i,\Theta)),\beta_j)\frac{\partial SA_{ij}}{\partial p_{kj}}]\end{aligned} \tag{5.2}$$

where p_i is shorthand for the market-clearing price in load period i. Let $\ell_d(\beta)$ denote the JxK dimensional vector of partial derivatives given in (5.2), where β is the vector composed of β_j for j=1,...,J. Assuming that the functional form for $C_j(q,\beta_j)$ is correct, the first-order conditions for expected profit-maximization with respect to daily bid prices imply that $E(\ell_d(\beta^0)) = 0$ where β^0 is the true value of β. Consequently, solving for the value of b which minimizes:

$$\left[\frac{1}{D}\sum_{d\ 1}^{D} \ell_d(b)\right] \left[\frac{1}{D}\sum_{d\ 1}^{D} \ell_d(b)\right] \tag{5.3}$$

will yield a consistent estimate of β. Let b(I) denote this consistent estimate of β, where "I" denotes the fact that the identity matrix is used as the GMM weighting matrix. Ican construct a consistent estimate of the optimal GMM weighting matrix using this consistent estimate of β as follows:

$$V_D(b(I)) \quad \frac{1}{D}\sum_{d\ 1}^{D} \ell_d(b(I))\ell_d(b(I)) \tag{5.4}$$

The optimal GMM estimator finds the value of b that minimizes

$$[\frac{1}{D}\sum_{d\ 1}^{D} \ell_d(b)]\ V_D(b(I))\ ^1[\frac{1}{D}\sum_{d\ 1}^{D} \ell_d(b)]. \tag{5.5}$$

Let b(O) denote this estimator, where "O" denotes the fact this estimator is based on a consistent estimate of the optimal weighting matrix..

Operationalizing this estimation procedure requires computing values for the partial derivative of $SA_{ij}(p,\Theta)$ with respect to p_i and p_{kj} and the partial derivative of $p_i(\epsilon_i, \Theta)$ with respect to p_{kj}. I use the same smoothing technique used in the previous section to compute the derivative of the residual demand function with respect to the market price to compute these partial derivatives. Define $SA_{ij}(p,\Theta)$ as:

$$SA_{ij}^{h}(p) \quad \sum_{k\ 1}^{10} q_{ikj}\Phi((p\ p_{kj})/h), \tag{5.6}$$

which implies

$$SA_{i}^{h}(p) \quad \sum_{j\ 1}^{J}\sum_{k\ 1}^{10} q_{ikj}\Phi((p\ p_{kj})/h). \tag{5.7}$$

This yields the following two partial derivatives:

$$\frac{\partial SA_{ij}}{\partial p_i} \quad \frac{1}{h}\sum_{k\ 1}^{10} q_{ikj}\phi((p\ p_{kj})/h) \quad and \quad \frac{\partial SA_{ij}}{\partial p_{kj}} \quad \frac{1}{h}q_{ikj}\phi((p\ p_{kj})/h). \tag{5.8}$$

The final partial derivative required can be computed by applying the implicit function theorem to the equation $DR_i(p,\epsilon_i) = SA_i(p,\Theta)$. This yields the expression:

$$\frac{\partial p_i(\epsilon_i,\Theta))}{\partial p_{kj}} \quad \frac{\dfrac{\partial SA_i(p_i(\epsilon_i,\Theta),\Theta))}{\partial p_{kj}}}{DR_i\,(p_i(\epsilon_i,\Theta),\epsilon_i) \quad SA_i\,(p_i(\epsilon_i,\Theta),\Theta)}, \tag{5.9}$$

where derivative of residual demand curve with respect to price used in this expression is given in equation (4.6) and the other partial derivatives are given in (5.8). Given data on market clearing prices and the bids for all market participants, Ican compute all of the inputs into equation (5.2). I only need to choose a value for h, the smoothing parameter that enters the smoothed residual demand function and the smoothed bid functions of Firm A. Once this smoothing parameter has been selected, these magnitudes remain constant for the entire estimation procedure.

This final step necessary to implement this estimation technique a choice for the functional form for the marginal cost function for each genset. Firm A owns two power plants. A one power plant has four identical gensets that the firm operates during the sample period. I will refer this facility as Plant 1. The gensets at Plant 1 have a maximum capacity of 660 MW and a lower operating limit of 200 MW.. The other power plant has three identical gensets that the firm operates during the sample period. I will refer this facility as Plant 2. This gensets at Plant 2 have a maximum capacity of 500 MW and a lower operating limit of 180 MW. Because it is physically impossible for a genset to supply energy safely at a rate below its lowest operating limit, I specify a functional form for marginal cost to take this into account. Consequently, I assume following parametric functional forms for our marginal cost functions:

$$C_1'(q,\beta_1) = \beta_{10} + \beta_{11}(q - 200) + \beta_{12}(q - 200)^2 \tag{5.10}$$

$$C_2'(q,\beta_2) = \beta_{20} + \beta_{21}(q - 180) + \beta_{22}(q - 180)^2. \tag{5.11}$$

These functional forms are substituted into (5.2) to construct the sample moment restrictions necessary to construct the objective function I minimize to estimate β. I now turn to summarizing the relevant features of the NEM1 market in Australia necessary to understand our empirical work.

6. 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) State Electricity Market (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 state than the three largest generators in Victoria control of their state.

6.1. Market Structure in NEM1

Restructuring and privatization of the State Electricity Commission of Victoria (SECV) in 1994 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. The new owners are 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 the VPX. 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 U.S. company GPU and renamed GPU-PowerNet.

[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.

In NSW it 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.

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 control 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 1100MW from Victoria to NSW, and 1500MW 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 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).

6.2. 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 period. 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. 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 in flows between the two markets.

6.3. Regulatory Oversight of NEM1

Under NEM1, the Office of the Regulator General in Victoria is responsible oversight of the Victoria Electricity Supply Industry. It set the 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 currently regulates the state transmission grids in the integrated national electricity market. Oversight of distribution companies remains with the two state regulatory bodies.

7. Recovering Implied Marginal Cost Functions and Hedge Contract Quantities

The section presents the results of applying the procedures described in Sections 4 and 5. This required collecting data on generators bids and market outcomes for a time period in which I also have information on the half-hourly values of QC, the quantity of the firm's forward contract obligations. I was able obtain in this information for a market participant in the Australian market for the period May 15, 1997 to August 24, 1997. As discussed earlier, a major source of potential error in our analysis is the possibility that I have not adequately modeled the actual price-setting process in the Australian electricity market. Wolak (2000a, Section 5) devotes significant attention to comparing different models of the half-hourly prices-setting procedure to determine which one does the best job of replicating observed half-hourly prices. This analysis found that the process I use in this paper–setting the half-hourly price equal to the price necessary to elicit sufficient supply from the aggregate half-hourly bid supply curve to meet the half-hourly market demand–replicates actual prices with a sufficient accuracy.

I first compute implied marginal cost estimates using bid data submitted by Firm A's competitors, actual market prices, and total market demand. To given some idea of the range of residual demand curves faced by Firm A within the same day, Figures 1 and 2 plot the actual ex post residual demand curve faced by Firm in a representative low total demand period and high total demand period for July 28, 1997. These curves have been smoothed using the expression for the residual demand curve given in (4.4) and (4.5), using a value of $h = 1$ \$AU. These curves confirm the standard intuition that Firm A possesses greater opportunities to exercise its market power during high market demand periods as opposed to low market demand periods. At every price level, Firm

A faces a significantly higher residual demand during the high demand load period than in the low demand load period. We use value of h used to plot these figures for all of the results reported in this section. Repeating these results for values of h = 10 \$AU and 0.10 \$AU did not alter any of the conclusions reported below.

Figure 3 is a plot of the marginal cost and associated output demanded pairs, $(C'(DR(p^E,\epsilon)),DR(p^E,\epsilon))$, for all values of p^E, the half-hourly market-clearing price. The figure also plots the predicted values from the following cubic regression of the implied marginal cost, $C'(q)$, on q, the associated implied output of Firm A:

$$C'(q) = a + b\,q + c\,q^2 + dq^3 + \eta.$$

Table 1gives the results of this implied marginal cost regression. Although there is a considerable amount of noise in the sample of implied marginal cost and output pairs, the regression results are broadly consistent with the magnitudes of marginal costs implied by the heat rates and fuel prices of the facilities owned by Firm A. In particular, in discussions with the management of Firm A, they confirmed that their best estimates of their own marginal costs fluctuate between 15 \$AU/MWh and 10 \$AU/MWh.

I now examine the accuracy of my procedure for estimating the half-hourly values of QC. This process requires selecting values for the marginal cost at any given output level. Consistent with the usual circumstances one is likely to face in market monitoring, I assume the form of the generator's cost function is unknown. Therefore, I perform this procedure assuming a rough estimate of the firm's marginal cost function. I assume a constant value for the marginal cost for all levels of output. More sophisticated marginal cost functions can be assumed, but the results with constant marginal cost should be the most informative about usefulness of this technique in market monitoring, because more accurate information on generating unit heat rates and output rates are generally unavailable. The two values of MC, the fixed level of marginal cost I selected bound the fitted marginal cost curve given in Figure 3. These values are 10 $AU/MWh and 15 $AU/MWh. Figures 4 and 5 plot the implied half-hourly values of QC and the associated actual half-hourly values of QC for MC equal to 10 $AU/MWh and 15 $AU/MWh, respectively. Both of the graphs also have a graph of the line QC(implied) = QC(actual) to illustrate visually how closely my procedure tracks the desired relationship between these two magnitudes. Both values of the marginal cost show a clear positive correlation between QC(implied) and QC(actual), although the consistency with the desired relationship seems greatest for an MC equal to 10 $AU/MWh.

The values of QC(actual) vary on a half-hourly basis within the day and across days. However, there are still systematic patterns to these changes within the day and across days. On average, QC(actual) is higher on weekdays than weekends and higher during the peak hours of the day than the off-peak hours of the day. Consequently, another way to determine the usefulness of my procedure is to see if it captures the systematic variation in the values of QC(actual) within the day and across days of the week. To do this I estimate the following regression for both QC(actual) and QC(implied) for all load periods, i=1,...,48, and days, d=1,...,D:

$$QC(J)_{id} \quad \alpha \quad \sum_{m\ 1}^{3} \rho_m DMN(m)_{id} \quad \sum_{p\ 1}^{6} \gamma_p DWKD(p)_{id} \quad \sum_{r\ 1}^{47} \psi_r DPD(r)_{i,d} \quad \nu_{id},$$

where $DMN(m)_{id}$ is a dummy variable equal to one when day d is in month m and zero otherwise, $DWKD(p)_{id}$ is a dummy variable equal to one when day d is on day-of-the week p and zero otherwise, and $DPD(r)_{id}$ is dummy variable equal to one when load period i is in load period-within-the-day r and zero otherwise. I compute estimates of the ρ_m, γ_p and ψ_r for both QC(actual) and QC(implied), by estimating (7.1) by ordinary least squares. Table 2 reports the results of this estimation for QC(implied) with MC set equal to 10 $AU/MWh. Figures 6 and 7 plot estimated values of γ_p (p=1,...,6) and ψ_r (r=1,...,48) for QC(implied) with MC equal to 10 $AU/MWh and for QC(actual). The first value of γ_p is associated with Sunday and the excluded day of the week is Saturday. The first value of ψ_r is the half-hour beginning at 4:00 am and ending at 4:30 am and the excluded load period is the one beginning at 3:30 am and ending at 4:00 am the following day. These figures show a remarkable level of agreement between the deterministic part of their respective within-day and across-day variation. These results provide strong evidence that even applying our procedure using this crude assumed marginal cost function, yields a considerable amount of information about the level and pattern of forward contracting that a firm has undertaken.

At this point is it important to note that a generation unit owners forward contract position is generally unknown to the market monitor. However, the above analysis demonstrates that using the assumption of expected profit maximization and data on actual bidding behavior, something that is readily available to the market monitor, accurate estimates of the hourly levels of forward contract holding can be obtained. Consequently, even this very rough procedure can be a very powerful tool for determining the those instances when a market participant is likely to attempt to exercise market power in the spot electricity.

I now examine the properties of our procedure for recovering genset-level marginal cost functions implied by best-reply bidding. As discussed in Section 5, Firm A has two types of identical gensets. Consequently, I estimate two genset-level marginal cost functions, applying the GMM estimation technique outlined in that section. I compute estimates of these unit level marginal cost functions using both the identity matrix and a consistent estimate of the optimal weighting matrix. For all of the estimations reported I assume h = 1 $AU, although the results did not change appreciably for values of h ranging from 0.10 $AU and 50 $ AU.

Table 3 reports the results of estimating $C_1'(q,\beta_1)$ and $C_2'(q,\beta_2)$ using the identity matrix as the weighting matrix and a consistent estimate of the optimal weighting matrix. The coefficient estimates are fairly precisely estimated across the four columns of results. As expected, the GMM estimates using a consistent estimate of the optimal weighting matrix appear to be more precisely estimated. The optimized value of the objective function from the GMM estimation with the consistent estimate of the optimal weighting matrix can be used to test the over-identifying restrictions implied by best-reply bidding. To estimate the six parameters of $C_1'(q,\beta_1)$ and $C_2'(q,\beta_2)$, I use 70 moment restrictions–10 bid increments for 7 gensets. From the results of Hansen (1982), the optimized value of the objective function is asymptotically distributed as a chi-squared random variable with 64 degrees of freedom–the number of moment restrictions less the number of parameters estimated–under the null hypothesis that all of the moment restrictions imposed to estimate the parameters are valid. The optimized value of the objective function using a consistent estimate of the optimal weighting matrix is 75.40, which is less than the 0.05 critical value from a chi-squared random variable with 64 degrees of freedom. This implies that the null hypothesis of the validity of the moment restrictions given in (5.1) cannot be rejected by the actual bid data.

Figures 8 to 11 plot the estimated genset level marginal cost functions for Plant 1 and Plant 2 along with point-wise 95% confidence intervals for the case of the Identity matrix and the consistent estimate of the optimal weighting matrix estimation results. The confidence intervals indicate that with exception of the identity weighting matrix estimates at high levels output from Plant 2 genset's, the marginal cost curves are precisely estimated. Both sets of results are broadly consistent with the results for the case of best-reply pricing. However, considerably more insight about the structure of Firm A's costs can be draw from these results. Specifically, these results indicate the Plant 1 gensets are, for virtually all ranges output for the case of the identity weighting matrix and for all output levels for the case of the optimal weighting matrix, lower cost than Plant 2 gensets. This result was also confirmed by discussions with plant operators at Firm A.

The other result to emerge from this analysis is the increasing at an increasing rate marginal cost curves for all cases except the identity weighting matrix and the Plant 1 genset. One potential explanation for this result comes from discussions with market participants in the California electricity market. The argument of these unit owners is based on hedging against the risk of unit outages when a generator has sold a significant amount of forward contracts. Because of the enormous financial risk associated with losing a unit in real-time combined with the inability to quickly bring up another unit in time to meet this contingency, generation unit owners apply a large and increasing opportunity cost to the last one-third to one-quarter of the capacity of each genset. That way they will leave sufficient unloaded capacity on all of their units in the hours leading up to the daily peak so that they can be assured of meeting their forward financial commitments for day even if one of their units is forced out. This desire to use other units as physical hedges against the likelihood of a forced outage seems to be a very plausible explanation for the form of the marginal cost functions we recover, in light of the following facts about Firm A. First, during this time period Firm A sold forward a large fraction of its expected output, and in some periods even more than its expected output. Second, all of Firm A's units are large coal-fired units which can take close to 24 hours to start-up and bring to their minimum operating level. Both of these facts, argue in favor of Firm A operating its units as if there were increasing marginal costs at an increasing rate as output approached the capacity of the unit.

8. Implications for Market Monitoring and Directions for Future Research

There are variety of uses for these results in market monitoring. Perhaps the most obvious one is in constructing an estimate of the magnitude of variable profits earned by the firm over some time period. A major topic of debate among policymakers and market participants is the extent to which price spikes are needed for generation unit owners to earn an adequate return on the capital invested in each generating facility. This debate is particularly contentious with respect to units that supply energy only during peak periods. The methodology presented in this paper can be used to inform this debate.

Using these estimated marginal cost functions and actual market outcomes, one can compute an estimate of the magnitude of variable profits a generating unit earns over any time horizon. This information can then be used to determine whether the variable profit level earned on an annual basis from this unit is sufficient to adequately compensate the owner for the risk taken. This calculation should be performed on a unit-by-unit basis to determine the extent to which some units earn higher returns that other units. By comparing these variable profit levels to the annual fixed cost and capital costs of the unit, a determination of the long-term profitability each unit can be made. These sorts of results should provide useful input into the regulatory decision-making process on the appropriateness of price spikes and the necessity of bid caps in competitive electricity markets. Determining the answers to these questions is particularly important in light of the events in all wholesale electricity markets throughout the U.S. during the summers of 1999 and 2000.

The framework outlined here can be extended in variety of directions. One extension involves using these methods in multi-settlement electricity markets such as the California electricity supply industry. Here market participants make day-ahead energy commitments in the Power Exchange and then purchase or sell any imbalance energy necessary to meet their actual supply and demand obligations in the ISO's real-time energy market. In this case the generator's profits from supplying electricity for the day are the result of selling into two sequential electricity markets. Consequently, one way to model this process is to assume best-reply pricing for the firm in both markets (and that the firm knows that it will attain best-reply prices in the real-time market when bidding into the PX market) and derive the implied marginal cost for the generator. Preliminary results from applying this procedure to California ISO and PX data is encouraging. Extending this procedure to the case of best-reply bidding in both markets in significantly more challenging.

A second direction for extensions is to specify Firm A's cost function as a multi-genset cost function such as $C(q_1,\ldots, q_7,\beta)$. Assuming this functional form, I can examine the extent to which their exist complementarities in the operation of different units. The marginal cost function for a given genset could also be generalized to allow dependence across periods within the day in the marginal cost of producing in a given hour, so that the variable cost for genset k might take the form $C_k(q_{1k},\ldots, q_{48,k},\beta_k)$, to quantify the impact of ramping constraints and others factor which prevent units from quickly moving from one output level to another.

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Table 1: Implied Marginal Cost Regression

$$C(q) = a + bq + c\,q^2 + d\,q^3$$

Parameter	Estimate	Standard Error	T-stat
a	3.10e+01	4.43e+00	7.00e+00
b	-2.21e-02	4.61e-03	-4.78e+00
c	8.47e-06	1.54e-06	5.49e+00
d	-1.11e-09	1.61e-10	-6.65e+00

Table 2: Contract Quantity Regression for QC(Implied) for (MC = $10)

Variable	Estimate	Standard Error	T-stat
Constant	1882.37	59.70	31.53
DWKD1	-126.34	25.02	-5.05
DWKD2	215.72	25.95	8.31
DWKD3	282.29	25.64	11.01
DWKD4	330.84	25.54	12.95
DWKD5	391.34	25.01	15.65
DWKD6	397.24	25.45	15.61
DMN1	-12.46	40.29	-0.31
DMN2	34.90	39.19	0.89
DMN3	398.21	39.10	10.19
DPD1	-165.64	67.18	-2.47
DPD2	-147.10	67.42	-2.18
DPD3	-26.59	65.32	-0.41
DPD4	-54.94	65.11	-0.84
DPD5	113.07	65.90	1.72
DPD6	315.23	66.53	4.74
DPD7	602.74	65.90	9.15
DPD8	581.09	66.56	8.73
DPD9	654.61	67.07	9.76
DPD10	674.01	66.62	10.12
DPD11	743.62	66.84	11.13
DPD12	736.64	67.07	10.98
DPD13	777.06	66.18	11.74
DPD14	822.59	66.18	12.43
DPD15	898.80	66.18	13.58
DPD16	877.76	66.16	13.27
DPD17	820.91	66.39	12.37
DPD18	800.76	66.15	12.10
DPD19	757.67	66.15	11.45
DPD20	714.33	66.15	10.80
DPD21	706.38	65.93	10.71
DPD22	648.04	65.72	9.86
DPD23	663.86	65.93	10.07
DPD24	692.77	65.93	10.51
DPD25	741.97	66.14	11.22
DPD26	876.84	65.95	13.30
DPD27	866.17	65.91	13.14
DPD28	793.67	67.74	11.72
DPD29	739.79	67.68	10.93
DPD30	624.01	68.45	9.12
DPD31	695.82	66.32	10.49
DPD32	770.62	66.36	11.61
DPD33	879.34	66.82	13.16
DPD34	858.81	66.38	12.94
DPD35	848.25	67.27	12.61
DPD36	623.35	66.17	9.42
DPD37	739.35	67.07	11.02
DPD38	522.93	66.41	7.87
DPD39	462.97	67.04	6.91
DPD40	432.56	66.62	6.49
DPD41	421.45	67.06	6.28
DPD42	300.60	67.06	4.48
DPD43	145.39	67.06	2.17
DPD44	138.65	66.60	2.08
DPD45	64.44	66.60	0.97
DPD46	87.50	66.13	1.32
DPD47	55.02	65.68	0.84

Table 3: Genset-Level Marginal Cost Functions

	Plant 1 (Identity)	Plant 1 (Optimal)	Plant 2 (Identity)	Plant 2 (Optimal)
β_{0k}	10.1	9.32	4.36	12.14
$SE(\beta_{0k})$	(1.23)	(1.14)	(1.53)	(0.74)
β_{1k}	-0.002	0.00103	-0.000448	0.0017
$SE(\beta_{1k})$	(0.006)	(0.000087)	(0.0041)	(0.000784)
β_{2k}	0.00000669	0.0000917	0.00031	0.0000686
$SE(\beta_{2k})$	(0.00001)	(0.00001)	(0.000085)	(0.00001)

Note: $SE(\beta)$ = estimated standard error of coefficient estimate using asymptotic covariance matrix given in Hansen (1982).

Figure 1

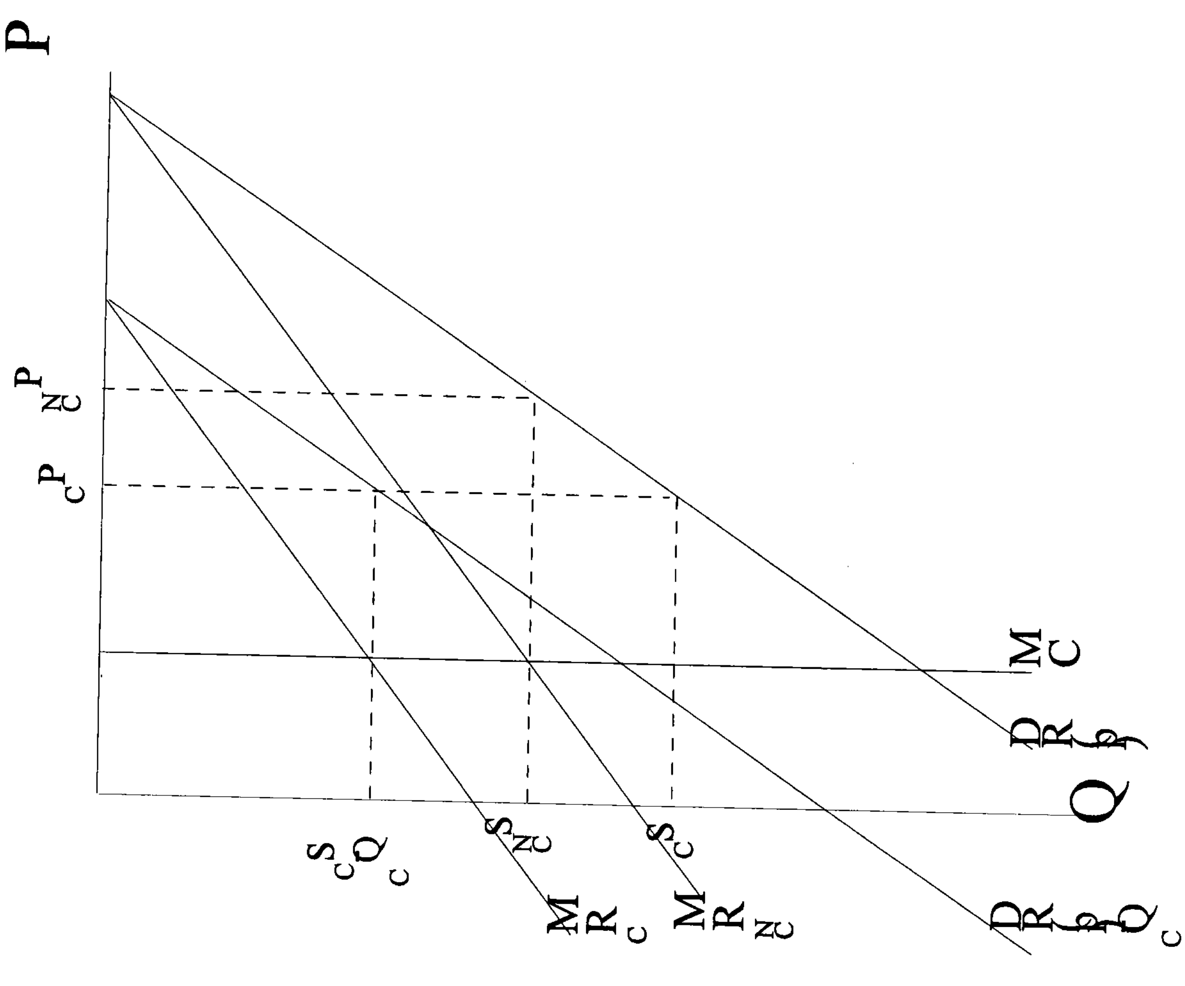


Figure 2: Sample Bid Functions for Australian Electricity Market

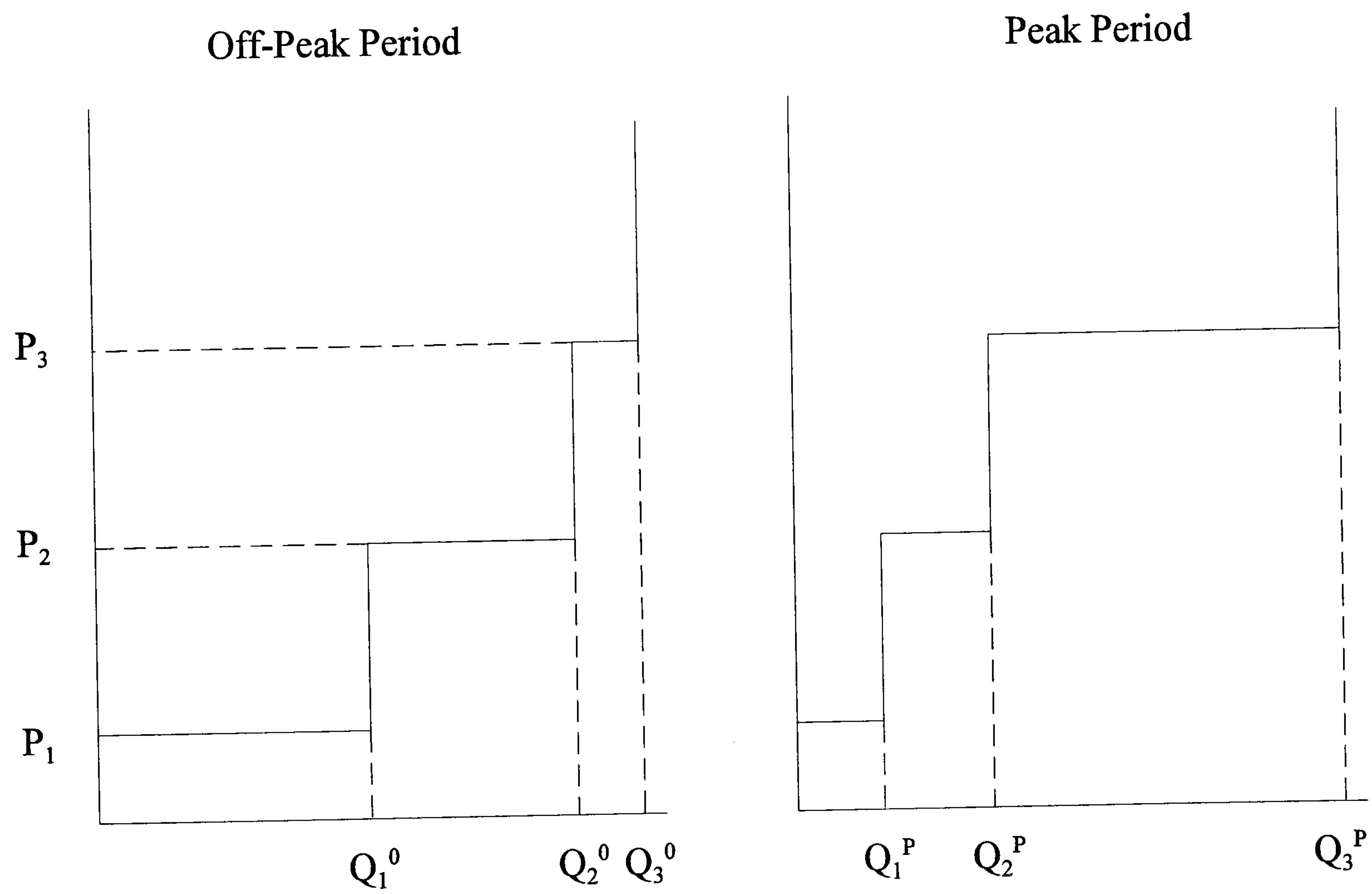


Figure 2

Residual Demand Curve for 7/28/97 Low Demand

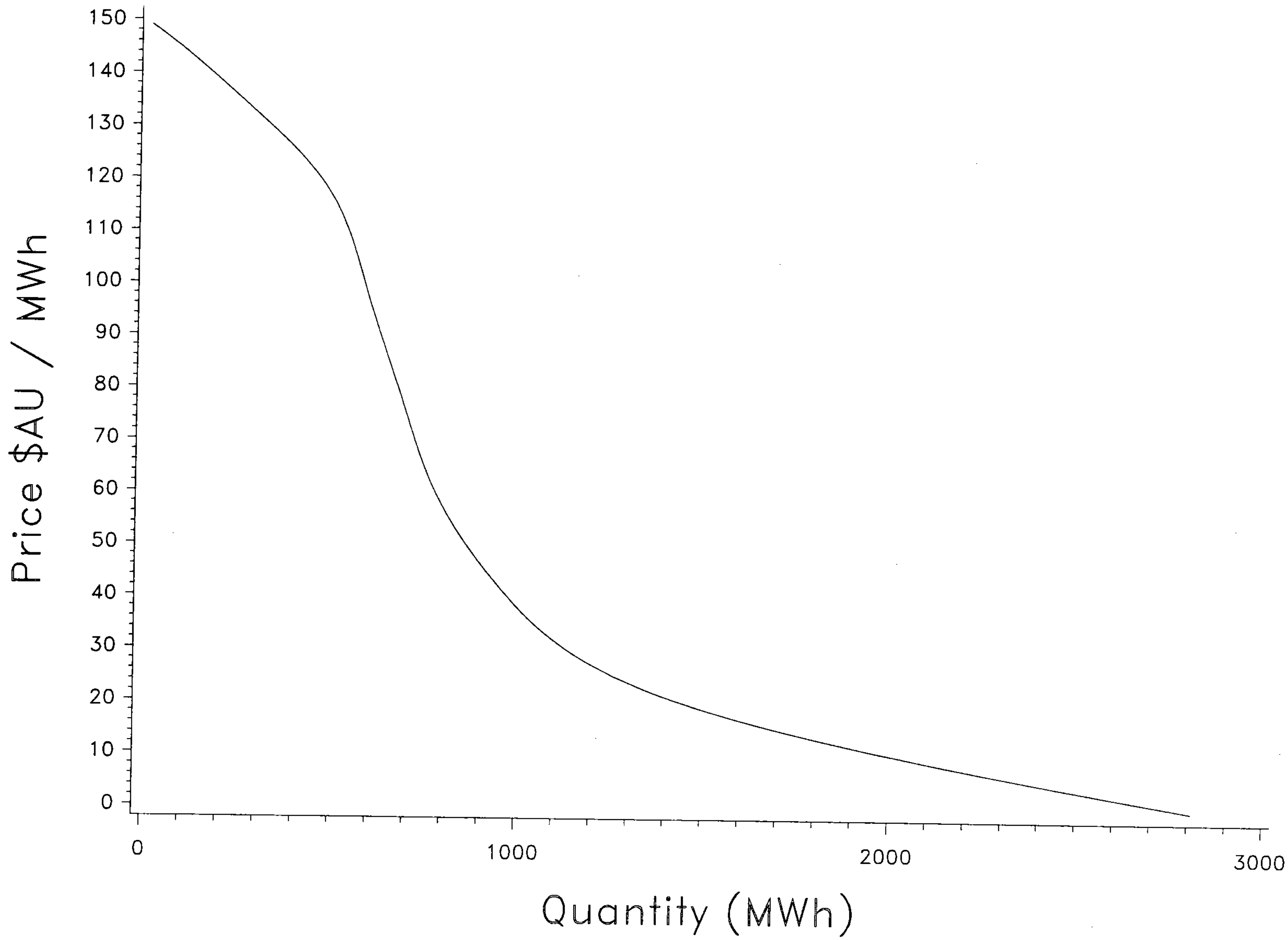


Figure 3

Residual Demand Curve for 7/28/97 High Demand

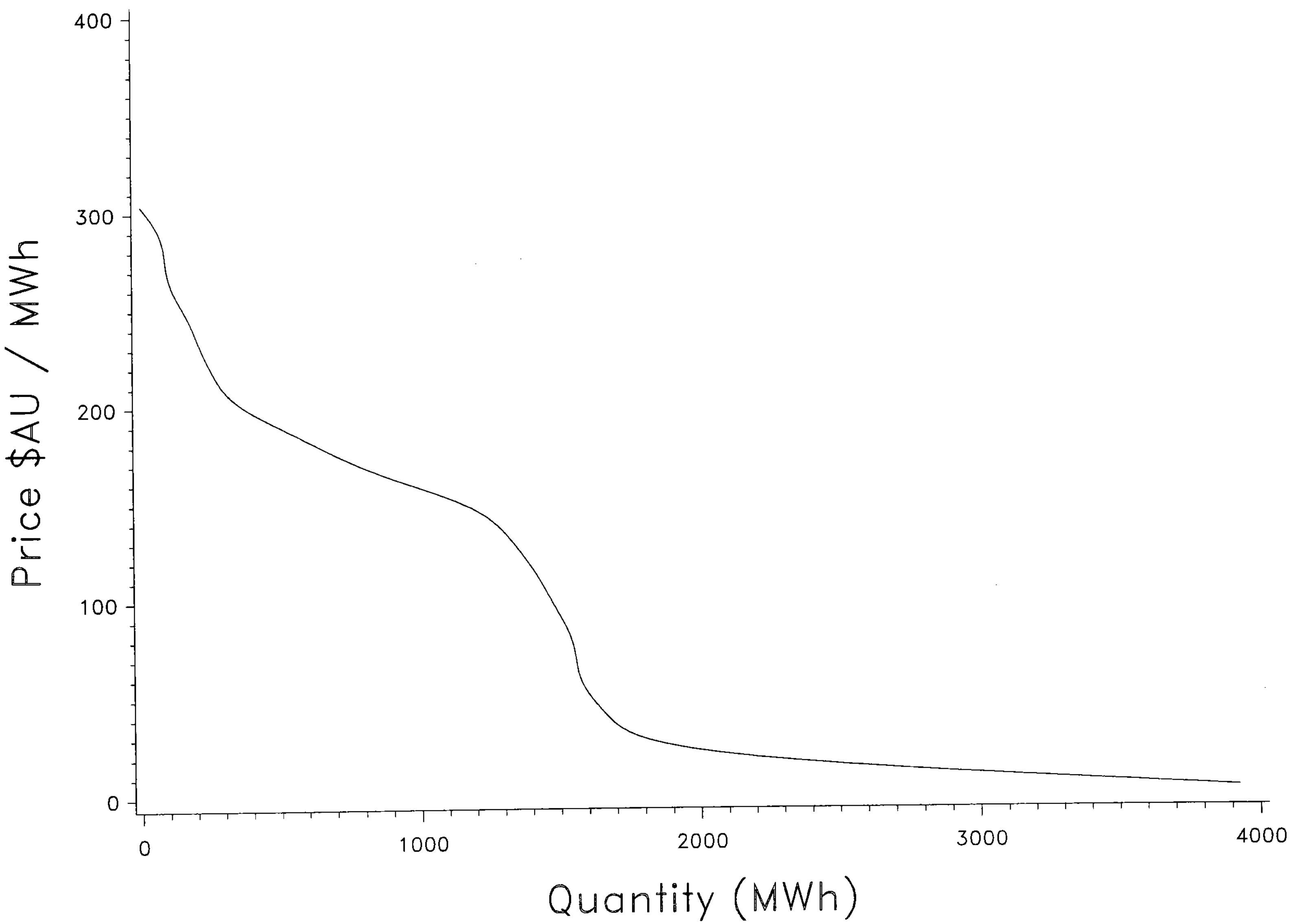


Figure 4

Implied Marginal Cost

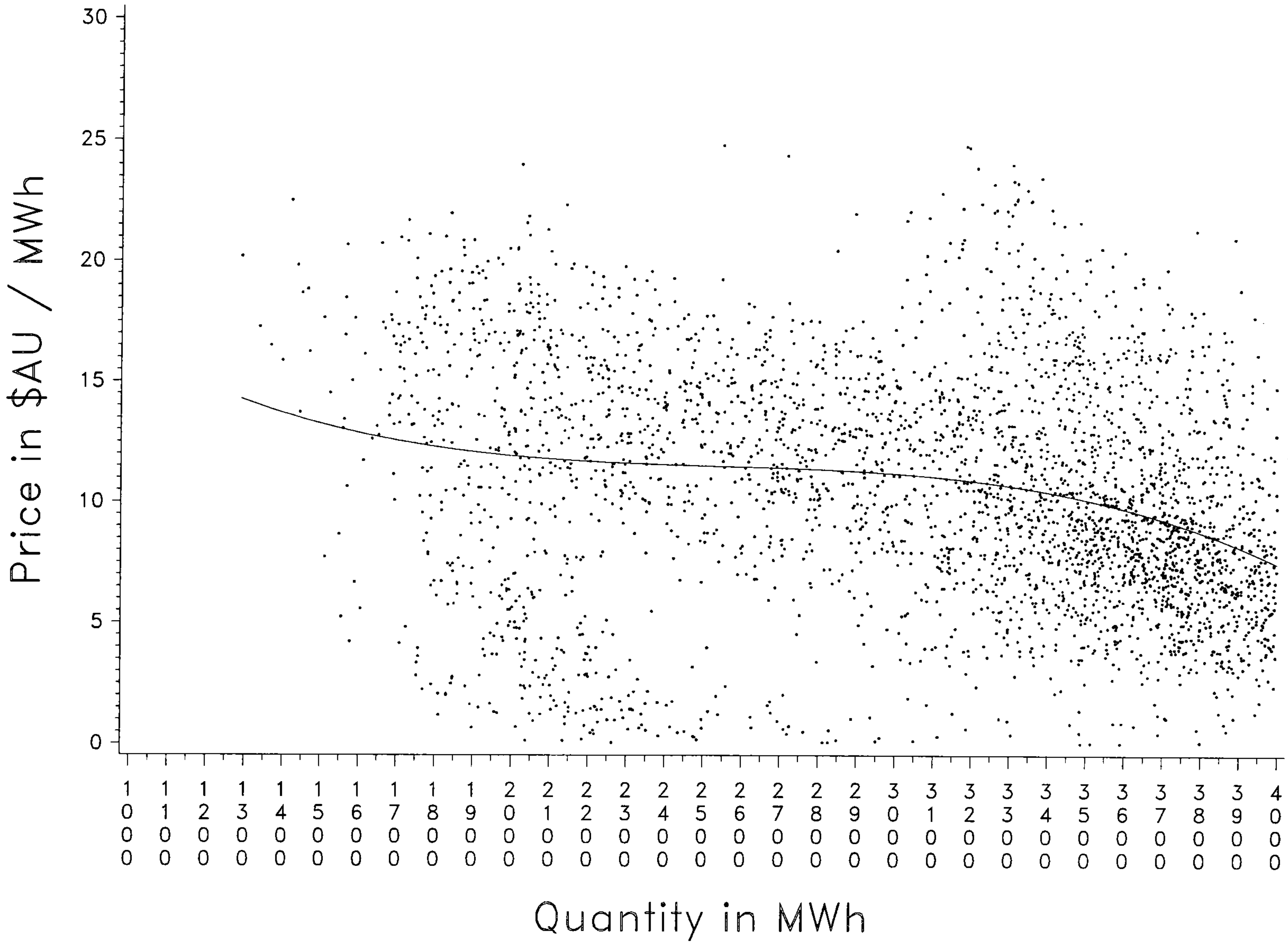


Figure 5 (MC = 10 $AU/MWh)

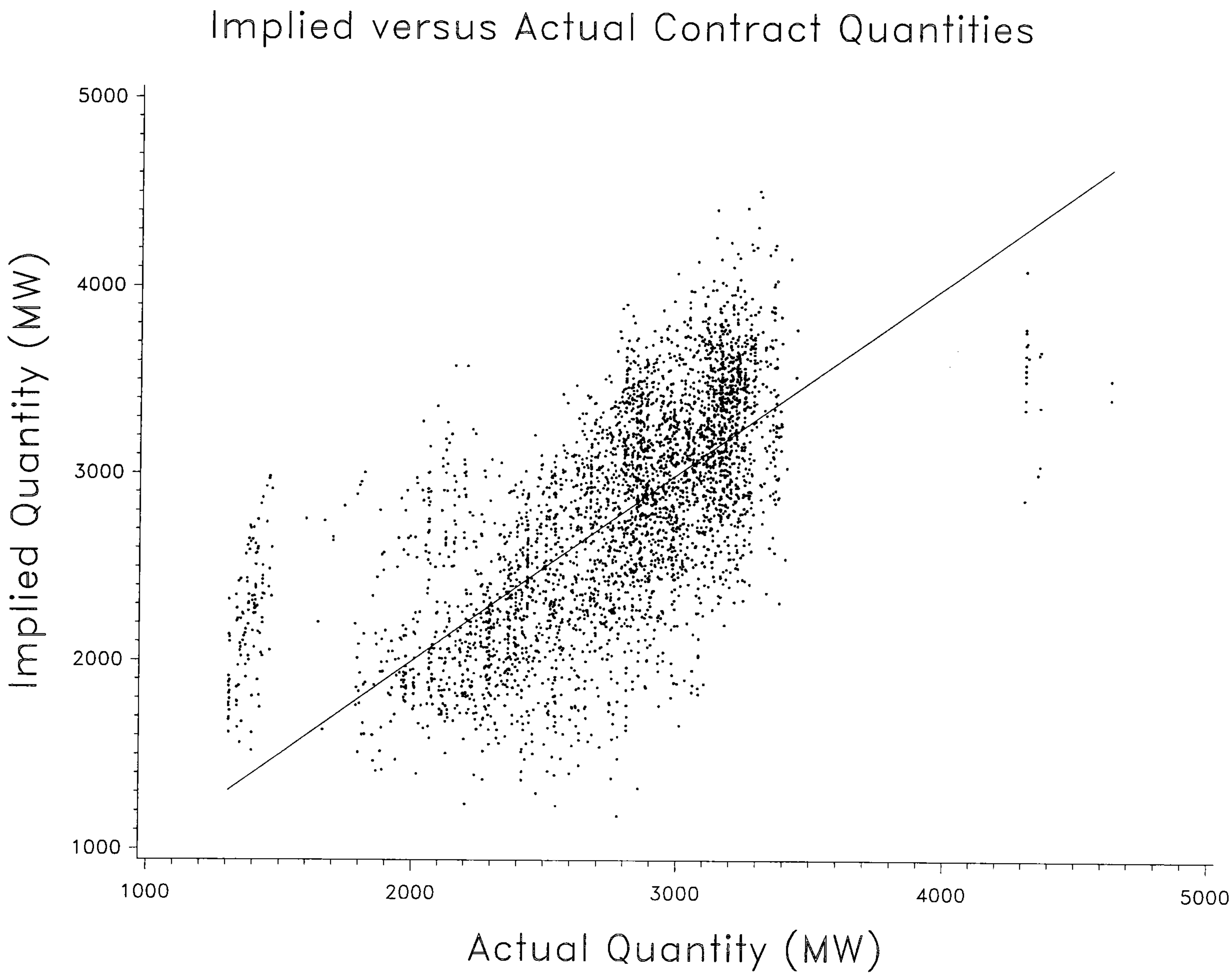


Figure 6 (MC = 15 $AU/MWh)

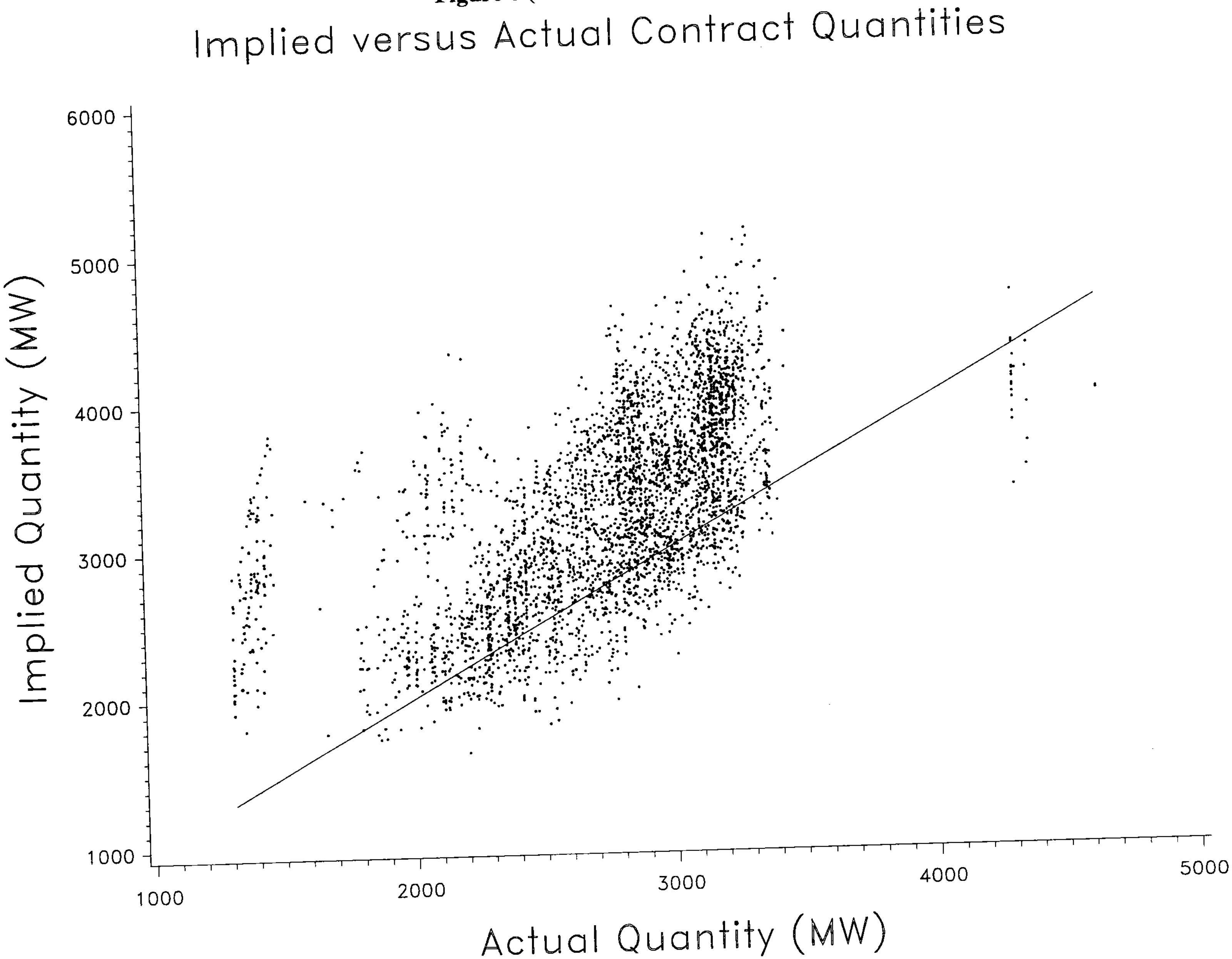


Figure 7

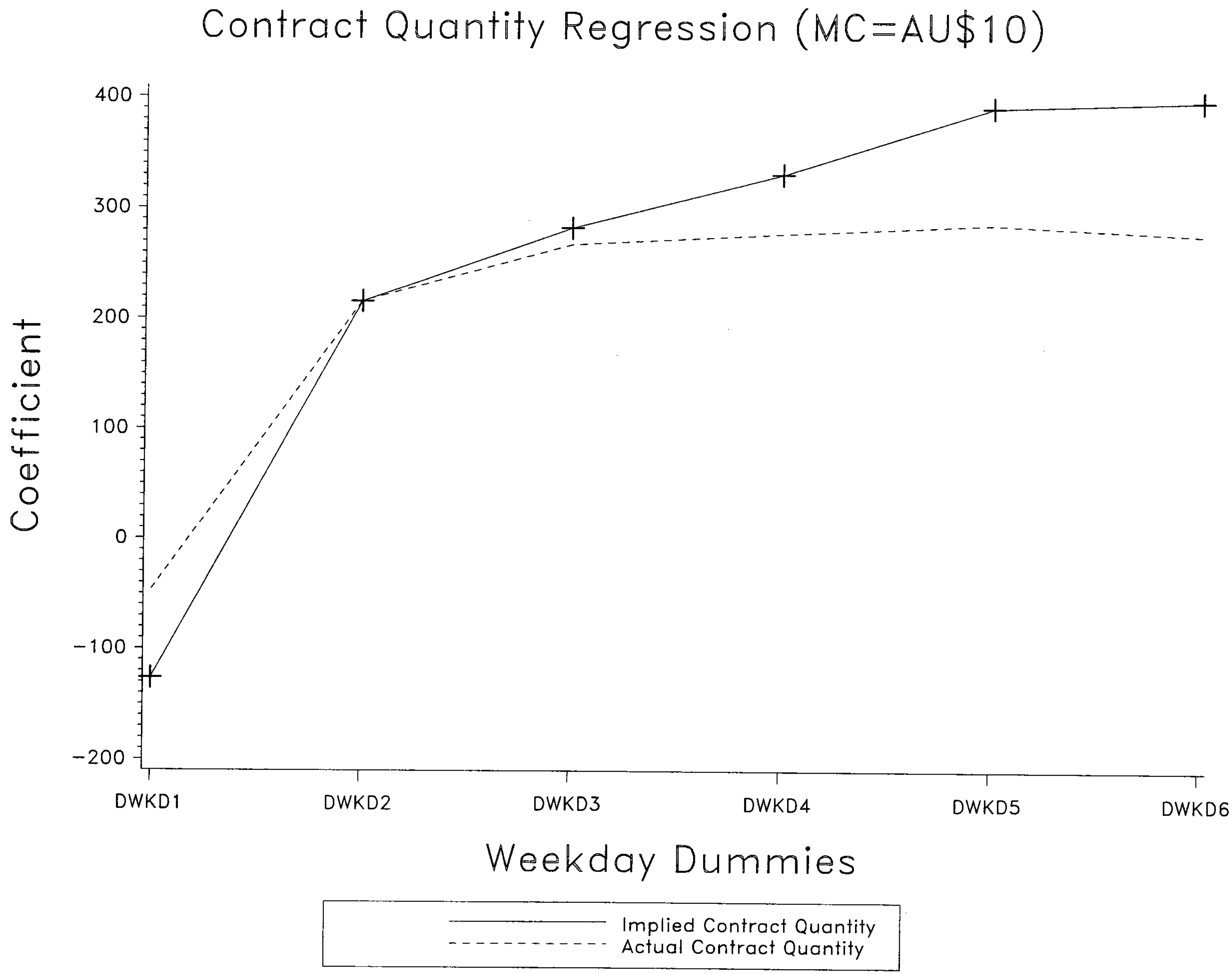
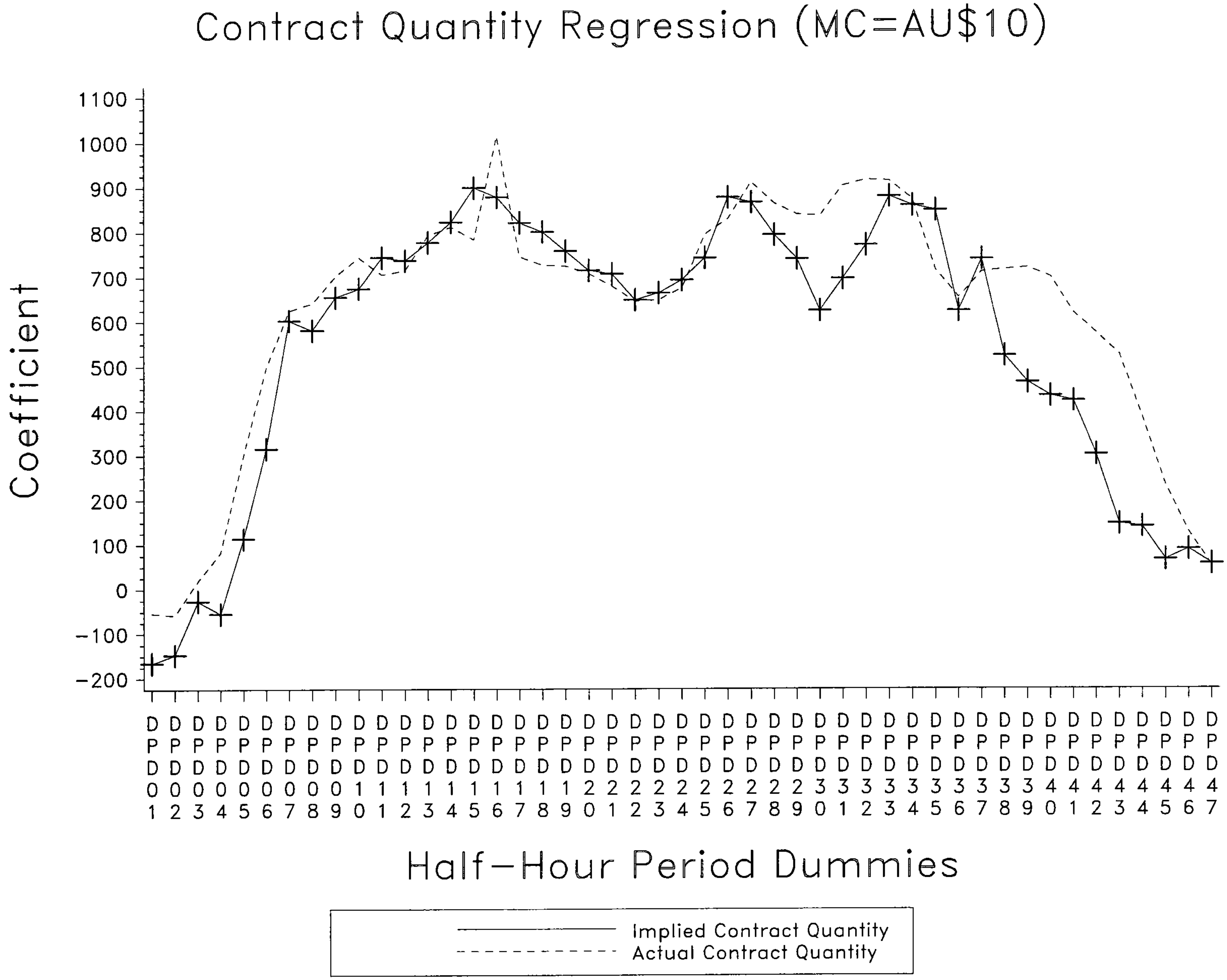
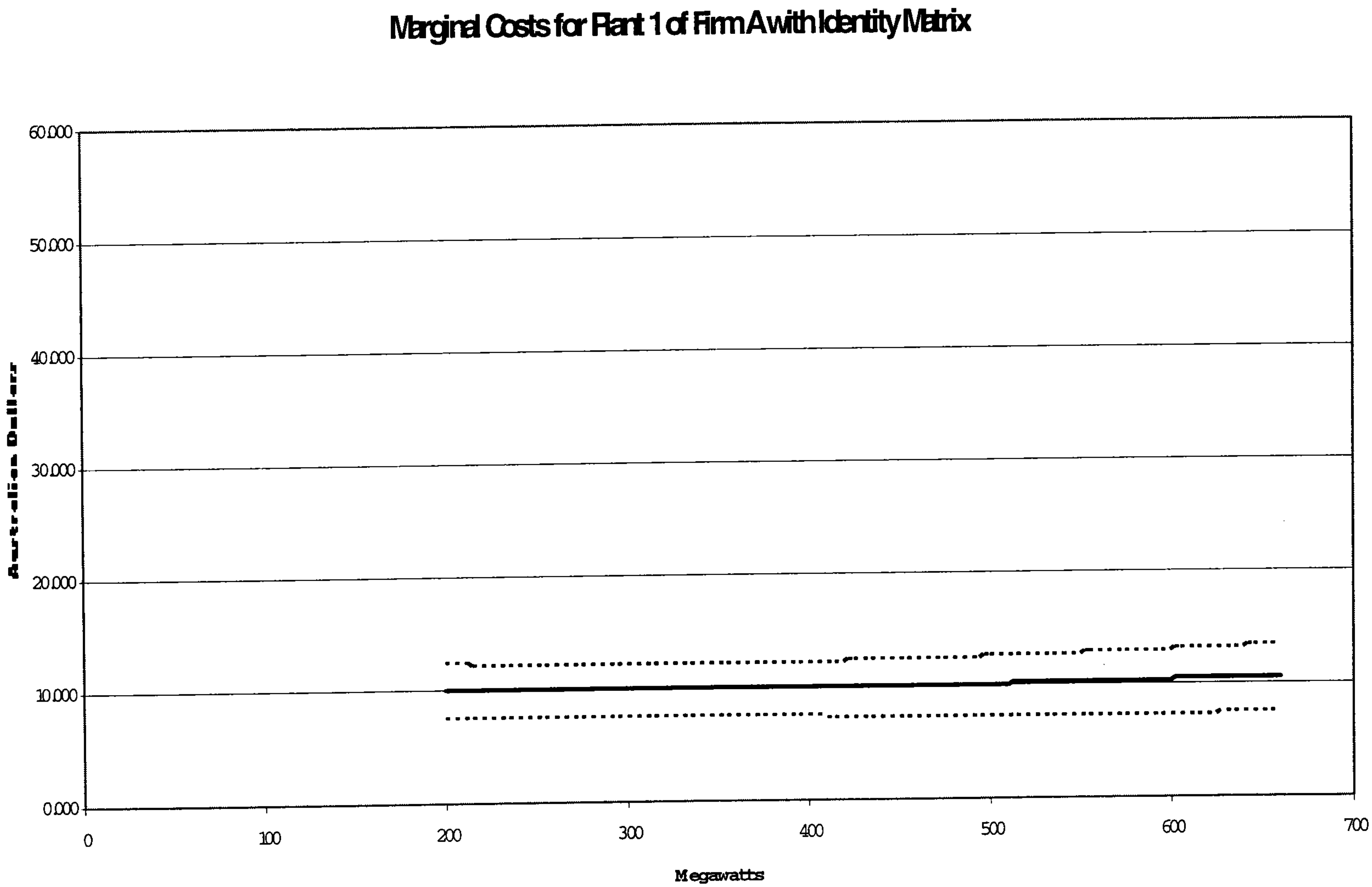

Contract Quantity Regression (MC=AU$10)
Coefficient
400
300
200
100
0
-100
-200
DWKD1
DWKD2
DWKD3
DWKD4
DWKD5
DWKD6
Weekday Dummies
Implied Contract Quantity
Actual Contract Quantity

Figure 8



Contract Quantity Regression (MC=AU$10)
Coefficient
1100
1000
900
800
700
600
500
400
300
200
100
0
−100
−200
DPD01 DPD02 DPD03 DPD04 DPD05 DPD06 DPD07 DPD08 DPD09 DPD10 DPD11 DPD12 DPD13 DPD14 DPD15 DPD16 DPD17 DPD18 DPD19 DPD20 DPD21 DPD22 DPD23 DPD24 DPD25 DPD26 DPD27 DPD28 DPD29 DPD30 DPD31 DPD32 DPD33 DPD34 DPD35 DPD36 DPD37 DPD38 DPD39 DPD40 DPD41 DPD42 DPD43 DPD44 DPD45 DPD46 DPD47
Half−Hour Period Dummies
Implied Contract Quantity
Actual Contract Quantity

Figure 9



Marginal Costs for Plant 1 of Firm A with Identity Matrix
60.000
50.000
40.000
30.000
20.000
10.000
0.000
Australian Dollars
0
100
200
300
400
500
600
700
Megawatts

Figure 10

Marginal Costs for Plant 2 of Firm A with Identity Matrix

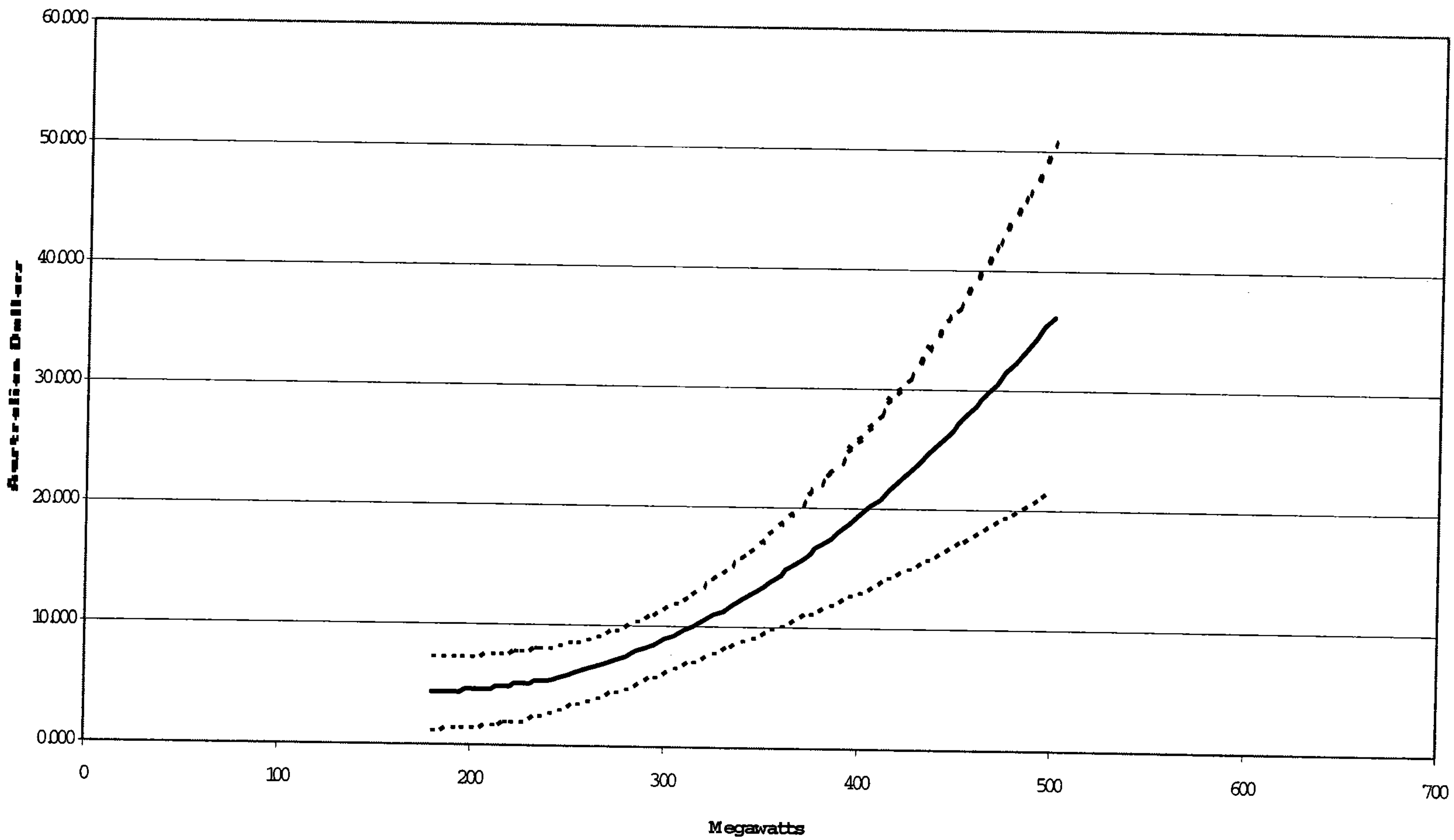


Figure 11

Marginal Costs for Plant 1 of Firm A with Optimal Weighting Matrix

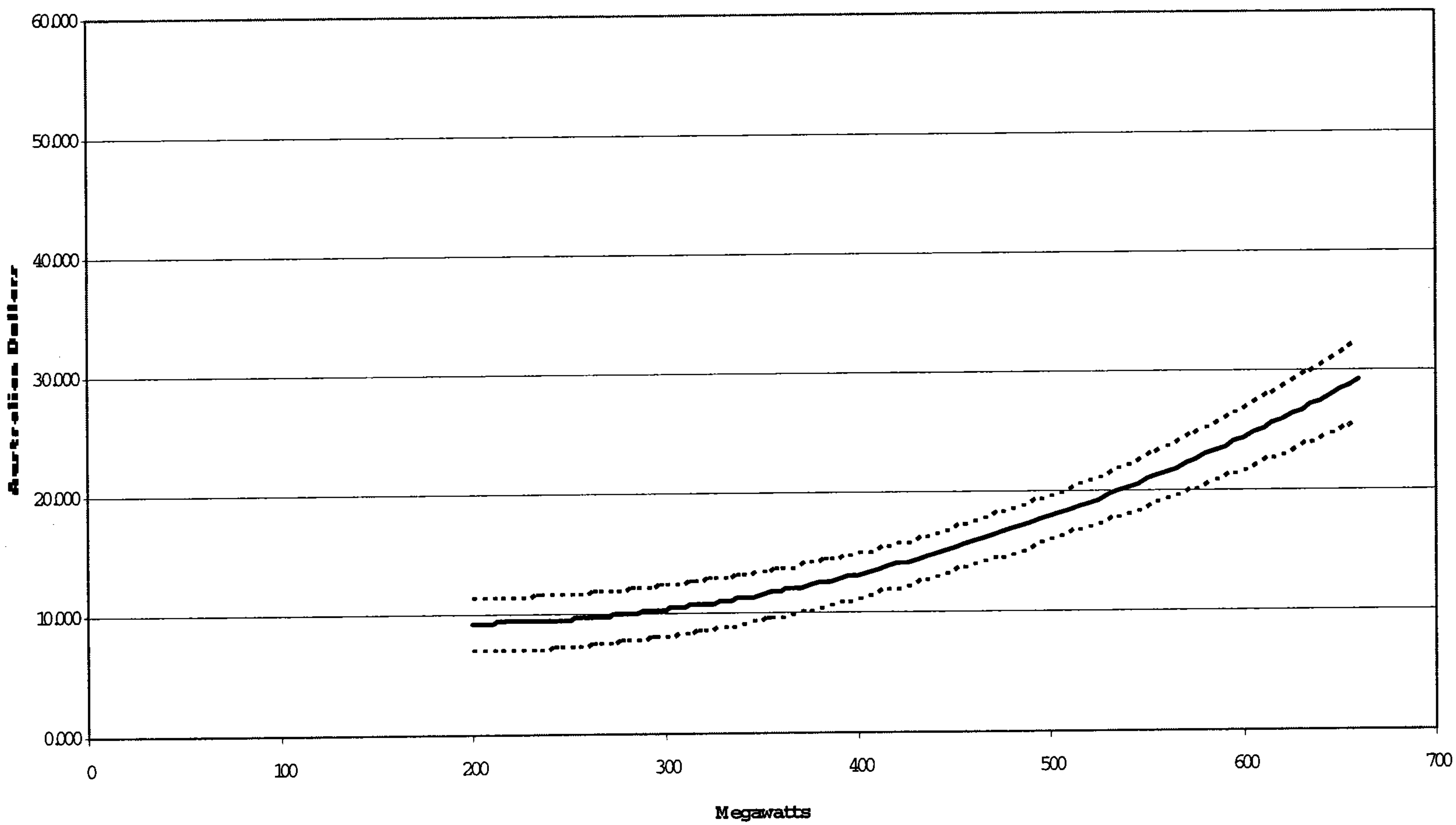
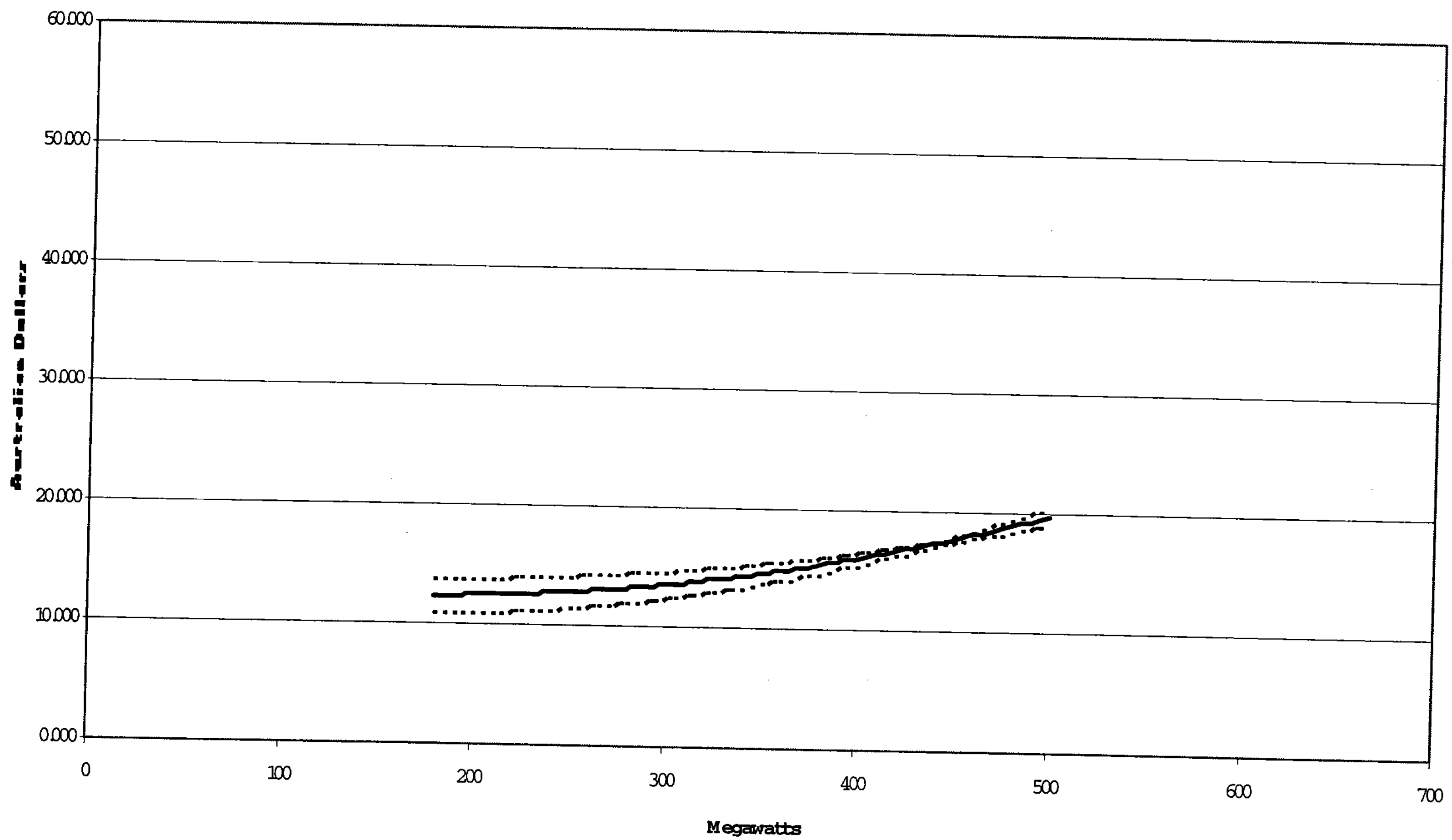


Figure 12

Marginal Costs for Plant 2 of Firm A with Optimal Weighting Matrix



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