

UC Berkeley

Recent Work

Title

Vertical Integration in Restructured Electricity Markets: Measuring Market Efficiency and Firm Conduct

Permalink

<https://escholarship.org/uc/item/26k8h7v9>

Author

Mansur, Erin T.

Publication Date

2003-10-01



CSEM WP 117

**Vertical Integration in Restructured Electricity Markets:
Measuring Market Efficiency and Firm Conduct**

Erin T. Mansur

October 2003

This paper is part of the Center for the Study of Energy Markets (CSEM) Working Paper Series. CSEM is a program of the University of California Energy Institute, a multi-campus research unit of the University of California located on the Berkeley campus.



2510 Channing Way, Suite 5
Berkeley, California 94720-5180
www.ucei.org

Vertical Integration in Restructured Electricity Markets: Measuring Market Efficiency and Firm Conduct

Erin T. Mansur*

October, 2003

Abstract

Unlike other studies that have found substantial inefficiencies in restructured electricity markets, this paper provides estimates that reveal relatively competitive behavior in the Pennsylvania, New Jersey, and Maryland market. This distinctive conclusion results from using a model that incorporates structural market features and particular production constraints that are not captured in previous studies. First, the vertical integration of firms in the PJM market reduces electricity producers' interest in setting high prices; producers sell wholesale electricity and also are required to buy power, which they provide to their retail customers at set rates. My model reflects this degree of vertical integration of PJM firms. Second, I account for production constraints that result in cost nonconvexities. Measures of price-cost margins based on a commonly used method that does not incorporate these nonconvexities imply that market imperfections during the summer following PJM's restructuring increased procurement costs 51% (\$950 million). That method further implies considerable welfare loss as actual production costs exceeded the competitive model's estimates by 12.5%. This paper develops a consistent estimate of competitive production decisions that respect important production constraints, and it presents estimates showing that costs were only 3.4% above competitive levels. Using this new method of estimating production, I compare behavior of two producers that have relatively few retail customers with other firms. Consistent with these vertically integrated firms' incentives, only firms with large net selling positions in the market reduced output relative to competitive production estimates. (*JEL* L13 L94)

*Yale School of Management and School of Forestry and Environmental Studies, 135 Prospect Street, New Haven, CT 06511 (e-mail: erin.mansur@yale.edu) URL: <www.som.yale.edu/faculty/etm7>. I thank Alan Auerbach, Peter Berck, Severin Borenstein, Jim Bushnell, Stephen Holland, Aviv Nevo, Sharon Oster, Steve Puller, Celeste Saravia, Fiona Scott Morton, Frank Wolak, and Catherine Wolfram for helpful suggestions. The financial support of the California Public Utilities Commission and the University of California Energy Institute is gratefully acknowledged.

1 Introduction

Over the past quarter century, there has been a movement towards restructuring wholesale electricity markets in several U.S. states and in other countries. Policy makers believed restructuring would impose market discipline and thus lead to lower production costs at existing power plants and more efficient investments. Unfortunately, the promises of restructuring have not always been realized. While studies have found substantial inefficiencies in some restructured markets, this paper demonstrates two reasons why performance is relatively competitive in the Pennsylvania, New Jersey, and Maryland (PJM) market. First, in this market, the vertical integration of firms reduces electricity producers' interest in setting high prices: Producers sell into the wholesale market and also are required to buy in the market in order to provide power to their retail customers at set rates. Second, I account for production constraints that result in cost non-convexities.

These production constraints are ignored in papers that use the standard methodology to measure market imperfections in electricity markets (for example, Borenstein, Bushnell, and Wolak, 2002 (hereafter BBW)). In applying this technique to determine PJM's price-cost margins, I extend the methodology by estimating an import supply function. Prices during the summer after PJM restructured were quite high. During this period, I find evidence that total energy procurement costs exceeded those of a perfectly competitive spot market by 51 percent, or \$262 million. If bilateral contracts exhibited similar margins, my measure of total transfers associated with market power increases to \$950 million. These are substantial wealth transfers, especially in a market where vertically integrated firms self-supply most of the electricity.

Given these measures of market power, I examine the welfare implications of restructuring that, in general, occur from allocative and production inefficiencies. However, wholesale electricity markets do not have allocative inefficiencies, in the short run, because derived demand is completely inelastic. There are two reasons for this. First, consumers have no incentive to reduce quantity demanded at higher prices because the regulatory structure of electricity retail markets has kept

consumers' rates constant.¹ Second, the firms that procure customers' electricity in the wholesale market are mandated to provide the power at any cost. Therefore, the only welfare effects result from inefficient production. Using the standard methodology of estimating competitive market outcomes, I measure actual production costs to have exceeded these competitive estimates by 12.5 percent during the post-restructuring summer.

However, by ignoring certain types of production constraints, this methodology overstates production inefficiencies from restructuring. This "single-period" technique assumes that power plants operate following an on-off strategy—producing at full capacity if and only if price equals or exceeds marginal production costs—while the process of producing electricity efficiently requires that firms consider several non-convexities in costs. For example, when power plants activate generating units to produce electricity, they pay between \$100 to \$7000 in "start up" costs.² These costs impose intertemporal constraints on production decisions.

This paper tests the importance of these constraints in measuring market efficiency. I use data from the pre-restructuring period to observe the factors involved in firms' actual production decisions. I model production as a function of prices, costs, and intertemporal constraints in a flexible format using a Heckman selection model while accounting for endogeneity of prices. For the control period, this model fits actual production decisions substantially better than the "single-period" model (as shown in figure 3). Then, using coefficient estimates, I extrapolate how firms *would* have behaved, given cost and demand shocks, had restructuring not occurred. Comparing actual production costs with these estimates of "competitive production" costs for the initial summer of restructuring, I estimate that actual costs exceeded competitive estimates by only 3.4 percent, substantially less than the estimates generated using the standard technique.

Finally, I use my competitive estimates of production to test whether firm behavior in the PJM market changed as a result of restructuring. For many hours during the post-restructuring

¹A few customers have "interruptible" contracts that are exercised when the quantity demanded approaches the capacity of supply, causing customers to curtail electricity demanded. As this does not depend on price, demand shifts but remains completely inelastic.

²This range represents the 5th and 95th percentile of start up costs for coal, oil and natural gas generating units in the U.S. Eastern grid using output data from the PROSYM model (Kahn, 2000).

period, a few vertically integrated firms were net sellers and, therefore, had incentives to exercise oligopoly power, i.e., raise wholesale prices. Other firms primarily purchased power, on net, from the spot market and had incentives to reduce prices. I examine how vertical integration affects firms' incentives to exercise market power in the PJM market with two methods. I treat restructuring as a natural experiment in order to test whether the two large net-selling firms, PECO and PPL, behaved differently from other firms after restructuring, controlling for shocks to competitive behavior. I estimate that these two firms produced approximately 14 percent less than they would have in a competitive environment. On average, other firms did not deviate from competitive levels. Also, as a benchmark, I examine the consistency of firm behavior with a structural model's first order condition for these large, vertically integrated firms. In this exercise, I also find supporting evidence that PECO and PPL exercised market power.

The paper proceeds with section 2 briefly discussing divestiture in restructured electricity markets, outlining the PJM wholesale electricity market, and modeling the incentives of strategic firms that are vertically integrated in generation and distribution. In section 3, I discuss the methodology of determining competitive benchmark estimates using the "single-period" model. I present the price-cost margin estimates, as well. Section 4 measures market inefficiencies by constructing an "intertemporal" model that accounts for unit commitment problems and compare actual production with a competitive counterfactual measure. Section 5 also uses these competitive measures of production to examine how vertical integration affects firms' incentives to exercise market power. I report my conclusions in section 6.

2 The PJM Electricity Market

The historical perspective of electricity generation as a natural monopoly led to markets being concentrated with few regulated firms or government agencies producing power. However, with technological advances and changes in perceptions, many argued that multiple firms could compete in generating electricity and a movement towards restructuring these markets began. Under deregulation, firms supplying generation will typically have incentives to withhold output and drive prices

above marginal costs. However, these incentives may be affected if firms are vertically integrated with other aspects of electricity markets, *i.e.*, owning the transmission and distribution systems of electricity markets.³

The England and Wales market, where the government historically had produced electricity, became one of the first to deregulate. In April, 1990, the market restructured and privatized, with many of the government generating assets being allocated to two firms: PowerGen and National Power. Generators signed long-term financial contracts that limited their incentives to increase energy spot market prices. Wolfram (1999) finds that these duopolists did exercise market power, but not to the level consistent with Cournot behavior. In her 1998 paper, Wolfram directly studies the bidding behavior of these two private companies and finds evidence that firms' observed bidding behavior is consistent with multi-unit auction theory: Firms charged more for power plant units with more "inframarginal" generation.

Prior to restructuring the most notorious U.S. electricity market, three utilities operated California's generation, transmission, and distribution. The potential for these utilities to exert vertical market power, such as by excluding market entrants, concerned regulators. Thus, regulators required the utilities to divest fossil-fuel burning power plants to five private companies. Furthermore, regulators prohibited (or at least discouraged) the utilities, which were still responsible for distributing electricity as Load Serving Entities (LSE's), from signing long-term contracts. The generating firms had clear incentives to exercise oligopoly power and have done so.⁴

While restructuring in New England also led utilities to divest, they signed vesting contracts that required new plant owners to supply a set quantity of electricity at predetermined prices to the LSE's. These vesting contracts reduce sellers' returns on higher spot market prices. Bushnell and Saravia (2002) study the competitiveness in the New England market. They find modest amounts of market power being exercised, in part because firms with contracts bid negative margins.

Wolak (2000) notes how long-term contracts affect firm incentives in Australia's experience

³Joskow and Tirole (2000) examine how rights over transmission affect firms' behavior in exercising market power. Wolak (2000) demonstrates how signing long-term contracts also alters firms' incentives to exercise market power.

⁴BBW and Joskow and Kahn (2002) find evidence of market power being exerted.

with electricity restructuring. When its market opened, prices exceeded the expectations of some market participants. As a result, LSE's started to sign hedge contracts. As consistent with Allaz and Vila (1993), after suppliers signed these contracts, spot market prices dropped. Having signed contracts at prices above those realized in the spot market, some frustrated LSE's discontinued signing *additional* contracts. When the initial contracts expired, the spot market prices once again increased, reflecting the incentives of suppliers.

Unlike in other markets, PJM did not require utilities to divest plants as a condition of restructuring. Appendix A details the divestment laws for each state in PJM. Little divestment occurred either preceding or initially following restructuring. In this paper, I focus on a period when the market structure was relatively stable by comparing firm behavior in the summer prior to restructuring with that of the following summer.

2.1 Market Rules

In the late 1990s, the PJM Interconnection L.L.C. (PJM) consisted of most or all of Pennsylvania, New Jersey, Maryland, Delaware and the District of Columbia, as well as some of Virginia. While integrated with the Eastern U.S. transmission grid, the market has been regulated as a single entity based on transmission reliability concerns. In 1997, PJM began facilitating trades among regulated utilities and independent producers involved in the generation, transmission, and distribution of electricity in an effort to lower utilities' costs of providing power to customers. Regulators required all participants to trade in the market's one central market. Financial arrangements may be made outside of the centralized market but, to ensure reliability, all transactions must be reported to the market. As PJM intended, this spot market only covers a small fraction of quantity demanded, or "load": 10 to 15 percent.

Every five minutes, the market clears by using a uniform-price, sealed bid auction for the right to supply electricity to the system. Market participants offer extremely flexible bid curves for supplying energy on a day-ahead basis. During the time period studied here, if a firm made an offer to supply electricity and the regulator accepted the bid, the firm had no obligation either to

produce or to otherwise cover the bid: The bids were financial commitments. However, these bids were used as a basis for the regulator at the time of production much like a Walrasian auction. The PJM operators post a single price when the system is not constrained by the capacity of the transmission grid (*i.e.*, there is no transmission congestion). In 1998, PJM adopted what is known as a “nodal” pricing system in order to accommodate transmission constraints.⁵

Power plants consist of several, independently operating “generating units,” each comprised of a boiler, a generator, and a smoke stack. When the nodal market first opened, suppliers were required to make “cost-based” bids for each unit. In other words, the producers had to bid their marginal costs of production that had been determined by years of regulation rate hearings. A notable step in restructuring PJM occurred in April, 1999, when the requirement on the energy bid component was relaxed. The Federal Energy Regulatory Commission granted firms the right to change generating units from making cost-based bids to offering a more flexible type of bid. These “market-based” bids were subject to price cap of \$1000 per megawatt-hour (MWh). While many utilities obtained the right to bid units as market-based, many units remained cost-based during most of the summer of 1999. Firms may have opted not to switch if they had little incentive to exercise market power. In particular, those firms that either purchased electricity in the market or supplied their own generation may have less incentives to increase wholesale prices.

2.2 Market Structure

For each of the eight major utilities in PJM, panel A of table 1 reports 1999 generation capacity categorized by primary fuel type. Firms produce electricity using a variety of technologies that is in part due to the longevity of outdated power plants. Furthermore, because of current technological limits on the storage and production of electricity, even a new generation system would require some “baseload” generating units that operate at low marginal costs most hours and other, more flexible “peaking” units that operate just a few hours a day.

⁵Each node is a point where energy is supplied, demanded, or transmitted. The PJM energy market can have over 2,000 prices every five minutes when congestion occurs. For more on nodal pricing, see Schweppe, *et al.* (1988). In the summers of 1998 and 1999, the transmission system was constrained about 15 and 18 percent of the hours, respectively.

The market consists of approximately 57,000 megawatts (MW) of capacity, including nuclear, hydroelectric, coal, natural gas, and oil energy sources (see figure 1). Nuclear and coal plants provide baseload generation capable of covering most of the demand. Nuclear power comprises 45 percent of generation but only 24 percent of capacity. In contrast, natural gas and oil burning units provide over a third of the market's capacity, yet they operate only during peak demand times. These utilization differences result from heterogeneous cost structures. Baseload units have low marginal costs and significant intertemporal constraints, like large start up costs, while the relatively flexible peaking units are more expensive to operate. Section 4 examines the importance of these constraints.

The utilities also own transmission wires and are responsible for providing electricity to their customers. These entities are vertically integrated; they both buy and sell electricity in the wholesale market. Firms purchasing electricity to meet customers' demand, or "native load," are called Load Serving Entities (LSE's). So far, the deregulation of wholesale electricity markets has coincided with retail rate freezes for incumbent utilities. Customers pay their LSE's a fixed rate for electricity, and therefore, these firms will want to purchase energy from the wholesale market as cheaply as possible. However, LSE's also generate electricity and some, after meeting their native load, may sell additional power to others.

The incentives of vertically integrated firms depend on the amount of power they must purchase in order to meet native load relative to the amount they would produce, and sell to the market, at competitive prices.⁶ In addition to serving native load, a utility's net position may be affected by contracts; LSE's in PJM meet approximately 30 percent of demand by signing short and long-term bilateral contracts with other utilities or independent producers.⁷ Net selling firms have incentives to set prices and can easily do so by withholding generation from its most expensive units (or

⁶The incentives of subsidiary companies will also depend on the regulatory treatment of their LSE affiliates. Furthermore, even with a clear net position, the objective of publicly-owned utilities may be other than to maximize profits.

⁷In a personal communication, Joe Bowring of the MMU estimated this level of contracts. In addition, 10 to 15 percent of supply comes from spot market purchases, one to two percent from imports, and the remaining 53 to 59 percent is self-supplied by firms.

setting the units' market-based bids above the competitive equilibrium price).

Generally, in a market with perfectly inelastic demand, a monopsonist cannot affect prices. However, if the firm is a net buyer that also sells in the market, then it can operate plants with marginal costs above the equilibrium price. This will reduce purchases in the spot market and lower wholesale prices. In PJM, there are several net buyers that may have incentives to exercise oligopsony power. However, it is unclear that firms would benefit from this behavior because of other regulatory constraints.⁸

I assume firms maximize profits by setting quantity. The resulting objective function for vertically integrated firm i will be:

$$\max_{q_i} P_i(q_i) \cdot (q_i - q_i^d - q_i^c) + r_i^d q_i^d + r_i^c q_i^c - C_i(q_i), \quad (1)$$

where, $P_i(q_i)$ is the inverse residual demand function firm i faces in the spot market, q_i is its production, r_i^d and q_i^d are the retail price and quantity (or native load), q_i^c is the net supply/demand position from bilateral contracts paid the contract price r_i^c , and $C_i(q_i)$ is total production costs. The resulting first order condition equals:

$$P_i + P_i' \cdot (q_i - q_i^d - q_i^c) = C_i', \quad (2)$$

where firms have incentives to increase prices only if they are net sellers: $q_i > q_i^d + q_i^c$.

While restructuring has allowed retail competition to change firms' native load, many customers stayed with their historic providers during this time period.⁹ Decisions over generation capacity, service territory, and contracts were initially determined under a regulatory environment and are assumed to be exogenous to firms' incentives after restructuring.

For 1999, panel B of table 1 reports each firms' market share of capacity, generation, generation when demand exceeded 40,000 MW, and peak demand. On average, three companies—Philadelphia

⁸Regulators required the firms to offer retail customers a fixed rate that was above the expected average wholesale price. This allowed firms to cover the costs of "stranded" assets. By depressing wholesale prices, an oligopsonist would make the "rate freeze" be lifted sooner (as the stranded assets would be paid off) which may or may not be beneficial to the firm.

⁹In Pennsylvania, though, some customers did change providers in 1999. On July 1, the percent of customers that had switched from GPU Energy, PECO, and PPL was 5.5, 16.0, and 3.5. In particular, large customers switched; For these three firms, 39.9, 37.1, and 19.2 percent, respectively, of their initial load switch. Source: www.oca.state.pa.us.

Electric Company (PECO), GPU, and Pennsylvania Power & Light (PPL)—generation exceeded their native load. However, GPU may have been less inclined to learn how to set prices in this new environment as it was in the process of selling its assets: It sold a 2012 MW coal fired plant to Edison in March and most the rest of its plants to Sithe, a transaction completed in November. In contrast, on average, the other firms either had a zero net position or were net buyers. Between the summers of 1998 and 1999, the market structure did not change substantially.¹⁰ In addition to often being net sellers, PECO and PPL, which account for only 32 percent of capacity, actively bid market-based offers into the spot market and together offered 84 percent of all the market-based bids. GPU offered only 14 percent of these bids. In a news article, Smith and Fialka (1999) note PECO and PPL bid to make “the most of steamy conditions:”

What PECO and PPL did was offer much of their output at low prices so that the majority of their plants would be called into service. But knowing demand was so high, they offered power from their tiniest plants at vastly higher bids, in a way that often set the peak price for a number of hours.

Given these firms’ incentives, I characterize PJM as having a set of quantity-setting, dominant firms that face a competitive, albeit large, fringe and completely inelastic demand. This model implies that the aggregate output of the dominant firms will be less than the competitive level while the fringe will increase production to meet demand. This implies two testable hypotheses: Actual prices were above perfectly competitive prices levels; and firms distorted production decisions that caused welfare loss.

Strategic firms with asymmetric costs, or firms with asymmetric strategies, distort production decisions from the competitive equilibrium (Borenstein and Farrell, 2000). This causes cross-firm production inefficiencies whereby—even though *individually* firms achieve given output levels by minimizing own production costs—the *aggregate* output level is not produced using the least costly technology. Furthermore, an individual oligopolist will not necessarily produce less than it would have in a perfectly competitive market.¹¹

¹⁰Other than GPU’s sale of the large coal plant, no other plant was sold or retired from 1998 through October 1999. Also we see no major construction in the period of study (less than 700 MW were built at this time by utilities and non-utilities) (EIA form 860 a,b).

¹¹Levin (1985) shows that, in an oligopoly with asymmetric costs, some producers may increase production relative

In addition to strategic reasons, production distortions may occur even if a firm does not intentionally exercise market power. Firms face uncertainty in demand and each other's bids in the day-ahead, blind auction. A firm will distort production by either (intentionally or unintentionally) bidding a low-cost unit above the competitive price, or opting not to operate regardless of the bid. Section 4 measures the welfare implications of these production distortions. First, however, I test the second hypothesis that prices exceeded competitive levels after restructuring.

3 Measuring Market Power in the PJM Market

Unlike much of the recent industrial organization literature, where price-cost margin estimates tend to depend of assumptions of economic behavior and estimates of demand functions, the functional form of the derived demand in wholesale electricity markets has been greatly simplified by economic regulations on retail electricity prices. Namely, constrained retail prices imply completely inelastic demand. Margin estimates in electricity market studies have centered on determining marginal costs in order to calculate competitive prices.

In this section, I measure margins in PJM by using a method that fails to account for intertemporal constraints. Nevertheless, this "single-period" approach is useful as it is relatively straight-forward to apply and allows comparisons with other markets where researchers have also used the technique. Furthermore, as discussed below, ignoring intertemporal constraints in measuring competitive prices causes two, potentially offsetting, biases. In contrast, when measuring welfare effects, as in section 4, the biases from ignoring these constraints compound, and may be substantially large.

Wolfram (1999) develops a methodology of studying market imperfections in electricity markets. She calculates the marginal cost of each generating unit in the England and Wales market in order to generate competitive prices. A comparison of actual prices with her counterfactual price measures provides evidence of firms exercising market power, but below levels consistent with Cournot

to competitive levels. Note that firms can potentially exercise market power without causing welfare losses; if all firms uniformly increase bids, the optimal order of production will not be distorted.

behavior. In analyzing the California electricity market, BBW use a Monte Carlo simulation to account for the convex relationship between the uncertain availability of power plants and competitive prices. Joskow and Kahn (2002) also extend Wolfram’s technique in estimating market power in California while noting that environmental permits substantially increased perfectly competitive price estimates, but that observed prices are even greater. Bushnell and Saravia (2002) study the New England market using the technique and find that margin estimates are quite sensitive to their determination of the appropriate price to use in comparisons. The PJM Market Monitoring Unit (MMU) examined firm behavior and found some evidence of market power being exercised, as well.¹²

3.1 Methodology of Single-Period Model

In order to calculate price-cost margins, I model competitive behavior for the generating units capable of being used to exercise market power. I assume these units operate following an on-off strategy by producing at full capacity if and only if price equals or exceeds marginal production. In other words, this method ignores intertemporal constraints on production choices. The perfectly competitive price equals the marginal production cost of generating an additional unit of electricity, given that the least costly technologies are already producing to meet demand.

Demand for energy services in the spot market, which does not depend on prices, is comprised of demand for electricity (q_t^d) and additional reserves (q_t^r) that are regulated to insure against blackouts.¹³ I categorize supply into four groups: fossil, nuclear, hydroelectric, and net imports. For a given competitive price (P_t^*), firms use fossil-fuel burning units, or “fossil units,” to generate q^f . These units, some of which have high marginal costs and are flexible, might be used strategically.

¹²Studies by Bowring, et al. (2000) and MMU (2000) center on three high demand days and find that prices may have resulted either from *scarcity* or firms *exercising market power*; however, the MMU does not attempt to separate out these effects. A more expansive study by the MMU (2001) compares units’ bids and marginal costs between April 1999 and December 2000. By their measures, firms exercised a modest amount of market power. MMU (2001) bases these price-cost margin estimates on the bid of the most expensive operating unit. This ignores market power exercised by power plants that have reduced output and will understate estimates of price-cost margins.

¹³Demand also includes energy lost in the process of transmission. Line losses equal approximately 4.5 percent of generation (www.pjm.com). PJM requires regulation to insure against system-wide outages. The operators require 1.1 percent of maximum of predicted load during early morning hours (1 to 5 AM) and the rest of the day (PJM Pre-Scheduling Operation Manual).

In contrast, nuclear power plants—which have low marginal costs, high start up costs, and change production rates slowly—generate q_t^n independently of P_t^* . While strategic firms will not alter q_t^n , they consider how prices impact revenue from this inframarginal nuclear generation. Hydroelectric generation (q_t^h) could potentially be used to set prices. However, as I argue in Appendix B, PJM has little hydroelectric capacity and treating q_t^h as independent of P_t^* is unlikely to substantially bias results. Net imports (imports less exports) into PJM (q_t^{IMP}) do respond to prices. I assume that imports from the surrounding regulated markets are competitive and, as described in section 3.1.2, depend on actual prices (P_t) as well as P_t^* . In equilibrium, P_t^* clears the market:

$$q_t^d + q_t^r = q^f(P_t^*) + q_t^n + q_t^h + q_t^{IMP}(P_t, P_t^*). \quad (3)$$

Figure 2 depicts a hypothetical example of how to solve for the equilibrium using PJM units' offer curve, supply ($q_t^f(P_t^*) + q_t^n + q_t^h$), and residual demand: $q_t^d + q_t^r - q_t^{IMP}(P_t, P_t^*)$. Assuming that the offer curve lies above the competitive supply curve, I determine the competitive price by moving along the residual demand curve from where it intersects the offer curve to where it intersects the supply curve. As the price falls to the competitive equilibrium, net imports are reduced and more of the quantity demanded must be met by PJM firms. I use this model to predict competitive prices and output decisions for each generating unit.

3.1.1 Sample Period

In the summer following restructuring, from April through September of 1999, PJM observed substantially higher prices than most seasons since the market restructured.¹⁴ I focus on this six month period when some firms began to make market-based offers. While prices averaged \$26 per MWh in the summer of 1998, they increased to an average of \$38 in the following summer, reaching the

¹⁴Since the summer of 1999, prices have been relatively low in the energy market. Notable exceptions when average prices exceeded \$40 per MWh include December 2000, August 2001, and the first three months of 2003. Since 1999, there have been notable changes in market rules and market structure. In June of 2000, PJM started a day-ahead market in addition to the real-time market. Allaz and Vila (1993) show how the presence of a two-settlement system can reduce market power. Changes in ownership resulted in less market concentration and increased the likelihood of some firms being net buyers, which could have increased oligopsony power. April of 2002, PJM expanded into western Pennsylvania, Ohio, and West Virginia.

market cap several times.¹⁵ In general, during high demand periods like that summer, generation and transmission capacity limits bind making firms' residual demand inelastic and market power more likely. Furthermore, regulators may have not foreseen all possible manners in which firms could exercise market power in this new and extensive restructuring of the market.

However, in order to determine the extent to which high prices resulted from market power (or other types of market imperfections), one must consider supply and demand shocks that would increase prices in a competitive market. For the summers of 1998 and 1999, table 2 provides summary statistics of some market characteristics. First, demand grew, in part, due to higher temperatures.¹⁶ While demand increased only 809 MW (2.7 percent) on average, matching the slow growth in generation capacity, peak demand increased by 3245 MW (6.7 percent) over the previous summer (www.pjm.com). Also, from 1998 to 1999, fuel input prices increased. Oil and natural gas prices increased substantially from \$16.30 to \$20.56 a barrel and \$2.33 to \$2.60 per mmBTU, respectively (see Appendix B).

In addition, two tradable pollution permit markets required the compliance of at least some PJM plants. From 1998 to 1999, prices in the Clean Air Act Amendments' sulfur dioxide (SO₂) market, which then regulated 23 PJM units, climbed from approximately \$150 to \$200 per ton. For some power plants, the largest cost increase resulted from a new regional nitrogen oxides (NO_x) tradable permits program. Beginning in 1999, the Ozone Transport Commission required units in Delaware, Pennsylvania, and New Jersey (and others in New York and New England), to dramatically reduce May through September emissions. In May of 1999, permit prices exceeded \$5000 per ton, increasing some units' marginal production costs by 50 percent, but fell precipitously to \$1093 by summer's end. These input price shocks increased marginal production costs of coal,

¹⁵PJM reports a load-weighted average of all nodal prices for each hour that I use as "the price" throughout this paper. In Appendix B, I describe why this price measure is used in comparison to competitive price estimates. This price exceeded \$130 per MWh, a value PJM's market monitoring unit (2000) deems the most expensive unit's marginal cost, almost three times as often in the summer of 1999 (96 hours) as the previous summer (37 hours). As shown in table 3, the load-weighted average price increased even more so over the summers of 1998 and 1999 than the unweighted average price.

¹⁶The mean of the daily temperature averages went from 73.3 to 74.3, and the mean of the daily maximum temperature went from 82.5 to 84.8 (www.noaa.gov).

natural gas, and oil units 23, 15, and 27 percent, respectively. My measure of competitive prices account for these demand and supply shocks.

For each firm, table 3 describes the capacity factor (the fraction of capacity used to generate), during the summers of 1998 and 1999. Over these summers, PECO and PPL reduced output by 8 and 19 percent, respectively. In contrast, on average during this period, the other firms' production levels were constant. These summary statistics do not, of course, account for changes in input costs and other market conditions that may have affected these firms asymmetrically. For example, all firms in Pennsylvania (including PECO and PPL) were greatly affected by the new NO_x environmental regulation while Maryland firms were not.

3.1.2 Net Imports

Firms inside and outside of PJM will choose which market to sell to depending on relative prices. If PJM firms increase prices above competitive levels, then actual net imports will also exceed competitive levels. With fewer net imports and completely inelastic demand, PJM's more expensive units will operate in a competitive market. For each summer, I estimate net import supply.¹⁷ Firms exporting energy into PJM probably behave as price takers because they are numerous, face regulatory restrictions in their regions, and are limited by PJM pricing rules.¹⁸ Margin estimates will be understated if this assumption fails.

When transmission constraints do not bind, PJM and surrounding regions are essentially one market. However, the multitude of prices and "loop flow" concerns make assuming perfect information implausible. The corresponding transaction costs make net imports dependent on both the sign and magnitude of price differences. Data on bilateral contracts in neighboring regions are not publicly available so I proxy regional prices using daily temperature in bordering states (New York, Ohio, Virginia, and West Virginia). I also model net imports as a function of monthly fixed effects

¹⁷In contrast, BBW aggregate confidential import bid curves for the day-ahead market in California. However, since the PJM bids were not financially binding during my sample period, I do not follow this method.

¹⁸At the time of my study, regions surrounding PJM were under rate-of-return regulation. New York restructured later in 1999. To set price, importers had to bid into the day-ahead market. Obviously this will not prohibit importers from exhibiting market power as they can still withhold or bid high in the day-ahead market. However, it makes them price takers in the real-time market.

to address input cost shocks. For a given summer, I model net imports as a linear-log function of actual price (P_t) in hour t :¹⁹

$$q_t^{IMP} = \beta_1 \ln(P_t) * Peak_t + \beta_2 \ln(P_t) * (1 - Peak_t) + \sum_{m=1}^M \alpha_m Month_{mt} + \delta Peak_t + \sum_{s=1}^S \gamma_s Temp_{st} + \varepsilon_t, \quad (4)$$

where $Peak_t$ indicates hours between 11 AM and 8 PM on weekdays, $Month_{mt}$ is an indicator variable for each summer month, $Temp_{st}$ measures temperature for bordering states, and ε_t is an error term.²⁰

Finally, I address the endogeneity of price using two stage least squares (2SLS) as ignoring this effect would result in attenuation bias. For both peak and off-peak hours, I instrument prices with the log of hourly quantity demanded in PJM: $\ln(q_t^d) * Peak_t$ and $\ln(q_t^d) * (1 - Peak_t)$. Typically quantity demanded is considered endogenous to price, however, since the derived demand for wholesale electricity is completely inelastic, this unusual instrument choice is valid in this case. I exclude demand from the second stage as it only indirectly affects net imports through prices.

Separately for 1998 and 1999, table 4 reports 2SLS coefficient and standard error estimates that account for serial correlation and heteroskedasticity.²¹ Panel A shows the coefficients on the instruments in the first stage, which suggest strong load instruments, while panel B displays β_1 and β_2 for each year. In the second stage for both years, $\hat{\beta}_1 < \hat{\beta}_2$, which suggests that import supply is more price sensitive during off-peak hours. In 1999, coefficients imply a price elasticity of net

¹⁹Other potential functional forms for net import supply would be to assume a constant elasticity or impose a linear relationship. However, net imports are negative in many hours, making a constant elasticity model inappropriate. A linear model would not account for the inelastic nature of supply (*e.g.*, transmission lines entering PJM occasionally bind and limit net imports). I opt for an alternative model linear in net imports and logarithmic in PJM prices. The model is smooth, defined for all net imports, and accounts for the inelastic nature of imports nearing capacity.

For robustness, I also estimate a linear model and find similar results: In the summer of 1999, the slope coefficients were 11.99 (2.23) and 52.56 (7.66) for peak and off-peak, respectively. Using peak and off-peak averages for net imports, 1404 and 407 MWh, and prices, \$74.21 and \$22.82, this implies price elasticities ($\hat{\beta}_i \cdot \bar{P}/q_t^{IMP}$) of net imports of 0.63 and 2.9.

²⁰The temperature variables for bordering states are modeled as quadratic functions for cooling degree days (degrees daily mean below 65° F) and heating degree days (degrees daily mean above 65° F). As such $Temp_{st}$ has four variables for each of the four states. These data are state averages from the NOAA web site daily temperature data.

²¹I test the error structure for autocorrelation (Breusch-Godfrey LM statistic p-value of 0.00) and heteroscedasticity (Cook-Weisberg test with a p-value of 0.00). First I estimate the IV coefficients assuming *i.i.d.* errors in order to calculate an unbiased estimate of ρ , the first-degree autocorrelation parameter. After quasi-differencing the data, I re-estimate the IV coefficients while using the White technique to address heteroscedasticity.

imports on peak equal to 0.79 at average imports, while off-peak the elasticity is 4.2.²²

In the following section, I solve for the competitive equilibria—as shown in (3)—by using these estimates to predict net imports. For a given summer, I assume that the observed bounds on net imports ($q_{MIN}^{IMP}, q_{MAX}^{IMP}$) represent capacity constraints on transmission lines into and out of PJM.²³ As in figure 2, q_t^{IMP} equals the actual net imports \tilde{q}_t^{IMP} plus the deviation in imports given that under competition price will be P_t^* , not the actual P_t :

$$\begin{aligned} q_t^{IMP}(P_t, P_t^*) &= \tilde{q}_t^{IMP}(P_t) + [\hat{\beta}_1 Peak_t + \hat{\beta}_2(1 - Peak_t)] \ln\left(\frac{P_t^*}{P_t}\right) \\ \text{s.t. } q_t^{IMP} &\in [q_{MIN}^{IMP}, q_{MAX}^{IMP}]. \end{aligned} \quad (5)$$

3.1.3 Fossil Unit Supply

Estimating competitive supply from fossil units requires the construction of a marginal cost curve. Historic regulatory rate hearings provide rich data sources and formulae, which are independent of output, to determine unit i 's marginal cost of production (c_{it}):

$$c_{it} = VOM_i + HR_i \cdot (W_{it}^{fuel} + W_{it}^{SO_2} r_i^{SO_2} + W_{it}^{NO_x} r_i^{NO_x}), \quad (6)$$

where VOM_i is variable operating and maintenance cost, HR is an efficiency measure called heat rate, and W_{it}^{fuel} , $W_{it}^{SO_2}$, and $W_{it}^{NO_x}$ are daily prices for unit i 's fuel usage, SO₂ emissions, and NO_x emissions. Emission rates for SO₂ and NO_x equal $r_i^{SO_2}$ and $r_i^{NO_x}$. Appendix B describes the data sources for these variables.

In addition to production costs, estimates of competitive prices must account for scarcity rents and opportunity costs. Note that the industry marginal cost curve forms a step-wise function. Therefore, scarcity rents may arise when the equilibrium price falls between the production marginal costs of two units. The market clears by recognizing the shadow price of the production constraints of the low cost unit. Scarcity rents also occur when demand exceeds the capacity of the entire market including transmission-constrained imports. Given the completely inelastic demand in this market,

²²Elasticity equals $\hat{\beta}_i / \tilde{q}_t^{IMP}$. In the summer of 1999, net imports averaged 1404 on peak and 407 off-peak.

²³The observed net imports for the summer of 1998 ranged from -5,882 to 3194. In the summer of 1999, it ranged from -3,304 MWh to 6,095 MWh. Given the infrequency of observations at these limits, I do not econometrically model censoring.

scarcity rents only occur with positive probabilities in this latter, extreme case. Two potentially important opportunity costs involve intertemporal and spatial trading. However, electricity cannot be stored making intertemporal opportunity costs irrelevant.²⁴ PJM firms do have the option of selling outside the region. In fact, some bilateral trades in neighboring states greatly exceeded the PJM price cap in 1998 and 1999. Yet, by estimating net import supply in section 3.1.2, I account for arbitrage opportunities such that no additional trade opportunities exist in equilibrium. The competitive price, therefore, will account for import response and be determined by marginal production costs from (6) or, if generation and transmission capacity are exceeded, by the price cap.

As well as computing units' marginal costs, the determination of competitive supply also requires knowing their production capability. Generating units cannot run constantly and must be shut off for routine maintenance, limiting available capacity. As this paper focuses on summer months, while scheduled outages primarily occur in the low demand Spring and Fall seasons, these scheduled outages are irrelevant. However, additional unplanned outages also affect units' availability. I account for these idiosyncratic shocks (ξ_{it}) in determining unit i 's output (q_{it}):

$$q_{it}(P_t^*) = \begin{cases} K_i^{\max} & \text{if } P_t^* \geq c_{it} \text{ and } \xi_{it} > FOF_i \\ 0 & \text{otherwise,} \end{cases} \quad (7)$$

where K_i^{\max} is maximum capacity. In each hour, the forced outage factor (FOF_i) states the probability a unit cannot produce electricity when called upon. If $\xi_{it} \leq FOF_i$, a forced outage prohibits the unit from producing. This is an important limitation in a market without storage capability. When firms exercise market power, outages can make a unit "pivotal" and enable it set the price at the cap. Even under perfect competition, forced outages may substantially increase prices if supply nears capacity.

A common technique to account for these outages is to "derate" the capacity of a unit such that production $\tilde{q}_{it}(P_t^*) = K_i^{\max} \cdot (1 - FOF_i)$ if $P_t^* \geq c_{it}$ and zero otherwise. However, given the convexity of the market's supply curve with respect to price, the expected costs will exceed the

²⁴I discuss two notable exceptions, pumped storage and hydroelectric power, in Appendix B.

costs of the expected supply for a given level of demand. Also, using actual outages as a basis for supply curve calculations would be biased, as they are endogenous for strategic firms (Wolak and Patrick, 1997). Therefore, as with BBW, I account for forced outages using historic forced outage factors in a Monte Carlo simulation. For each hour in the sample, I simulate outages by drawing ξ_{it} from a $[0, 1]$ uniform distribution.

After concatenating the supply curve for all available units based on (7), I determine the equilibrium as the intersection of fossil supply and residual demand, which depends on price as given by (3) and (5). If residual demand intersects supply between operating units, the I determine scarcity rents from residual demand. If residual demand exceeds fossil supply such that all generation and transmission capacity binds, scarcity rents exist and I set price to the \$1000 cap. For each hour, I repeat the process 100 times and calculate the mean of these simulations of the equilibrium price, \bar{P}_t^* , that will be an unbiased estimate of the expected price under perfect competition. Noting that the competitive price equals the marginal cost of producing an additional MWh, I measure price-cost markups ($P_t - \bar{P}_t^*$) using these cost estimates.

3.2 Price-Cost Margin Results

For each month in the summers of 1998 and 1999, table 5 reports hourly averages for demand, actual price, and competitive price estimates assuming a linear-log functional form for net import supply.²⁵ From April through September, 1999, the competitive equilibrium price averaged \$28.94 per MWh, approximately nine dollars below the actual price average. In contrast, during the previous summer, the observed prices (\$26.04) only slightly exceeded marginal costs (\$23.33). Examining market performance in specific months, one notes substantial variation in price-cost markups. On the one hand, during June and July of 1999, actual prices surpassed competitive price estimates by \$6.79 and \$53.85, respectively. In contrast, all other summer months of that year had small positive or

²⁵As a robustness check, I also assume a linear functional form for net import supply and report measures of the market's performance similar to those above. Relative to the linear-log model, the linear model results in more competitive estimates of market performance, 22 percent, and smaller procurement cost increases. In 1999, the overall costs equal \$623 million (s.e. \$119 million) and the spot market costs increase \$170 million (s.e. \$39 million). In 1998, costs increase \$175 million (s.e. \$28 million) and \$51 million (s.e. \$8 million), respectively. However, as discussed in footnote 19, this functional form is not account for transmission capacity constraints.

negative margins. Margins in 1998, however, exhibited less monthly variation. Margins also vary substantially by time of day: Prices during peak hours, which are between 11 AM and 8 PM on weekdays, were twice as great as costs in 1999 while I estimate negative margins during off-peak hours. I discuss the implications of negative margins in section 3.2.1.

In order to measure overall market performance in an industry that lacks storage and has substantial intra-day variation in quantity demanded, I follow the practice of constructing a quantity-weighted Lerner index (for example, BBW). This highlights the economic significance of high demand hours in measuring the cost of procuring electricity. For a given set of hours (S), I define market performance ($MP(S)$) as:

$$MP(S) = \frac{\sum_{t \in S} (P_t - \bar{P}_t^*) \tilde{q}_t}{\sum_{t \in S} P_t \tilde{q}_t}, \quad (8)$$

where \tilde{q}_t equals electricity sold at prices reflecting those in the spot market. PJM's vertically integrated firms self-supply the majority of electricity, limiting the effect on energy costs of market imperfections in the spot market. However, spot purchases will be subject to firms exercising market power. Also, many bilateral contracts probably will be affected by strategic behavior. For example, firms index some contracts to spot prices. Assuming risk neutrality and efficient markets, even those contracts not explicitly indexed will, in expectation, equal the spot price.²⁶ Therefore, I define \tilde{q}_t as energy purchased on the spot market or through bilateral contracts.²⁷

Using this measure for the entire summer of 1999, I estimate $MP = 0.34$ (see table 5). This reflects an increase in procurement costs through the spot market for \$262 million above actual procurement costs. I estimate that this increase in procurement costs has a standard error of \$41

²⁶The cost of market power from the bilateral contracts will be the difference between the expected prices and the expected costs, multiplied by the volume of contracts. In expectation, this will be the same as if the quantity passed through the spot market. However, this market was just beginning and suppliers may have not foreseen the high prices and may have agreed to low prices. The sellers could not profit by ignoring the contracts and selling their power to the spot market instead. According to the MMU report (2000): "An energy sale contract typically includes a liquidated damages provision specifying the amount that the seller, for example, owes the buyer if the seller does not perform, *i.e.*, does not delivery energy when agreed. A typical liquidated damages provision would require the seller to pay the buyer the price the buyer actually had to pay to obtain replacement energy from the market, if the seller were unable to deliver."

²⁷The PJM Market Monitoring Unit's annual report (2000) summarizes average spot market purchases by month and time of day (disaggregating peak (11 AM to 8 PM) and off-peak). Each hour, I assume contracts equal 0.3 times total quantity demanded plus regulated reserves: $.3^*(q_t^d + q_t^r)$.

million (see Appendix C for a discussion of the estimation methodology). My measure of total transfers associated with market power increases to \$950 million if bilateral contracts exhibited similar margins.²⁸ To put these procurement cost increases in context, these estimates are 51 percent greater than those from a competitive market (i.e., $\sum_{t \in S} \bar{P}_t^* \tilde{q}_t$).

3.2.1 Pricing Model Discussion

In some months and some times of day, I report actual prices below competitive estimates. In 1999, May and September exhibit negative margins, which may have resulted from these (historically regulated) firms ignoring some marginal costs. For example, the NO_x emissions regulation began trading in May at extremely high prices and increased some units' marginal cost by \$13 per MWh. As regulators did not require compliance of firms until year's end, some firms may have ignored this new market's high costs.²⁹ In these months, cost estimates ignoring NO_x permits result in competitive price estimates similar to actual prices.³⁰ In addition, intertemporal constraints may have also biased cost estimates over these months.

In general, off-peak hours also display negative margins. However, plants do actually operate when price falls below their marginal costs. Recall the single-period model cost estimates ignore the shadow price of intertemporal constraints. Unit commitment problems, including start up costs, impose a dynamic optimization problem. If a firm expects prices to increase in the future and its unit has large start up costs, then it will be less expensive to run in low demand hours than to shut down and restart. Actual margins that consider these unit commitment problems will be nonnegative. However, by omitting intertemporal constraints during off-peak hours, the single-period methodology overstates marginal costs.

²⁸The total cost standard error (s.e.) is \$126 million. Using similar calculations for the previous summer, overall procurement costs equal \$282 million (s.e. \$59 million), while spot market costs alone total \$82 million (s.e. \$17 million).

²⁹Furthermore, Kolstad and Wolak (2003) find that, in the California electricity market, firms do not account for tradable permits to the full extent as other production costs. In 2000, they find that firms in the southern California NO_x tradable permits market (RECLAIM) produced more than the competitive level, as predicted in BBW, in comparison to relative behavior in 1998 and 1999.

³⁰Prices are \$3.9 above costs in May and \$1.4 below costs in September. This suggests that some firms may have either disregarded or discounted current NO_x prices when determining marginal production costs.

In contrast, during peak hours, start up costs and other intertemporal constraints may delay firms from operating even when expected prices exceed marginal production costs; firms may expect the price-cost differences to be temporary and insufficient to cover their unit commitment costs. By ignoring shadow prices during peak hours, those most subject to the exercise of market power, the single-period methodology biases marginal cost estimates downwards. While the overall implications of ignoring intertemporal constraints may be ambiguous, BBW argue that the overall effect is negligible when including margins from peak and off-peak hours. However, as will be discussed in section 4, the effects may be substantial in measuring market inefficiencies as peak and off-peak biases cumulate rather than offset.

4 Measuring Market Inefficiencies

In this market, short run market inefficiencies only result from deviations in production that I measure by comparing actual production costs with competitive counterfactual estimates. This section defines the optimization problem of competitive firms while accounting for intertemporal constraints. I then explain the econometric estimation technique of this intertemporal model that requires observing a baseline of competitive behavior. While regulated, I argue that the short run operation of power plants prior to restructuring, in 1998, was consistent with such behavior. Surely this regulated market did not exemplify *perfect* competition; firms invested inefficiently and probably distorted marginal production costs by making inefficient decisions regarding maintenance, labor, and capital allocation including environment abatement technologies. However, *given these costs*, operators likely dispatched units in a least-cost manner.³¹ Using the coefficient estimates from the pre-restructuring period, I predict a competitive counterfactual for production decisions

³¹Under regulation, some argue that firms had incentives to minimize effort rather than costs and therefore did not operate efficiently. Firms may have let units operate during low demand times instead of stopping and restarting them. If restructuring improved efficiency then, conditional on market conditions, more starts would be expected in the summer of 1999 than in that of 1998. Without controlling for market conditions, the number of fossil unit starts went from 4473 to 9006.

Further, even in 1998, firms could have withheld production from units that would have operated in a competitive market. However, as cost-based bids determined prices, the ability to move prices may have been limited. In contrast, in 1999, the flexibility of using bids as well as quantity may have facilitated exercising market power to the degree that firms circumvented constraints, such as regulatory surveillance. In addition, these historically regulated utilities may have undergone a learning process about how to exercise market power.

for the post-restructuring period. Finally, I present the empirical results of the welfare impacts of market imperfections in electricity markets using both the single-period and intertemporal models.

4.1 Intertemporal Model of Competitive Production

Several technologically-induced intertemporal constraints limit firms ability to produce electricity. As previously mentioned, after unit i shuts down, in order to resume operation at hour t , the firm pays “start up” costs ($START_i$). In addition to marginal production costs, firms incur some “no load” costs ($NOLOAD_i$), such as running conveyor belts and fans, regardless of the amount produced. Ramping rates (RMP_i) limit the speed at which units increase or decrease hourly production. After being shut down, minimum down times ($DOWN_i$) limit how quickly units can restart. Finally, minimum (K_i^{\min}) and maximum (K_i^{\max}) operating capacity levels restrict a unit’s range of operation.

These intertemporal constraints create non-convexities in firms’ production cost functions. Price-taking firms obtain profit maximization by optimizing units’ production separately. Neither a firm’s production at other plants nor its contractual agreements (including native load) affect optimization. Given price (P_t) and variable production costs ($C_{it}(q_{it})$) at unit i and hour t , a competitive firm chooses production (q_{it}) to solve the dynamic program:

$$V(q_{i,t-1}, t) = \max_{q_{it}} \{P_t q_{it} - C_{it}(q_{it}) - START_i q_{it}^+ q_{i,t-1}^0 - NOLOAD_i q_{it}^+ + \delta E_t[V(q_{it}, t + 1)]\} \text{ s.t. :} \quad (9)$$

- (i) Capacity: $q_{it} \in \{0, [K_i^{\min}, K_i^{\max}]\}$,
- (ii) Ramping: $\frac{|q_{it} - q_{i,t-1}|}{K_i^{\max}} \leq RMP_i$,
- (iii) Min. Down: $q_{it} > 0 \Rightarrow (q_{i,t-1} > 0 \text{ or } q_{i,t-s} = 0, \forall s \in \{1, \dots, DOWN_i\})$,

where, $V(q_{i,t-1}, t)$ is the value function this hour,³² q_{it}^+ indicates operation this period, (while $q_{i,t-1}^0$ indicates no production last hour), and $\delta E[V(q_{it}, t + 1)]$ is the discounted expectation of the value function next hour.

³²Bellman equations typically have an additional state variables S_t . However, in this case, the state variable simply refers to the initial production level going into period t , \vec{q}_{t-1} ; therefore, I avoid introducing an extra variable.

I assume $C_{it}(q_{it})$ to be a linear function: $c_{it}q_{it}$. Noting that competitive firms take P_t as given, a heuristic representation of the first order condition of (9) is:

$$PCM_{it} \equiv P_t - c_{it} = \lambda_{it}(\vec{q}_{it}), \quad (10)$$

where $\vec{q}_{it} = (q_{i,0} \dots q_{i,T})$, T equals total hours, PCM_{it} is the price-cost markup (ignoring intertemporal constraints), and λ_{it} is a general function accounting for intertemporal constraints that can have a positive or negative effect on the true marginal cost: $c_{it} + \lambda_{it}(\vec{q}_{it})$. Intertemporal constraints may reduce a unit's marginal cost; for example, postponing shutting down at low prices may improve overall profits since the firm avoids restarting the unit later on when prices rise. Intertemporal constraints may also increase marginal costs. Again, using the case of start up costs, a firm will not operate even when prices exceed marginal production costs if rents are not substantial enough to cover the cost of starting. When intertemporal constraints are inconsequential, the price-taking firms' optimization problem can be simplified further; these firms operate units at full capacity when price exceeds (or equals) marginal cost of production (c_{it}). Given this description of competitive firms' optimization problem and estimates of c_{it} as in (6), the following section explains the methodology used to account for intertemporal constraints in order to determine a competitive counterfactual market outcome.

4.2 Methodology of Intertemporal Model

For the pre-restructuring period, when I assume competitive behavior, I estimate the policy function: q_{it}^* equals the *argmax* of (9). Effectively inverting (10), the price-taking firm will choose output as a function of historic, current, and future price-cost markups and intertemporal constraints. Unlike production models that estimate the optimal mix of inputs, I know production costs but must estimate how constraints affect the firm's dynamic optimization problem. An alternative approach would be to make a direct calculation of the dynamically optimal solution. However, this would require information on the exact methodology the system operators use to dispatch units and on the ways firms form expectations about future prices. Rather, I opt for a

reduced-form approach relating output decisions to price-cost markups and constraints using in a flexible format.

The dependent variable, “utilization rate” (UR_{it}), measures the fraction of a unit’s capacity operating in a given hour. I model $UR_{it} = X'\beta$ so that the predictions of \widehat{UR}_{it} for 1999 are consistent with competitive behavior. To do this, I need consistent measures of the β parameters but also X variables unlikely to be subject to strategic behavior. For example, while the shadow price of intertemporal constraints depends on historic and future behavior (see (10)), including lagged and lead dependent variables could potentially bias competitive estimates in 1999 (e.g., a unit that reduces output to exercise market power may be unable to produce at full capacity because of ramping constraints). Instead, I identify firm choices by substituting in a vector of past, current, and future price-cost markups ($\overrightarrow{PCM}_{it}$) and unit characteristics: RMP_i , K_i^{\max} and $START_i$. I set $\overrightarrow{PCM}_{it}$ to consist of six variables: markups during the previous, current, and following hour as well as the daily average markup for yesterday, today, and tomorrow. I write utilization rate as a function of these variables and an idiosyncratic shock (ε_{it}):

$$UR_{it} = f(\overrightarrow{PCM}_{it}, RMP_i, K_i^{\max}, START_i) + \varepsilon_{it}. \quad (11)$$

In the estimation procedure described below, each of the six markup variables are interacted with each of the three unit characteristic variables. To further account for non-linear relations, I estimate each of these 27 variables ($6+3+6*3$) as a piece-wise linear, or spline, function that is separated by quintile. Finally, I allow these choices to differ by time of day by estimating 24 sets of hourly coefficients.

Using data described in Appendix B, I estimate firm production choices in three steps of an instrumental variables-Heckman selection model. First, as prices may be endogenous, I predict fitted values of price-cost markups (\widehat{PCM}_{it}) that are orthogonal to production. Even before restructuring, a large unit sustaining a forced outage will likely move the market price. Furthermore, if firms behave strategically after restructuring, markups will be inconsistent with that of a competitive equilibrium. I instrument the actual markups using the predicted competitive markups from sec-

tion (3): $\overrightarrow{PCM}_{it}^* \equiv \overline{P}_t^* - c_{it}$. These instruments include predicted competitive markups of six types: the previous, current, and following hour and the daily average markup for yesterday, today, and tomorrow. Like all other variables, I allow these instruments to enter as piece-wise linear functions separated by quintile and to differ by hour of day. For markup measure j in $\overrightarrow{PCM}_{it}$ —which varies by type, quintile, and hour—I run an OLS regression:

$$PCM_{jit} = f_1(\overrightarrow{PCM}_{it}^*, RMP_i, K_i^{\max}, START_i) + \varepsilon_{1,it}. \quad (12)$$

In the second stage, I estimate the binary choice of whether a unit operates or not. Using a probit model, I estimate ON_{it} , an indicator that $UR_{it} > 0$, as a function of fitted markups and intertemporal constraints:

$$ON_{it} = f_2(\widehat{PCM}_{it}, RMP_i, K_i^{\max}, START_i) + \varepsilon_{2,it}. \quad (13)$$

I estimate the probability of operating ($\Pr(\widehat{ON}_{it})$) and the inverse Mill's ratio (\widehat{MILLS}_{it}). Finally, conditional on operation, I estimate utilization rates as a function of fitted markups, ramping rates, capacity, and their interactions. Conditional on operation, I assume start up costs do not affect production:

$$UR_{it|ON_{it}} = f_3(\widehat{PCM}_{it}, RMP_i, K_i^{\max}, \widehat{MILLS}_{it}) + \varepsilon_{3,it}, \quad (14)$$

where I use weighted least squares, with K_i^{\max} as the weight, so that predicted system-wide production—namely the sum over all units of $(\widehat{UR}_{it|ON_{it}} * \Pr(\widehat{ON}_{it}) * K_i^{\max})$ —is consistent with actual system-wide production in 1998.

Given the high degree of periodicity of a unit's hourly utilization rate, serial correlation must be taken into account. Maximum likelihood estimation of (12), (13), and (14) that accounts for serial correlation would require imposing a specific functional form on the error structure and would be quite cumbersome to estimate. Rather, I determine the models' coefficients and standard errors using a bootstrapping method. I account for serial correlation by grouping observations in seven-day increments: For a given bootstrap draw, I pick an observation (with replacement) as well as the following six days' observations. I repeat the estimation procedure using the new sample, which

has the same number of observations as in the initial regression.³³ I repeat the process 200 times to determine the sample mean and standard deviation of these draws in order to estimate firm competitive decisions, as well as their aggregate production costs. In contrast, sections 3.1.2 and 3.2 estimate standard errors using parametric approaches and thus are treated differently in the following section.

I have defined a flexible relationship between output decisions and key variables that makes the interpretation of any individual coefficient difficult. In brief, on average, higher price-cost markups in the current hour increase the likelihood of operation and the output from operating units. Units with high capacity, quick ramping rates, and low start up costs operate more. Conditional on operating, units with slow ramping rates tend to have higher utilization rates. Appendix D provides a detailed discussion of the coefficient estimates.

For the summer of 1998, in order to determine the importance of intertemporal constraints, I compare production estimates from the intertemporal and single-period models with actual output. The intertemporal model fits the actual production data better than the single-period model.³⁴ Figure 3 plots a kernel regression of price-cost markups (ignoring intertemporal constraints) ranging from -\$30 to \$30/MWh, marking the 5th and 95th percentiles, on actual utilization rates (black line). As price-cost markups increase, the average utilization rate rises slowly from 0.2 to 0.8. In comparison to actual utilization rates, single-period model utilization rates (light gray line) are low during negative price-cost markups, increase quickly, and are high for positive markups.³⁵ In

³³Robinson (1982) demonstrates that estimation of limited dependent variable models will be consistent when serial correlation is not modeled explicitly in the likelihood function.

³⁴The correlation of actual utilization rates to single-period utilization rate estimates is 0.56 while with intertemporal utilization rate estimates the correlation is 0.69. The correlation of the two estimates is 0.82.

A more formal test requires the use of some non-nested test, since there does not exist a mapping of one utilization rate estimate to the other. I follow the methodology of an encompassing test, as described in Davidson and MacKinnon (1993, pages 386-387). This is done by testing one hypothesis and including the variables from the second hypothesis that are not already in the model. In this case, I regress actual utilization rates on the intertemporal model estimates, and also include the single-period model's estimates. The coefficient on the intertemporal model's estimate is 0.9948 (with OLS s.e. of 0.0027) while the single-period model's estimate is insignificant: a coefficient of 0.0021 (0.0015). Accounting for serial correlation increases the standard errors. I repeat the process using a least absolute deviation estimator: The intertemporal model coefficient is 1.071 (0.002) and the single period one is 0.101 (0.001).

³⁵Recall that the single-period model requires that units operate at 100% capacity whenever the *perfectly competitive price* exceeds the estimated marginal cost. However, the single-period model estimates of the utilization rate do not jump from zero to one when the *actual price* exceeds marginal costs in figure 3. This is because the single-period

contrast, the intertemporal model (dark gray line) closely fits observed behavior. This suggests that intertemporal constraints matter.

Figure 3 implies that the single-period model fails to account for intertemporal constraints that may substantially affect output decisions and lead the model to underestimate welfare effects based on direct production costs, namely the variable costs excluding start up and no load costs. During peak hours, intertemporal constraints will lead to units with moderate marginal production costs not starting and others with low marginal production costs not being able to ramp up to full capacity. This will require units with high marginal production costs to operate, increasing the direct production costs. In contrast, during the middle of the night, intertemporal constraints will lead to moderate cost units operating at a loss but avoiding start up costs the next morning. Again, the direct costs of production will be greater than implied by the single-period model. Therefore, unlike in the case of measuring price-cost margins where the intertemporal biases were potentially off-setting, in the case of measuring welfare, the single-period model will overstate welfare losses.

4.3 Estimating Welfare Effects

In general, firms increasing prices cause two types of welfare loss: allocative inefficiencies (as consumers purchase less at high prices) and production inefficiencies (when multiple firms have asymmetric costs or strategies). These production inefficiencies are only across firms, as each firm produces a given quantity in a least cost manner. Given the completely inelastic demand for wholesale electricity, these cross-firm production inefficiencies are the only welfare implications in the short run. Calculating welfare effects then becomes a matter of comparing actual total production costs with competitive estimates. For a sample of T hours and N units in PJM, I measure the welfare effect to be:

$$W^* - \widehat{W} = \sum_{t=1}^T \left\{ \sum_{i=1}^N [C_{it}(\widehat{q}_{it}) - C_{it}(q_{it}^*)] + \int_{\sum_{i=1}^N q_{it}^*}^{\sum_{i=1}^N \widehat{q}_{it}} p_t(q_t^d - x) dx \right\}, \quad (15)$$

model and actual prices are not perfectly correlated. Note that utilization increases at negative markups; this suggests that my marginal cost estimates overstate firms' perceived costs.

where W^* is social welfare under perfect competition and \widehat{W} is actual welfare. Similarly, q_{it}^* and \widehat{q}_{it} are the optimal and actual production levels of PJM firms. The inverse net import competitive supply function is given by $p_t(q_t^d - x)$ and q_t^d is demand. As in section 4.1, I assume variable costs $C_{it}(q_{it})$ to be a linear function: $c_{it}q_{it}$. As in section 3.1, actual hydroelectric and nuclear production are assumed to be consistent with competitive behavior. In order to calculate (15), I use the EPA's Continuous Emissions Monitoring System (CEMS) data on actual hourly production of fossil fuel units (\widehat{q}_{it})—which I discuss in Appendix B—and competitive estimates for these units (q_{it}^*) based upon the intertemporal and single-period models. I determine changes in net imports using the estimated net import supply curve described in section 3.1.2.

In table 6, I examine the welfare implications of restructuring and the importance of intertemporal constraints in measuring these welfare effects. The first method of calculating production under perfect competition, q_{it}^* , uses the intertemporal model estimates. This model provides a consistent estimate of competitive behavior; for firms in PJM during the summer of 1998, both the actual production costs and my cost estimates totaled \$1.34 billion. However, in 1999, actual production costs were \$1.64 billion while my production estimates were only \$1.59 billion.³⁶ These cost differences imply production inefficiencies of \$54 million, or 3.4 percent, after restructuring. Recall the intertemporal model coefficients and standard errors are estimated using a bootstrapping method. As a measure of the production inefficiencies' standard errors, I report the standard deviation of 200 bootstrap draws, which is \$4.2 million.

In contrast, using the standard methodology, which does not account for intertemporal constraints, I predict welfare effects even *before* restructuring. For 1998, this single-period model's estimates of production costs were \$71 million, or 5.6 percent, less than actual production costs.

Recall from section 3.2, I estimate the standard errors for this model using a linear estimation pro-

³⁶For 1999, I calibrate the intertemporal model so that the summer's aggregate production equals that of the single-period model. For each hour, I determine the equilibrium production level implied by the single-period model: $\sum_{i=1}^N q_{it}^*(S)$. Using units' marginal production costs and intertemporal model's production decisions ($q_{it}^*(I)$), I construct a supply curve. Equilibrium is defined to be where: $\alpha \sum_{i=1}^N q_{it}^*(S) = \sum_{i=1}^M q_{it}^*(I)$, where M is the least-cost set of units and α scales the equation such that the summer's aggregate generation is equal for both models: $\sum_{i=1}^T \alpha \sum_{i=1}^N q_{it}^*(S) = \sum_{i=1}^T \sum_{i=1}^M q_{it}^*(I)$. In this case, α equals 1.03.

cedure. For the pre-restructuring period, I estimate welfare loss standard errors to be \$1.2 million. In the summer of 1999, the single-period model cost estimates were only \$1.46 billion, implying production inefficiencies totaled \$182 million (with a standard error of \$1.4 million). Welfare losses were 12.5 percent of competitive production cost estimates.³⁷ In each year, the intertemporal model predicts less welfare loss than the single-period model.

During hours when actual prices exceeded their competitive estimates, I measure additional inefficiencies due to the production costs paid to imports. For both competitive models, I use the same import estimates of welfare and production. Assuming imports are competitive, the additional production costs from market distortions is \$3.2 million and \$2.3 million in the summers of 1998 and 1999, respectively. Using the delta method to estimate the standard errors of additional imports, I find no significant difference in import costs between 1998 and 1999.³⁸ Including net import costs, total welfare losses are more than three times as great using the single-period model (\$185 million) than using the intertemporal model (\$56 million).

Relative to wealth transfers—as measured in section 3.2—deadweight losses were small, only six percent the size. (Recall that during the summer of 1999, the costs of procuring electricity from the PJM spot market exceeded the estimated procurement costs of a perfectly competitive market by \$262 million and that, if similar markups affected demand met with bilateral contracts, total costs increased \$950 million.) Of the \$56 million in costs likely to have resulted from intertemporal constraints, less than half can be attributed to start up costs. The actual start up costs in the six month period of 1998 totaled \$23.2 million for the plants in the CEMS data. In 1999, start up costs for the observed production decisions were \$26.7 million, suggesting that other intertemporal

³⁷One way to account for intertemporal constraints is to treat the 1998 single-period model estimates as a control group. Assuming that the 1998 welfare loss estimates resulted *solely* from the bias of ignoring these constraints, the welfare effects from restructuring related market imperfections equal the change in total welfare losses from 1998 to 1999, or \$111 million. Note that if the bias is not constant over time, this method will inaccurately measure welfare effects.

³⁸Standard errors of additional production costs from increased imports are estimated using the delta method and the log(price) coefficients' standard errors shown in table 5. For each hour, I estimate the partial derivative of additional import supply costs with respect to the log(price) coefficient and multiply by the coefficients' standard error. I dropped nine outliers that occurred July 30, 1998, when the estimated gradient was extremely larger than other hours.

constraints affect firms' production decisions. If firms operated as suggested by the single-period model, the number of starts would be twice as great and start up costs would have totaled \$44.4 and \$41.0 million in these two summers. In contrast, the intertemporal model predicts firms rarely shut units down and start up costs equal \$5.7 and \$10.2 million, respectively. Given these welfare measures and earlier findings on overall competitiveness of the market, I now address the issue of whether specific firms were exercising market power.

5 Vertical Integration and Firm Conduct

This section asks whether PJM firms' behavior changed after restructuring. More specifically, I ask: Do firms with net selling positions behave differently from other firms? Does vertical integration affect firms incentives to exercise market power? I address these questions using two tests: I treat restructuring as a natural experiment in measuring firm production; and, as a benchmark, I examine the consistency of firm behavior with a structural model's first order condition.

5.1 Testing the Effects of Vertical Integration on Firm Incentives using a Natural Experiment

As a natural experiment, I test whether output from two firms, PECO and PPL, differed after the PJM market restructured relative to the other firms. Since market conditions may asymmetrically affect competitive firms, I control for estimates of competitive production decisions. I isolate these firms because, relative to others, they:

- offered unregulated, "market-based" bids (section 2.2);
- had net selling positions (table 1); and
- reduced output from 1998 to 1999 (table 3).

As previously discussed, GPU also had a net selling position (and reduced output slightly) but, unlike PECO and PPL, offered few market-based bids. For robustness, I test the sensitivity of my results to the definition of "oligopolist" by including and excluding GPU. This first approach simply addresses whether PECO and PPL behaved differently than others on average.

As with the welfare analysis, I use two estimates of firm i 's competitive production (\widehat{q}_{it}), based on the single-period and intertemporal models, to account for cost and demand shocks. Estimates of fossil units' competitive production are aggregated by firm (table 1 lists these firms).³⁹ Furthermore, I control for unobservable shocks that are common to *all* firms in the summer after the policy of restructuring is enacted ($Policy_t$). In addition, I include a vector of exogenous variables (Z_t) with indicators of hour of day and day of week, as well as a piece-wise linear function of demand that is separated by decile. Firm fixed effects (η_i) are also included.

In this difference-in-differences approach, I estimate behavioral changes following restructuring for oligopolists PECO and PPL ($Olig_i$) relative to the “fringe” suppliers. Even though some firms in the fringe have large market shares, I model them as price-takers because they are unlikely to have either incentives or the ability to affect prices. u_{it} is an idiosyncratic shock. For firm i at hour t , firm aggregate observed production (q_{it}) is modeled as follows:

$$\ln(q_{it}) = \phi \ln(\widehat{q}_{it}) + \zeta Policy_t + \gamma Policy_t \cdot Olig_i + Z_t' \Pi + \eta_i + u_{it}. \quad (16)$$

Table 7 reports the OLS coefficients with Newey-West standard errors. I assume the moving average process to include 24 hourly lags. In column (i), I do not control for competitive production, setting ϕ in (16) to zero. The $\widehat{\gamma}$ coefficient measuring production by oligopolists after restructuring is -0.20, implying a reduction in output of 20 percent, on average, by these two firms in the summer of 1999. In column (ii), I control for competitive output estimates based on the intertemporal-period model. Here, $\widehat{\gamma}$ equals -0.16 and the coefficient on the log of the estimated production, $\widehat{\phi}$, is 0.69. Uncertainty in production, such as forced outages, will result in attenuation of the ϕ coefficient. To address potential bias from including a variable with measurement error, I set $\phi = 1$. In column (iii), the dependent variable is the difference between the log of actual output and the log of the estimated competitive output. The model suggests that oligopolists reduced output by 14 percent after restructuring while other firms did not behave differently. Using a Hausman specification test, the column (iii) $\widehat{\gamma}$ estimate is significantly different from that in column (i) suggesting that some,

³⁹All small firms are aggregated as firm “other” since none of them would be large enough to exercise significant market power.

but not all, of the actual reduction in output was due to competitive market conditions. Regressions based on the single-period competitive model support these findings.⁴⁰ In addition, as a robustness check, I repeat the analysis including GPU and estimate qualitatively similar coefficients.⁴¹ Given the potential biases from including regressors with measurement error (\widehat{q}_{it}), as in column (ii), I find the results of column (iii) to be the most convincing of these regressions. These results support the hypothesis that market power was exercised by these two net selling firms, PECO and PPL, after prices were deregulated in this market. A formal test of this conclusion uses a structural model of firms' first order conditions.

5.2 Structural Test of Firm Behavior

This method tests a particular structural model of firm behavior to explore firm behavior after restructuring. As a benchmark, I write the first order condition, (2), assuming firms optimize in a static game setting by choosing quantities. If firms are playing a dynamic game or are optimizing by choosing prices, the first order condition will change. However, the purpose of my estimation is not to determine the consistency of behavior with one specific strategy, but rather to use this model to benchmark behavior for comparisons over time and across firms.

In this setting, a firm with a larger net position will have more incentive to drive the price above marginal costs (conditional on a firm's inverse residual demand). For firm i , year j , and hour t , I modify (2) by using the assumptions from section 4—constant marginal production costs (c_{ijt}) and shadow price of intertemporal constraints (λ_{ijt}). Like Puller (2000), I also model a conduct parameter for each firm, allowing it to vary by year (θ_{ij}):⁴²

$$P_{jt} + \theta_{ij} P'_{ijt} \cdot (q_{ijt} - q_{ijt}^d - q_{ijt}^c) = c_{ijt} + \lambda_{ijt}. \quad (17)$$

⁴⁰I estimate the regressions in columns (ii) and (iii) using estimates of competitive production from the single-period model. In column (ii), the coefficient on oligopolists after restructuring is -0.162 (s.e. 0.032). The coefficient on competitive production γ is only 0.283 (0.014). In column (iii), the model predicts oligopolists reduced output by 8.3 percent while all firms increased output 7.7 percent.

⁴¹For example, when including GPU, the coefficients for column (ii) are $\gamma = -0.116$ (0.025) and $\zeta = -0.010$ (0.014). For Column (iii), they are $\gamma = -0.089$ (0.024) and $\zeta = -0.012$ (0.014).

⁴²Puller tests whether firm behavior in the California market was consistent with static or dynamic pricing models. He estimates a firm conduct parameter and cannot reject Cournot behavior.

As in section 2, I denote inverse residual demand P_{ijt} , production q_{ijt} , native load q_{ijt}^d , and net supply/demand position from bilateral contracts q_{ijt}^c . A firm’s marginal cost ($c_{ijt} + \lambda_{ijt}$) equals its most expensive unit that is operating but at less than capacity (K_i^{\max}):

$$c_{ijt} + \lambda_{ijt} \geq c_{ljt} + \lambda_{ljt}, \forall l \neq i : q_{ljt} \in (0, K_i^{\max}). \quad (18)$$

If all units are at capacity, then the firm’s marginal cost is the marginal cost of its next most expensive unit.

As shown in (17), a strategic firm ($\theta_{ij} = 1$) will determine output as a function of price, marginal production cost, the shadow price of intertemporal constraints, the slope of the inverse residual demand facing firm i , and the net position of production ($q_{ijt} - q_{ijt}^d - q_{ijt}^c$). In contrast, the first order condition of a firm behaving competitively ($\theta_{ij} = 0$) will be as shown in (10); the overall amount a firm generates does not affect its decision on at the marginal generating unit.

For purpose of estimation, using the notation in (10), I write (17) as:

$$PCM_{ijt} = \alpha_{ij} + \beta_{ij}(q_{ijt} - q_{ijt}^d) + \varepsilon_{ijt}, \quad (19)$$

where ε_{ijt} is an idiosyncratic shock. I assume λ_{ijt} to be monotonically increasing with c_{ijt} within a the set of a firm’s operating units in a given hour. Thus, the price-cost markup (PCM_{ijt}) is the difference between the market price and the marginal production cost of the most expensive unit operating below capacity.⁴³ I now define “net position” (q_{ijt}^{net}) as the difference between production and native load. The intercept, α_{ij} , equals the average over T hours of the firm’s responsiveness to net contract coverage plus the shadow price of the constraints: $\alpha_{ij} = \frac{1}{T} \sum_{t \in T} (\theta_{ij} P'_{ijt} q_{ijt}^c + \lambda_{ijt})$. If a firm is a price-taker, then $\alpha_{ij} = \bar{\lambda}_{ij}$. Recall from section 3.2.1, the impacts of λ on prices depend on time of day, and may be offsetting. So, the overall impact on price-cost markups can be either positive or negative. As this shadow price, as well as some contract specifications, differ by time of day, I allow α to vary for peak (*Peak*) and off-peak hours.⁴⁴ The β_{ij} coefficient on the net position

⁴³ As with Puller (2000), if the marginal unit’s production exceeds 90 percent of its capacity, I redefine the firm’s marginal cost as the cost of its *next* most expensive unit that has operated during the previous week.

⁴⁴ As in previous sections, I define peak as hours between 11 AM and 8 PM on weekdays.

equals $-\theta_{ij}P'_{ijt}$ (which is nonnegative) and any other correlation between net supply and the price-cost margin: For a competitive firm, β_{ij} equals the covariance of the firm's net position and the shadow price of intertemporal constraints ($\sigma_{\lambda,q^{net}}/\sigma_{q^{net}}^2$). For both α_{ij} and β_{ij} , I use observations from 1998, the control period, to separate these effects. Identification depends on assuming that, for a given firm and time of day, $\bar{\lambda}$ and $\sigma_{\lambda,q^{net}}/\sigma_{q^{net}}^2$ are constant over the two summers. The econometric model is:

$$PCM_{ijt} = a_i + \alpha_i Policy_j + a_i^{PK} Peak_{jt} + \alpha_i^{PK} Peak_{jt} Policy_j + b_i q_{ijt}^{net} + \beta_i q_{ijt}^{net} Policy_j + \varepsilon_{ijt}. \quad (20)$$

I estimate (20) using 2SLS as q^{net} is endogenous. The instruments are daily temperatures for both states in PJM and for those bordering the region.⁴⁵ Appendix B discusses data sources. I model the idiosyncratic shock as a heteroskedastic, first-order autoregressive error term.⁴⁶

Table 8 reports the \widehat{b}_i and $\widehat{\beta}_i$ coefficients and robust standard errors from estimating (20) for each firm. For each firm, column (i) reports \widehat{b}_i , the impact of net position on markups during 1998. Relative to this baseline, column (ii) reports the additional impact in 1999: $\widehat{\beta}_i$. Recall that regardless of net position, a positive $\widehat{\beta}$ is consistent with exercising market power. Two net sellers, PECO and PPL, have significant and positive $\widehat{\beta}$ coefficients implying that, on average, they exhibited behavior consistent with exercising market power after restructuring. In contrast, the other net seller (GPU) did not behave statistically differently after restructuring. One other firm has a significantly positive $\widehat{\beta}$ coefficient; Public Service, the largest buyer in this market, may have been exercising monopsony power and dampened prices from being even higher than observed. This behavior will also exacerbate production inefficiencies, and therefore, welfare loss. For Potomac, Baltimore, Delmarva, Atlantic, and "other" firms, I estimate a negative $\widehat{\beta}$ coefficient, suggesting that the covariance of firms' net positions and intertemporal constraint shadow prices

⁴⁵Temperatures are modeled as quadratic functions for daily means, with coefficients allowed to vary above and below 65 degrees Fahrenheit (cooling and heating degree days, respectively).

⁴⁶I correct for serial correlation by estimating an AR(1) coefficient (ρ) and quasi-difference the data, namely calculate $Dx=x(t)-\rho*x(t-1)$ for all data. Then, I estimate the 2SLS results using these quasi-differenced data and report robust standard errors estimated using the Huber/White/sandwich estimator of variance.

were not constant over the two summers. If the change in this covariance was negative for all firms, then the findings that Public Service, PECO, and PPL did take other firms' responses (P'_{ijt}) into consideration are even more likely. In columns (iii) and (iv), I limit the sample to only those hours when q_{it}^{net} is positive, testing whether all firms exercised monopoly power when they had incentives to do so. However, during these hours, only PECO and PPL have positive β coefficients. These firms seem the most culpable for the wealth transfers and welfare losses previously measured.

6 Conclusions

This paper examines the pricing and production choices of firms in the newly deregulated PJM electricity market. During the initial summer of restructuring, prices spiked more frequently than in other recent summers. I find evidence of market imperfections and that some PJM firms behaved strategically. Using a technique based on Wolfram (1999), this paper estimates prices for a competitive market in determining estimates of price-cost margins and finds substantial wealth transfers and welfare effects. For this post-restructuring summer, I find an increase in procurement costs of \$262 million, 51 percent above the costs of a perfectly competitive spot market. If similar markups affected demand met with bilateral contracts, the measure of the increase in procurement costs is \$950 million. In using this methodology of estimating competitive market outcomes, I calculate that actual production costs were greater than these competitive estimates by 12.5 percent.

However this "single-period" model ignores intertemporal constraints, and therefore, overstates production inefficiencies. In this paper, I develop a consistent measure of competitive production decisions to estimate welfare. Relative to the standard technique, my model accurately predicts production behavior substantially better during the control period. Comparing actual production costs with these competitive production cost estimates for the summer after restructuring, I estimate that actual costs exceeded competitive estimates by only 3.4 percent, substantially less than the estimates using the standard technique.

These transfers and welfare effects resulted from strategic behavior. Treating restructuring as a natural experiment, this paper's findings show that the two large net-selling firms, PECO and

PPL, produced approximately 14 percent less than they would have in a competitive environment. Furthermore, as a benchmark, I examine the consistency of all large PJM firms with a structural model's first order condition. Here, I also find supporting evidence that PECO and PPL increased prices. These results do not imply that divesting power plants was a poor decision. However, it does caution regulators that, if they do require divestiture, then they also enable firms to sign contracts that will limit incentives to distort the market.

References

- [1] Allaz, Blaise and Jean-Luc Vila. 1993. "Cournot Competition, Forward Markets and Efficiency," *Journal of Economic Theory*, 53(1), February, pp. 1-16.
- [2] Borenstein, Severin, James Bushnell, and Christopher Knittel. 1997. "A Cournot-Nash Equilibrium Analysis of the New Jersey Electricity Market," *New Jersey Board of Public Utilities. Review of General Public Utilities' Restructuring Petition, Appendix A. Docket No. EA97060396*.
- [3] Borenstein, Severin, James B. Bushnell, and Frank A. Wolak. 2002. "Measuring Market Inefficiencies in California's Restructured Wholesale Electricity Market," *American Economic Review*, 92(5): 1376-1405.
- [4] Borenstein, Severin, and Joseph Farrell. 2000. "Is Cost Cutting Evidence of X-Inefficiency?" *American Economic Review Papers and Proceedings*, 90. (May).
- [5] Bowring, Joseph E., William T. Flynn, Robert E. Gramlich, Michael P. McLaughlin, David M. Picarelli, and Steven Stoft. 2000. "Monitoring the PJM Energy Market: Summer 1999," *Fifth Annual POWER Research Conference on Electricity Restructuring, March 17*.
- [6] Bushnell, James B. and Celeste Saravia. 2002. "An Empirical Assessment of the Competitiveness of the New England Electricity Market," *CSEM Working Paper CSEM WP-101*.
- [7] Davidson, Russell and James G. MacKinnon (1993) *Estimation and Inference in Econometrics*, Oxford University Press, 875 pages.
- [8] Joskow, Paul L. and Edward Kahn. 2002. "A Quantitative Analysis of Pricing Behavior In California's Wholesale Electricity Market During Summer 2000," *Energy Journal* 23(4): 1-35.
- [9] Joskow, Paul L. and Jean Tirole. 2000. "Transmission Rights and Market Power on Electricity Power Networks," *RAND Journal of Economics*, 31(3): 450-487.
- [10] Kahn, Edward. 2000. *Workpapers in Public Utilities Commission of Ohio, Case No. 99-EL-ETP*.
- [11] Kolstad, Jonathan and Frank A. Wolak. 2003. "Using Environmental Emissions Permit Prices to Raise Electricity Prices: Evidence from the California Electricity Market" CSEM Working Paper WP-113.

- [12] Levin, Dan. 1985. "Taxation within Cournot Oligopoly," *Journal of Public Economics*, 27(3): 281-290.
- [13] Mansur, Erin T. 2001. "Environmental Regulation in Oligopoly Markets: A Study of Electricity Restructuring," *POWER Working Paper-088*.
- [14] Market Monitoring Unit (MMU). 2000-2001. *PJM Interconnection State of the Market Report*.
- [15] Puller, Steven L. 2000. "Pricing and Firm Conduct in California's Deregulated Electricity Market," *POWER Working Paper PWP-080*.
- [16] Robinson, Peter M. 1982. "On the Asymptotic Properties of Estimators of Models Containing Limited Dependent Variables," *Econometrica*, 50(1): 27-41.
- [17] Schweppe, Fred C., Michael C. Caramanis, Richard E. Tabors, and Roger E. Bohn. 1988. *Spot Pricing of Electricity*. Kluwer Academic Publishers.
- [18] Smith, Rebecca and John J. Fialka. 1999. "Electricity Firms Play Many Power Games That Jolt Consumers," *The Wall Street Journal*, August 4.
- [19] Wolak, Frank A. 2000. "An Empirical Analysis of the Impact of Hedge Contracts on Bidding Behavior in a Competitive Electricity Market," *International Economic Journal*, 14(2): 1-39.
- [20] Wolak, Frank A. and Robert H. Patrick. 1997. "The Impact of Market Rules and Market Structure on the Price Determination Process in the England and Wales Electricity Market," *POWER Working Paper PWP-047*.
- [21] Wolfram, Catherine D. 1998. "Strategic Bidding in a MultiUnit Auction: An Empirical Analysis of Bids to Supply Electricity in England and Wales," *RAND Journal of Economics*, 29(4): 703-25.
- [22] —. 1999. "Measuring Duopoly Power in the British Electricity Spot Market," *American Economic Review*, 89(4): 805-26.

Appendices

Appendix A: Divestiture Policies

The Energy Information Administration's December 1999 report "The Changing Structure of the Electric Power Industry 1999: Mergers and Other Corporate Combinations" summarizes the laws affecting divestment in Investor-Owned Electric Utilities (IOUs) for each state as of September 1999. Among the top ten utilities having to divest, Potomac Electric Power Company sold 6,000 MW and Duquesne Light sold 4,400 MW. The following is an excerpt from table 11 on the status of state restructuring provisions on divestiture of power generation assets, as of September 1999.

Maryland: HB 703 passed 4/99. HB 703 forbids mandated divestiture. However, Potomac Electric Power Co. is selling all its generation assets.

Delaware: HB 10 passed 3/99. HB 10 allows the Public Service Commission (PSC) to decide if divestiture is needed to alleviate market power "in extreme situations and as a last resort." Stranded cost recovery is not an issue for the IOU in Delaware. Delaware Cooperative's stranded cost recovery will be addressed by the PSC.

New Jersey: A10 and S5 passed 2/99. Laws A10 and S5 leave divestiture and the issue of stranded cost recovery up to the Board of Public Utilities which may require divestiture.

Pennsylvania: HB 1509 passed 12/96. HB 1509 does not require divestiture. Some Pennsylvania utilities are selling generation assets to reduce stranded costs and/or restructure their companies into "wire" companies by getting out of the generation side of the business. Duquesne Light to divest generation. Allegheny Energy to transfer generation to affiliated generation company or divest.

Appendix B: Data Sources

Prices

The PJM energy market can have thousands of different locational prices at a given time. An accurate model of a nodal price system would account for transmission constraints and “loop flow” concerns in addition to calculating marginal costs.⁴⁷ Such a model would have to recreate the dispatch decisions of the PJM operators, an impossible task given the “black box” nature of the decisions. I look at the marginal costs of a market with no transmission constraints within PJM. This makes this study tractable and enables me to accurately estimate costs at least for a subset of hours rather than trying to replicate the market exactly. Therefore, I also determine prices for an unconstrained transmission system for the observed market. Some papers, including Bushnell and Saravia (2002), estimate a market-wide unconstrained price using bid data. However, during my sample period, the PJM bids were not financially binding and may misrepresent the market price. An alternative measure of a single price uses information from the hourly nodal prices in PJM. PJM reports the load-weighted average of all nodal prices for each hour. While constraints increase total costs, the impact on average price is indeterminate *ex ante*. The effect of congestion on pricing when firms have market power is further confounded. Congestion reduces the elasticity of residual demand but congestion rules cap some bids near costs. Given these caveats, I use this load-weighted average price measure to approximate the unconstrained market-clearing price.

Hydroelectric and Nuclear Generation

Unlike other types of generation, hydroelectric generation faces limited reservoirs of how much energy it can produce between periods of precipitation. The costs of producing power are negligible, but the opportunity costs of generating can be quite high. A price-taking firm maximizes profits by producing only in the highest price hours; producing at any other time will forgo the opportunity of receiving a higher price.⁴⁸ Firms optimize subject to constraints of minimum flow rates of rivers,

⁴⁷Loop flow refers to the concept that electricity does not simply flow directly from source A to receptor site B but rather will travel over all wires making up the transmission grid, as a complex function of transmission capacities.

⁴⁸Similarly, a firm exercising market power will optimize by producing in the hours with the highest marginal revenue.

capacity constraints of generating power, and these reservoir constraints. I assume hydroelectric generation will not vary from the observed levels. This biases down the measure of market power as discussed in BBW.

I measure hydroelectric production using hourly bid data and monthly production data. Hydroelectric generators bid into the market differently than other producers. They cannot bid market-based rates. In fact, they are required to bid a price of zero and are thus called “zero-priced” bids. While hydroelectric producers are restricted in the *price* they bid, they are allowed to alter the *quantity* bid for each hour (unlike most of the market that bids a common offer curve for the entire day). Since the bids were not binding at this time, they are not likely to be consistent with actual generation. In fact, the monthly sum of “zero-priced” bids was as much as 20 times the monthly total of hydroelectric generation, as reported by the Energy Information Administration (1998, 1999).⁴⁹ I model hydroelectric generation by assuming that the hourly generation was consistent with the scheduled “zero-priced” bids, which are primarily hydroelectric. These bids schedule more generation in peak hours. I scale hourly production so total generation matched the EIA Form 759 total production.⁵⁰ I determine the efficiency rate of pumped storage units from data on consumption and net generation in the EIA Form 759, which reports net generation by month. The run of river production plus the implied gross production of the pumped storage compose the monthly production.

In addition, nuclear generation is not likely to be used to move prices. Huge start up costs and low marginal costs result in these units running near capacity for long periods of time. Their marginal costs average less than \$10/MWh and do not set the market price. Firms are unlikely to use nuclear plants to move price since these plants are expensive to restart and are never the cheapest technology a firm owns (*i.e.*, they are “inframarginal”). When firms do shut down nuclear

⁴⁹ Another reason that the zero-priced bids may have been so large is that some other generation types can also place zero-priced bids. Recall that all generation *must* be dispatched in the spot market pool. In order to ensure that they are called upon, bilateral contracts will also be “bid” in at a price of zero. PJM reports all of the zero-priced bids for the entire system by hour.

⁵⁰ For 1998, lacking data on zero-priced bids, I proxy the hourly distribution within a month of hydroelectric generation. I predict the hourly share of monthly hydroelectric generation by regressing the hourly share of monthly zero-priced bids on a cubic function of load and hourly fixed effect during 1999.

plants for maintenance, the units are typically down for weeks. During the summer of 1999, the median fraction of capacity in operation was 98 percent for all PJM nuclear plants and no outages were reported. I assume a constant level of production within a month for these units.

Fossil Fuel Data Sources

To determine PJM fossil units' marginal production costs, I use publicly available PROSYM model output (Kahn, 2000) that provide data for 392 fossil units, including aggregations of some small units. These data include summer capacity, heat rate at maximum capacity, forced outage factors, primarily fuel burned, variable operating and maintenance costs, SO₂ and NO_x emissions rates, and coal units' marginal costs.

I measure fuel prices using spot prices of oil and natural gas while assuming constant coal costs.⁵¹ EIA provides data on the daily spot price of New York Harbor No. 2 heating oil and BTU/gallon conversion rates. Natural Gas Intelligence provided daily natural gas spot prices for Transco Zone 6 non-New York. For oil and natural gas units, I add fuel distribution costs that I approximate as the difference between the average spot price in the region and the price PJM firms reports for delivered fuel over the summers of 1998 and 1999 (EIA form 423, 1998 and 1999). To calculate SO₂ regulation costs, I use the mean of two monthly price indices of SO₂ permit prices that brokerage firms Cantor Fitzgerald and Fieldston report to the EPA. I use monthly price index data on NO_x costs from Cantor Fitzgerald. The EPA lists which units had to comply with the Acid Rain program during Phase I (including "substituting" units). Plants in Pennsylvania, New Jersey, and Delaware had NO_x regulatory compliance obligations in 1999.

Intertemporal Model Data Sources

The intertemporal model utilizes detailed data about each unit's hourly production, costs, and emissions. The EPA's Continuous Emissions Monitoring System (CEMS) provides hourly production data for the fossil units. CEMS records hourly gross production of electricity, heat input, and three pollutants—sulfur dioxide, nitrogen oxides, and carbon dioxide—for most fossil

⁵¹While spot markets for coal exist, the heterogeneous product trades on more dimensions than simply price and quantity. Factors such as moisture, ash content, sulfur content, and location determine the type of coal being traded. Rather than modeling each plants coal costs, I impose constant prices for delivery of coal.

units in the country.⁵² This study defines utilization rate as current gross production divided by the maximum observed gross production over the summers of 1998 and 1999. The sample excludes units not operating in the previous week. During the summers of 1998 and 1999, CEMS monitored 234 units that accounted for over 97 percent of PJM’s fossil fuel capacity.⁵³ CEMS data are highly accurate and comprehensive for most types of fossil units (Joskow and Kahn, 2002). I use the same marginal cost estimates as in the single-period model. In addition, I use the PROSYM data (Kahn 2000) on start up costs and a proxy for ramping rates (“minimum up time” is the number of hours a unit must remain operating before it can be shut off, which related to the inverse of ramping rates). For those observations without start up cost data, I use fitted values from a regression of start up costs on marginal production costs, capacity, and the interaction of these two variables.

Firm Conduct Tests Data Sources

Calculating firms’ hourly net position requires data on production, demand, and contract positions. I aggregate CEMS gross production data by firm and add nuclear and hydroelectric generation. Contract data are not publicly available. I proxy for firm native load: For each large firm, I use summer peak demand, which occurred July 6, 1999, to determine market shares. The share is multiplied by system-wide hourly demand to form the proxy. In addition, data on market share of a firm’s customers on direct access are available at: <http://www.oca.state.pa.us/cinfo/instat.htm>.

Appendix C: Estimating Standard Errors

This appendix estimates the standard errors of the total costs of market imperfections. I assume that demand levels and prices are known with certainty and the uncertainty stems from measurement errors in costs. The cost estimates are assumed to be unbiased but noisy measures. The noise originates from measurement errors of heat rates, emission rates, and input prices, from differences between realized outages and those in the Monte Carlo simulation, and unit commitment problems.

⁵²Gross generation includes the electricity generated for sales (net generation) as well as the electricity produced to operate that power plant. Typically net generation is approximately 90 to 95 percent of gross generation.

⁵³In order to comply with the 1990 Clean Air Act, fossil-fuel generating electric producers are required to report hourly emissions and electricity production by unit. Regulation affects units of 25 MW capacity plus new units under 25 megawatts that use fuel with a sulfur content greater than .05% by weight.

I note that for each hour t the markup equals:

$$P_t - \bar{P}_t^* = E(P_t - \bar{P}_t^*) + \varepsilon_t. \quad (\text{C1})$$

Assume ε_t has a homogenous, first-degree autocorrelation error structure: $\varepsilon_t = \rho\varepsilon_{t-1} + u_t$ and $u_t \sim N(0, \sigma_u^2)$, where σ_u^2 is the variance of the underlying i.i.d. error term and ρ is the AR(1) lag coefficient. Then, a consistent approximation for the variance of the total change in costs will be:

$$\text{Var}\left(\sum_{t=1}^T (P_t - \bar{P}_t^*) \tilde{q}_t\right) = \text{Var}\left(\sum_{t=1}^T \varepsilon_t \tilde{q}_t\right) = \frac{\sigma_u^2}{1 - \rho^2} \sum_{i=1}^T \sum_{j=1}^T q_i q_j \rho^{|i-j|}. \quad (\text{C2})$$

I estimate σ_u and ρ to calculate the standard errors of the total costs. For a given summer and net import supply curve, I run generalized least squares—using the Prais-Winsten methodology—to express markup ($P_t - \bar{P}_t^*$) as a quartic function of fossil load and indicators of month, hour of day, and day of week. For the linear-log model in the summer of 1999, the resulting estimates $\hat{\sigma}_u$ and $\hat{\rho}$ are 40 and 0.70, respectively.

This technique is also used to estimate standard errors in welfare loss using the single-period model. For each summer, I regress the hourly excess production costs (actual production costs less estimated production costs) on quartic function of fossil load and indicators of month, hour of day, and day of week, using the Prais-Winsten methodology. The standard error of the total excess production costs, or welfare loss, is given by the square root of the sum of squared residuals.

Appendix D: Production Estimation Results

Table D1 summarizes the results that follow from estimating (12), (13), and (14). As an example, for the probit equation (13) and the conditional production regression (14), panel A displays the coefficient estimates' mean and 5th and 95th percentile. I focus on one hour (6pm) and one quintile of each spline (third). Note that I do not have data on ramping rates and use a proxy (minimum up time) that is negatively correlated with ramping rates.

For this sample, price-cost markups and capacity did not directly affect the probability of operation. As consistent with expectations, higher start up costs significantly reduce the probability of operating. Units with higher start up costs were more likely to operate if the margins were

high during the proceeding hour or overall during that day (though high margins the proceeding day reduce the probability of these units operating). Units with slower ramping rates tend to operate more when the next day's markups are high, though they operate less when the current daily markups are high. Conditional on operation, firms generate more given higher current hour markups, lower proceeding hour markups, and quicker ramping rates. Units with slower ramping rates produce more when the current daily markup is greater. Units with more capacity produce more if the proceeding or following day have high markups (though they produce less if the current day's markups are high). The high degree of correlation among variables makes the interpretation of any single one difficult.

Therefore, to understand the impact of intertemporal constraints, panel B summarizes the overall impact of the main variables: the six types of markups, capacity, ramping rates, and start up costs. For each variable, I state the mean of all observations' marginal effects and the marginal effect of the median observation using the entire sample. In the probit regressions, current hour markups increase the probability of a unit operating while lag and lead markups reduce this probability. A similar pattern is seen in daily averages. On average, units with high capacity, quick ramping rates, and low start up costs operate more. For the median observation, this trend is reversed. Conditional on operating, units increase production when markups are high during the previous, current, or following hour. The marginal effects of daily markup averages and of capacity on utilization do not exhibit clear patterns. Finally, condition on operating, units with slow ramping rates tend to have higher utilization rates.

Figures and Tables

PJM Supply Curve

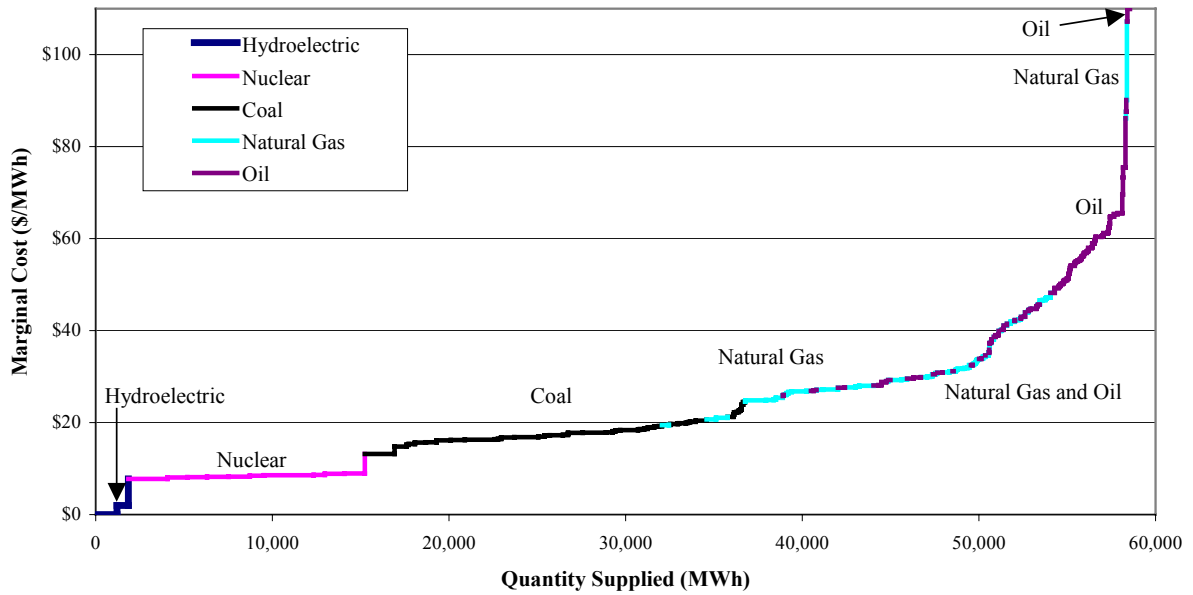


Figure 1: PJM Supply Curve (April 1, 1999)

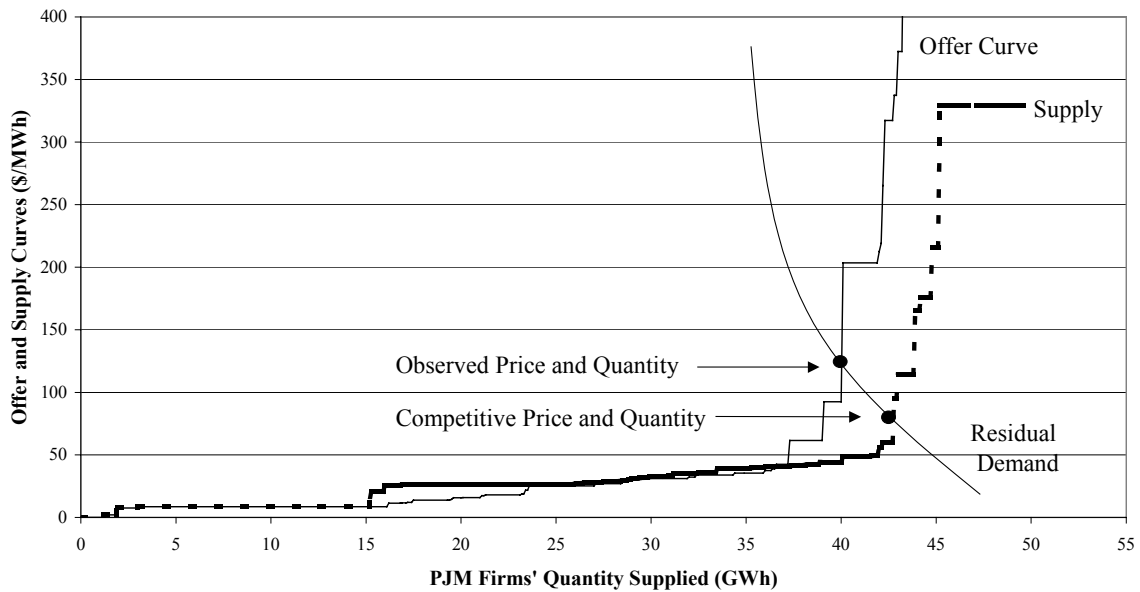


Figure 2: Determining the Competitive Equilibrium Based on an Offer Curve, Supply, and Residual Demand (Demand less Net Imports)

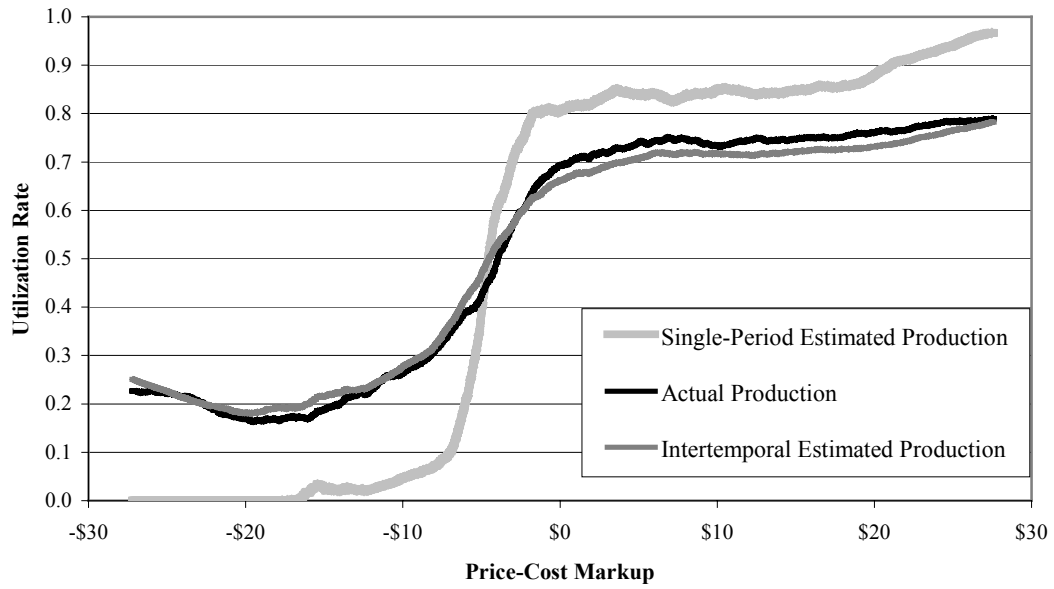


Figure 3: Goodness-of-Fit Comparison of Utilization Rates across Price-Cost Markup

Table 1**PJM Firm Characteristics**Panel A: Generation Capacity by Firm and Fuel Type in 1999^a

Firm	Coal	Oil	Gas	Water	Nuclear	Total
Public Service Electric ^b	1,607	1,842	3,311	-	3,510	10,269
PECO	895	2,476	311	1,274	4,534	9,490
GPU, Inc.	5,459	1,816	203	454	1,513	9,445
PP&L Inc.	3,923	478	1,701	148	2,304	8,554
Potomac Electric Power	3,082	2,549	876	-	-	6,507
Baltimore Gas & Electric	2,265	925	755	-	1,829	5,773
Delmarva Power & Light	1,259	888	311	-	-	2,458
Atlantic City Electric	391	436	482	-	-	1,309
Other ^c	2,087	353	-	439	-	2,880
Total	20,967	11,762	7,949	2,316	13,690	56,685
Market Share	37%	21%	14%	4%	24%	

Panel B: Market Shares of Capacity, Generation, and Demand by Firm in Summer of 1999^d

Firm	Capacity	Generation ^e	Peak Generation ^f	Demand Served ^g
Public Service Electric	18.1%	14.0%	16.8%	17.3%
PECO	16.7%	17.8%	19.9%	8.8%
GPU, Inc.	16.7%	19.8%	16.4%	14.7%
PP&L Inc.	15.1%	15.9%	16.1%	9.9%
Potomac Electric Power	11.5%	10.1%	10.2%	10.4%
Baltimore Gas & Electric	10.2%	12.5%	11.3%	11.2%
Delmarva Power & Light	4.3%	3.2%	3.3%	6.0%
Atlantic City Electric	2.3%	1.1%	1.3%	4.3%
Other	5.1%	5.6%	4.7%	17.4%

Notes:

- a) Capacity, in megawatts (MW), is listed by primary fuel type used in each generating unit at a power plant, as determined by the EIA. Coal includes anthracite, bituminous coal, and petroleum coke. Oil includes No. 2, 4, and 6 fuel oil and kerosene. The other categories are natural gas, hydroelectric, and nuclear. Source: Energy Information Administration (EIA), Form 860 (1999).
- b) In 1999, the GPU parent company owned Jersey Central, GPU Nuclear, Metropolitan Edison and Pennsylvania Electric.
- c) "Other" includes the following utilities: Safe Harbor Water Power, Easton Utilities, UGI Development, Allegheny Electric Coop, A&N Electric Coop, and cities of Berlin, Dover, Lewes, Seaford, and Vineland. Also I include Edison, which purchased Homer City from GPU in March 1999.
- d) Summer is defined as April 1 to September 30.
- e) Source: EIA Form 759, 1999. I aggregate monthly generation for April through September.
- f) Source: EPA Continuous Emissions Monitoring System, 1999. Peak generation share is share during hours with demand above 40,000 MW.
- g) Source: www.oca.state.pa.us. Demand served is share summer peak demand less direct access customers. On July 6, 1999, the system-wide demand reached a peak of 51,700 MW. Source: EIA Form 861, 1999. In 1999, many Pennsylvania customers switched to alternative providers, leaving GPU (3.4 percent of total market demand), PECO (5.6 percent), and PP&L (2.5 percent). "Other" demand includes direct access customers.

Table 2

PJM Market Summary Statistics During Summers of 1998 and 1999

Panel A: Summer of 1998

Variable	Units	Mean	Std. Dev.	Min	Max
Quantity demanded hourly ^a	MWh	29,650	6,482	17,461	48,469
Price of:					
Electricity ^a	\$/MWh	\$26.04	\$43.46	\$0.00	\$999.00
Electricity (Q weighted)	\$/MWh	\$29.82	\$53.45	\$0.00	\$999.00
Natural Gas ^b	\$/mmbtu	\$2.33	\$0.25	\$1.80	\$2.81
Oil ^c	\$/Barrel	\$16.30	\$1.36	\$13.99	\$19.17
SO ₂ Permit ^d	\$/Ton	\$172.44	\$24.40	\$136.50	\$198.50
NO _x Permit ^e	\$/Ton	N/A	N/A	N/A	N/A
Marginal costs: ^f					
Coal Units	\$/MWh	\$19.70	\$5.17	\$13.15	\$37.51
Natural Gas Units	\$/MWh	\$36.75	\$11.73	\$17.23	\$115.81
Oil Units	\$/MWh	\$46.94	\$11.54	\$22.79	\$113.49

Panel B: Summer of 1999

Variable	Units	Mean	Std. Dev.	Min	Max
Quantity demanded (hourly)	MWh	30,459	7,156	17,700	51,714
Price of:					
Electricity	\$/MWh	\$37.97	\$100.99	\$0.00	\$999.00
Electricity (Q weighted)	\$/MWh	\$47.92	\$47.92	\$0.00	\$999.00
Natural Gas	\$/mmbtu	\$2.60	\$0.27	\$2.08	\$3.28
Oil	\$/Barrel	\$20.56	\$2.91	\$16.55	\$26.04
SO ₂ Permit	\$/Ton	\$202.71	\$9.23	\$188.00	\$211.50
NO _x Permit	\$/Ton	\$2,406	\$1,756	\$0	\$5,244
Marginal cost of:					
Coal Units	\$/MWh	\$24.16	\$6.58	\$13.18	\$50.92
Natural Gas Units	\$/MWh	\$42.08	\$14.24	\$19.44	\$138.01
Oil Units	\$/MWh	\$59.56	\$15.68	\$25.25	\$158.58

Notes:

- a) Electricity price and quantity data from PJM Interconnection: www.pjm.com
- b) Natural gas prices at Transco Zone 6 non-New York from Natural Gas Intelligence.
- c) No. 2 heating oil sold at New York Harbor from the U.S. Energy Information Agency.
- d) EPA reports monthly average trades of SO₂ permits at two brokerage firms (Cantor Fitzgerald and Fieldston).
- e) NO_x costs are from Cantor Fitzgerald's monthly price index.
- f) In addition to the above input costs, data from the PROSYM model (Kahn 2000) are used to determine marginal costs.

Table 3

Capacity Factor for Fossil Units by Firm and Year

Firm	Summer of 1998	Summer of 1999	Percent Change
Public Service Electric	0.142	0.171	20.3%
PECO	0.230	0.211	-8.1%
GPU, Inc.	0.604	0.575	-4.7%
PP&L Inc.	0.546	0.442	-19.0%
Potomac Electric Power	0.466	0.490	5.1%
Baltimore Gas & Electric	0.515	0.519	0.9%
Delmarva Power & Light	0.371	0.377	1.6%
Atlantic City Electric	0.233	0.267	14.7%
Other	0.698	0.636	-8.9%
Fringe	0.441	0.442	0.2%

Notes:

- a) Capacity factor is the fraction of total fossil fuel burning generation capacity being used in generating electricity for each large firm in PJM and for both the summer of 1998 and the summer of 1999. The numerator is the aggregate of gross generation (including electricity used at the power plant) for fossil units over a summer. The denominator, gross capacity, equals the aggregation, within a firm, of each unit's maximum observed hourly gross generation during the sample, times the number of hours in the summer.
- b) Source: Environmental Protection Agency (EPA) Continuous Emissions Monitoring System, 1999.
- c) Summer is defined as April 1 to September 30.
- d) Fringe is the quantity-weighted average of all firms except PECO and PPL.
- e) "Other" includes the following utilities: Safe Harbor Water Power, Easton Utilities, UGI Development, Edison (Homer City), Allegheny Electric Coop, A&N Electric Coop, and cities of Berlin, Dover, Lewes, Seaford, and Vineland.

Table 4

IV Estimation of Net Import Supply Function, Summers of 1998 and 1999

Panel A: First-stage dependent variable is log of hourly PJM prices by year and time-of-day.

Variable	1998 Peak ln(Price)	1998 Off-Peak ln(Price)	1999 Peak ln(Price)	1999 Off-Peak ln(Price)
ln(Load)*Peak	2.21* (0.08)	0.47* (0.10)	2.72* (0.09)	0.50* (0.10)
ln(Load)*Off-Peak	0.16* (0.05)	2.18* (0.06)	0.15* (0.06)	2.35* (0.06)
R-squared	0.96	0.94	0.94	0.93

Panel B: Second-stage dependent variable is hourly net imports into PJM by year.

Variable	1998	1999
ln(Price)*Peak	295.7* (85.6)	1110.2* (128.8)
ln(Price)*Off-Peak	484.1* (65.6)	1717.2* (82.7)
R-squared	-	-
AR(1) coef (ρ)	0.89	0.84
Sample size	4,330	4,341

Notes:

Table presents 2SLS coefficients. First I estimate 2SLS and use the errors to correct for serial correlation by estimating an AR(1) coefficient (ρ). Then I quasi-difference the data by calculating $\Delta x = x(t) - \rho * x(t-1)$ for all data. I re-estimate the 2SLS results using these quasi-differenced data. Robust standard errors are given in parentheses. Significance is marked with (*) at the 5% level and (#) at the 10% level. Regression includes month fixed effects, peak indicator (between 11 AM and 8 PM weekdays) and weather variables for bordering states (New York, Ohio, Virginia, and West Virginia), which are modeled as quadratic functions for cooling degree days (degrees daily mean below 65° F) and heating degree days (degrees daily mean above 65° F). In the first stage, I regress PJM ln(price) on the exogenous variables and instruments of hourly ln(load) in PJM.

Table 5

Demand, Actual Price, Competitive Price, and Market Performance

Month or Time of Day	Hourly Demand (MW)	Actual Price (\$/MWh)	Competitive Price ^a (\$/MWh)	Market Performance ^b (MP)
April, 1998	25,427	19.20	18.45	0.06
May	26,775	24.15	21.59	0.16
June	29,739	24.98	24.87	0.08
July	32,863	34.23	28.51	0.24
August	33,183	29.58	24.35	0.24
September	29,780	23.53	22.05	0.12
April, 1999	25,612	21.44	20.58	0.06
May	25,871	22.68	27.20	-0.17
June	31,542	37.10	30.32	0.31
July	36,957	91.67	37.81	0.64
August	33,461	31.77	31.75	0.07
September	29,140	22.06	25.67	-0.14
Peak 1998 ^c	35,068	41.72	28.71	0.35
Off-Peak	27,347	19.32	21.04	-0.05
Overall	29,650	26.04	23.33	0.17
Peak 1999	35,722	74.21	35.23	0.58
Off-Peak	28,221	22.56	26.27	-0.10
Overall	30,459	37.97	28.94	0.34

Notes:

- a) Competitive price is the average of Monte Carlo simulations of the competitive equilibrium price for a set of hours (e.g., a month). Competitive prices and market performance are reported for the linear-log model of net import supply.
- b) For a given time period, similar to a Lerner index, market performance is the ratio of additional procurement costs (relative to the competitive estimates) over actual procurement costs.
- c) Peak indicates hours between 11 AM and 8 PM on weekdays.

Table 6

Welfare Implications of Production Inefficiencies (\$ millions)

	1998	1999	Change	Percent Change
<i>PJM Production Costs</i>				
Actual Costs	\$1,338.75	\$1,642.31	\$303.56	22.68%
Intertemporal Model				
- PJM Cost Estimates	\$1,335.58	\$1,588.26	\$252.68	18.92%
- PJM Welfare Loss	\$3.16	\$54.05	\$50.89	1609.30%
	(\$6.12)	(\$4.24)	(\$7.45)	(134.19%)
- Loss Share of Cost	0.24%	3.40%	20.14%	
Single-Period Model				
- PJM Cost Estimates	\$1,267.60	\$1,460.03	\$192.42	15.18%
- PJM Welfare Loss	\$71.14	\$182.28	\$111.14	156.23%
	(\$1.15)	(\$1.38)	(\$1.80)	(1.94%)
- Loss Share of Cost	5.61%	12.48%	57.76%	
<i>PJM Net Import Costs</i>				
Actual Costs	\$11.56	\$7.54	-\$4.02	-34.78%
- Competitive Estimates	\$8.34	\$5.19	-\$3.15	-37.73%
- Import Welfare Loss	\$3.22	\$2.35	-\$0.87	-27.15%
	(\$0.07)	(\$0.06)	(\$0.09)	(2.49%)
Total Welfare Loss				
- Intertemporal Model	\$6.36	\$56.35	\$49.99	785.70%
	(\$6.12)	(\$4.24)	(\$7.45)	(66.70%)
- Single Period Model	\$74.34	\$184.58	\$110.24	148.29%
	(\$1.15)	(\$1.38)	(\$1.80)	(1.86%)
Losses Ratio (I/S)	8.56%	30.53%	45.34%	529.83%

Notes:

Standard errors in parentheses. For the intertemporal model, standard errors are determined using bootstrap draws. I calculate the single-period model's standard errors following the methodology described in Appendix C. The standard errors on net import supply are determined using the delta method and the standard errors from table 5. The costs include those observations when actual price exceeded the single-period model's competitive estimate. In calculating the standard errors on the changes in costs over time, I assume that the errors are uncorrelated across years. In calculating the standard errors for the percent change in costs: $((\text{costs}_{99}/\text{costs}_{98}) - 1)$, I treat the 1998 cost estimates as constants.

Table 7

Test of Firm Behavior Based upon Hourly Firm-Level Production

Dependent variables: (i) and (ii): $\ln(\text{actual production})$ by firm and hour.
 (iii): $\ln(\text{actual production}) - \ln(\text{intertemporal estimated production})$ by firm and hour.

	(i)	(ii)	(iii)
Restructuring	-0.017 (0.014)	-0.012 (0.012)	-0.010 (0.012)
Oligopolist*Restructuring	-0.202* (0.033)	-0.162* (0.032)	-0.144* (0.031)
$\ln(\text{Estimated Production})$		0.689* (0.040)	
Sample Size	78,907	78,474	78,474
F-Prob	618*	909*	21*

Notes:

Table presents OLS coefficients. Newey-West corrected standard errors are in parentheses. I assume a 24-hour moving average process. Significance is marked with (*) at the 5% level and (#) at the 10% level. Regressors include indicator variables for firm, hour of day, and for day of week. In addition, the model includes a piece-wise linear function of demand that is separated by decile.

Table 8

Test of Firm Behavior Based on Price-Cost Markups

Dependent variable: price-cost markup by firm and hour.

Firm	Net Q all observations		Net Q > 0 Sample	
	(i)	(ii)	(iii)	(iv)
Public Service Electric	-0.138* (0.026)	0.247* (0.052)	0.040 (0.024)	-0.083 (0.061)
PECO	-0.176* (0.021)	0.491* (0.068)	-0.193* (0.024)	0.323* (0.051)
GPU, Inc.	-0.021* (0.005)	-0.035* (0.017)	-0.018* (0.005)	-0.060* (0.014)
PP&L Inc.	-0.044* (0.010)	0.131* (0.021)	-0.046* (0.011)	0.089* (0.012)
Potomac Electric Power	0.045* (0.009)	-0.077* (0.019)	-0.194* (0.052)	-0.046 (0.041)
Baltimore Gas & Electric	0.056* (0.018)	-0.202* (0.039)	0.013 (0.011)	-0.084* (0.010)
Delmarva Power & Light	0.174* (0.035)	-0.472* (0.084)	.	.
Atlantic City Electric	0.364* (0.093)	-1.013* (0.212)	.	.
Other	0.090* (0.028)	-0.290* (0.064)	.	.

Notes:

For each firm, I separately estimate these coefficients using 2SLS. I correct for serial correlation by estimating an AR(1) coefficient (ρ) and quasi-difference the data, namely calculate $\Delta x = x(t) - \rho * x(t-1)$ for all data. Then, I estimate the 2SLS results using these quasi-differenced data. Robust standard errors are given in parentheses. Significance is marked with (*) at the 5% level and (#) at the 10% level. Columns (i) and (ii) examine entire sample. Columns (iii) and (iv) are conditioned on positive net output positions. Delmarva Power & Light, Atlantic City Electric, and "other" firms always have negative net positions. Independent variable, *Net Q*, is firm net output (in MWh). In columns (i) and (iii), the coefficients are for both summers while in columns (ii) and (iv), the coefficients are the incremental effect for the summer of 1999. Regression includes a constant (α) and an indicator of restructuring (α). In the first stage, I regress net quantity on the instruments of daily temperatures for both states in PJM and for those bordering the region. Temperatures are modeled as quadratic functions for cooling degree days (degrees daily mean below 65° F) and for heating degree days (degrees daily mean above 65° F).

Table D1
Intertemporal Competitive Model Estimation

Dependent variables: ON = indicator of operation by hour and unit
UR = utilization rate, conditional on operation, by hour and unit.

Panel A: Example of Bootstrap Coefficients Mean, 5th and 95th percentile (e.g., third quintile for 6:00 pm)

Variable	ON			UR			
	Coef.	90% Conf. Interval		Coef.	90% Conf. Interval		
Hourly PCM (hr-1)	15.35	-2.36	37.30	-0.17	-0.24	-0.09	*
Hourly PCM (\$)	-13.99	-34.41	2.44	0.14	0.05	0.26	*
Hourly PCM (hr+1)	4.21	-0.19	9.75	-0.01	-0.09	0.07	
Daily PCM (day-1)	-0.51	-1.25	0.17	-0.03	-0.06	0.00	
Daily PCM (\$)	0.18	-0.73	1.02	0.00	-0.05	0.05	
Daily PCM (day+1)	0.83	-0.04	1.72	-0.01	-0.03	0.01	
RMP (hours)	2.35	-0.29	5.57	-0.03	-0.05	-0.01	*
K (GW)	-206.37	-479.87	15.65	1.01	-0.30	2.42	
SRT (\$1000s)	-2.14	-3.99	-0.22	.	.	.	*
Hourly PCM (hr-1) * RMP	0.07	-0.23	0.40	0.01	-0.01	0.02	
Hourly PCM * RMP	-1.74	-4.11	0.25	0.01	-0.01	0.03	
Hourly PCM (hr+1) * RMP	2.15	-0.48	5.42	0.00	-0.02	0.02	
Daily PCM * RMP (day-1)	-2.01	-4.65	0.29	-0.01	-0.03	0.00	
Daily PCM * RMP	-0.66	-1.25	-0.20	0.01	0.00	0.02	*
Daily PCM * RMP (day+1)	0.36	0.09	0.61	0.00	-0.01	0.02	*
Hourly PCM (hr-1) * K	-118.55	-292.78	26.35	1.14	0.39	1.98	*
Hourly PCM * K	203.18	-14.54	460.60	-1.67	-3.01	-0.43	*
Hourly PCM (hr+1) * K	-200.23	-444.95	5.53	1.08	0.24	2.07	*
Daily PCM * K (day-1)	88.83	-5.01	194.52	0.06	-0.49	0.56	
Daily PCM * K	71.12	-6.43	169.12	-0.39	-1.05	0.26	
Daily PCM * K (day+1)	-76.66	-199.02	22.64	0.04	-0.51	0.58	
Hourly PCM (hr-1) * SRT	3131.70	56.90	6187.10	.	.	.	*
Hourly PCM * SRT	-1598.20	-3836.20	685.10	.	.	.	
Hourly PCM (hr+1) * SRT	-1434.30	-5145.00	1863.70	.	.	.	
Daily PCM * SRT (day-1)	-1186.50	-2223.60	-140.70	.	.	.	*
Daily PCM * SRT	1325.10	214.60	2497.20	.	.	.	*
Daily PCM * SRT (day+1)	3480.40	-1308.30	9537.60	.	.	.	

Panel B: Summary of Marginal Effect for the Nine Primary Variables (Total Sample)

Variable	ON		Utilization Rate	
	Mean of marginal effects	Marginal effect at median	Mean of marginal effects	Marginal effect at median
Hourly PCM (\$)				
- lag	-1.207	-0.035	0.034	0.006
- current	1.102	0.019	0.049	0.014
- lead	-0.821	-0.006	0.154	-0.015
Daily PCM (\$)				
- lag	-0.431	-0.015	0.086	-0.000
- current	1.530	0.025	-0.132	0.198
- lead	-0.965	-0.013	0.100	-0.165
RMP (hours)	-3.182	2.623	0.028	0.022
K (GW)	41.174	-142.976	2.061	-0.713
SRT (\$1000s)	-4.835	5.017	.	.

Notes:

PCM is price-cost markup, RMP is the inverse ramping rate (minimum up time), K is capacity, and SRT is start up cost. PCM is instrumented with variables constructed using competitive price estimates from section 3. Each independent variable is modeled separately by hour and as a piece-wise linear function separated by quintile.