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Upstream Competition and Vertical Integration in Electricity Markets

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Abstract

Many studies have found substantial market failures in electricity markets that have been restructured to allow wholesalers to set prices. Vertical integration of firms may partially mitigate market power since integrated firms have a reduced interest in setting high prices. These producers sell electricity and also are required to buy power, which they provide to their retail customers at set rates. This paper examines the importance of vertical integration in explaining firm behavior during the first summer following the restructuring of the Pennsylvania, New Jersey, and Maryland wholesale market. I compare the behavior of other firms with that of two producers that, owing to variation in state policy, had relatively few retail customers. I conclude that restructuring led to an increase in anticompetitive behavior by large net sellers but that overall vertical integration both mitigates market power and diminishes its distributional impacts.

1. Introduction

Over the past quarter century, there has been a movement toward the deregulation of electricity markets. Policy makers believed that restructuring these markets would impose market discipline, leading to lower production costs at existing power plants and more efficient investments. Unfortunately, the promise of restructuring has not always been realized. Many studies have shown that wholesalers have exploited market power in electricity markets that have been restructured (see, for example, Wolfram 1998, 1999; Wolak 2000; Borenstein, Bushnell, and Wolak 2002; Joskow and Kahn 2002; Bushnell and Saravia 2002).

Restructuring typically consists of three things: (1) allowing wholesale pricing, (2) divesting generation assets from retailers, and (3) fixing retail prices of incumbents. In order to assess the consequences of restructuring and to make policy recommendations, researchers must disentangle these three aspects. In general, this is a difficult task. The Pennsylvania, New Jersey, and Maryland

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(PJM) market, however, provides a venue in which to partially separate them because this market did not require retailers to divest their generating assets. Rather, most firms have remained vertically integrated in that they both sell in the wholesale market and are also required to buy in that market to provide energy to their retail customers. This study examines the importance of vertical integration in upstream competition by testing firm behavior in the PJM market.

Theory suggests that vertical integration may mitigate market power. Since incumbents' retail rates are fixed by regulation, these firms will not profit from high wholesale prices on electricity produced for their retail customers. In other words, for completely integrated firms, marginal revenue equals price. For these firms, charging high prices would simply transfer resources from one division of the firm (the distribution side) to another (the generation side). This observation—that vertical integration may be socially beneficial—directly contrasts the prevailing view in these markets; vertical divestiture was thought to be necessary for effective competition by preventing foreclosure of competitive retail providers.[1]

While most firms remained nearly completely integrated after restructuring, two firms, Philadelphia Electric Company (PECO) and Pennsylvania Power & Light (PPL), were large net sellers and thus had incentives to exercise oligopoly power by raising wholesale prices. The reason for this variation in firms' net positions is due, in part, to differences in state policies. Both PECO and PPL are located in Pennsylvania, where regulators enacted an aggressive retail choice policy that rewarded customers for leaving their historic providers. These firms were no longer completely integrated and, because of regulatory action, were large net sellers in the wholesale market. In other states in the PJM region, which did not follow such a policy, customers stayed with their incumbent utilities.[2] The differential impacts of state policies on firms' net positions allow me to test whether the scope of vertical integration affected firm behavior.

This study focuses on the summers before and after restructuring. It is only during this period that the retail policies had differential impacts. Shortly afterward, many of the Pennsylvania customers returned to their incumbent providers. This occurred because the retail prices of the incumbents' competitors increased for reasons other than the wholesale energy market.[3]

[1] Vertical foreclosure has not occurred in restructured electricity markets because of the presence of independent system operators. These separate intermediaries operate the regional transmission systems, thereby preventing vertically integrated firms from excluding rival retailers. Therefore, this paper's conclusion—that vertical integration has led to more competitive markets—does not necessarily apply to other markets that lack independent intermediaries.

[2] In the late 1990s, the PJM Interconnection L.L.C. consisted of most or all of Pennsylvania, New Jersey, Maryland, Delaware, and the District of Columbia, as well as some of Virginia.

[3] Incumbents have the obligation of providing to retail customers in their historic service territory. Furthermore, the rates that they can charge these customers are fixed by regulation. In contrast, the alternative retail providers can charge any fee, although this market is relatively competitive. Starting in 2000, the retailers' costs increased substantially. In addition to buying electricity from the wholesale market, each retailer is required to acquire capacity resources. This is done, in part, through purchases in the capacity credit markets. These markets experienced high prices in the summer of 2000 and

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This study uses several tests to determine whether vertical integration mitigates market power in restructured electricity markets. The main test is whether the two firms with net selling positions behaved differently than the other firms after the market allowed wholesale pricing. I use a difference-in-differences model that looks at firm production during the summers before and after restructuring. The model controls for demand and input cost shocks by using a measure of firm behavior in a competitive wholesale market. I find that, after restructuring, the firms with incentives to set high prices reduced output by approximately 13 percent relative to other firms.

A second test uses an alternative specification to examine firm behavior, providing a robustness check of the main findings. In particular, I examine whether firms behaved in a manner consistent with profit maximization for a Cournot-Nash equilibrium. For each firm and each summer, I compare the relationship between a firm's price-cost markup and its net position. Again, the behavior of the two net sellers, PECO and PPL, is consistent with exercising market power after restructuring, while the behavior of the other large firms is not. From these tests, I conclude that restructuring the PJM market led to an increase in anticompetitive behavior by the two large net selling firms. However, the other large firms, which were nearly perfectly vertically integrated, did not set high prices. Therefore, vertical integration can mitigate market power.

The anticompetitive behavior of the two net sellers had consequences for wealth transfers. Since retail rates are frozen, these are transfers from some utilities (the retailers) to other firms (in particular, the two net sellers and importers). I compare the actual prices with simulations of the prices that would have occurred had the wholesale market been competitive. To do this, I construct the industry marginal cost curve, namely, the competitive supply curve, and use this to measure price-cost margins. Wolfram (1999) and Borenstein, Bushnell, and Wolak (2002) developed this method to study the England-Wales and California markets, respectively. I extend the method by estimating a supply function for importers into the PJM market.

Using this competitive benchmark, I find evidence that the cost of providing retail customers with electricity exceeded that of a perfectly competitive wholesale market by $1.6 billion. However, because firms are vertically integrated, most of these higher procurement costs are just transfers within a firm. For the transactions between firms, my measure of total transfers associated with anticompetitive behavior is at most $676 million. Vertical integration limited the distributional impacts of market power.

In short, the experience in the PJM market suggests that vertical integration both mitigates market power and limits its distributional impacts. These findings

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winter of 2001 (PJM Interconnection 2000c, 2001b, 2002). As these rates were passed on to customers, many switched back to the incumbents. For example, from April 2000 to July 2001, the percent of Pennsylvania Power & Light's (PPL's) customer load that was served by alternative suppliers fell from 26 percent to 2 percent (see Pennsylvania Office of Consumer Advocate, Pennsylvania Electric Shopping Statistics [http://www.oca.state.pa.us/Industry/Electric/elecstats/instat.htm]).

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suggest that the policy recommendation of requiring retailers to divest generating assets may have exacerbated the market failures seen in the England-Wales and California electricity markets.

The paper proceeds with Section 2, which outlines the PJM wholesale electricity market and models the incentives of strategic firms that are vertically integrated in generation and distribution. In Section 3, I discuss the method of determining competitive benchmark estimates and present the price-cost margin estimates. Section 4 examines how vertical integration affects firms' incentives to exercise market power. Section 5 draws some policy conclusions.

2. The Market and Firm Incentives

2.1. The Pennsylvania, New Jersey, and Maryland Electricity Market

The PJM spot market facilitates trades among regulated utilities and independent producers involved in the generation, transmission, and distribution of electricity in an effort to lower the costs to utilities of providing power to customers. As regulators intended, the spot market covers only a small fraction, about 12 percent, of quantity demanded. When the market first opened in 1998, suppliers were required to make cost-based offers to produce electricity. 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 offer a more flexible, market-based bid.[4]

Unlike other markets, PJM did not require utilities to divest plants as a condition of restructuring.[5] 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 spot market for wholesale electricity during the summer prior to restructuring with that during the following summer.

In 1999, PJM consisted of eight major utilities and approximately 57,000 megawatts (MW) of capacity. For each large utility, Table 1 reports the generation capacity categorized by primary fuel type. Given technological constraints on the storage and production of electricity, generation systems require some base-load units that operate at low marginal costs most hours and some flexible,

[4] While many utilities obtained the right to offer market-based bids, most continued to make cost-based bids 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 fewer incentives to increase wholesale prices. See Mansur (2003) for a more detailed discussion of the Pennsylvania, New Jersey, and Maryland (PJM) market.

[5] Energy Information Administration (1999) summarizes the laws affecting divestment in investor-owned electric utilities for each state as of September 1999.

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Table 1

Generation Capacity by Firm and Fuel Type in 1999

Firm	Coal	Oil	Gas	Water	Nuclear	Total
Public Service Electric	1,607	1,842	3,311	. . .	3,510	10,269
Philadelphia Electric Company	895	2,476	311	1,274	4,534	9,490
GPU Energy	5,459	1,816	203	454	1,513	9,445
Pennsylvania Power & Light	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	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	

Note. Capacity, in megawatts (MW), is listed by primary fuel type used in each generating unit at a power plant, as determined by the Energy Information Administration (EIA). Coal includes anthracite, bituminous coal, and petroleum coke. Oil includes nos. 2, 4, and 6 fuel oil and kerosene. The other categories are natural gas, hydroelectric, and nuclear. (EIA, Form EIA-860 Database [http://www.eia.doe.gov/cneaf/electricity/page/eia860.html]). In 1999, the GPU parent company owned Jersey Central, GPU Nuclear, Metropolitan Edison, and Pennsylvania Electric. "Other" includes the following utilities: Safe Harbor Water Power, Easton Utilities, UGI Development, Allegheny Electric Coop, A&N Electric Coop, and the cities of Berlin, Dover, Lewes, Seaford, and Vineland. Also I include Edison, which purchased Homer City from GPU in March 1999.

though expensive, peaking units that operate just a few hours a day.[6] In PJM, nuclear and coal plants provide baseload generation capable of covering most of the demand. 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. In Section 3, I treat the various technologies differently in modeling the competitive equilibrium.

2.2. Incentives of Vertically Integrated Firms

The major utilities are vertically integrated. In addition to producing energy, they are responsible for providing electricity to their customers, so they both buy and sell in the wholesale market. Firms purchasing energy to meet customers' demand, or native load, are called load-serving entities (LSEs). So far, the restructuring of wholesale electricity markets has coincided with retail rate freezes for incumbent utilities. Customers pay their LSEs a fixed rate for electricity, and, therefore, these firms will want to purchase energy from the wholesale market as cheaply as possible. However, LSEs 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. In addition to serving native load, a utility's net position may be affected by contracts; LSEs

[6] Power plants consist of several independently operating generating units, each comprising a boiler, a generator, and a smoke stack.

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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 high prices and can easily do so by withholding generation from their most expensive units (or equivalently, by setting these units' market-based bids above the competitive equilibrium price).

The ability to exercise market power depends, in part, on the price elasticity of demand. The derived demand for wholesale electricity is perfectly inelastic for two reasons. 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.[8] Second, the firms that procure customers' electricity in the wholesale market are mandated to provide the power at any cost.

Generally, in a market with perfectly inelastic demand, a monopsonist cannot affect prices. However, if the firm is a net buyer that also produces energy, 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.[9]

I assume firms maximize profits by setting quantity.[10] The resulting objective function for vertically integrated firm i will be

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

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 that are paid the contract price r_i^c, and $C_i(q_i)$ is total production costs. The resulting first-order condition equals

$$P_i + P_i' \times (q_i - q_i^d - q_i^c) = C_i', \tag{2}$$

[7] Allaz and Vila (1993) show how long-term contracts affect the spot market equilibrium. In a January 2001 telephone conversation with the author, Joe Bowring, of PJM Interconnection's Market Monitoring Unit, estimated this level of contracts for this time period. In addition, 10–15 percent of supply comes from spot market purchases and 1–2 percent from imports; the remaining 53–59 percent is self-supplied by firms.

[8] A 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 perfectly inelastic.

[9] Regulators 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.

[10] Firms offer a set of price-quantity bid pairs for energy plus bids for no-load and start-up costs. The latter are allowed to be changed only semiannually. When price is being determined, the only control variable that a firm has left is how much to produce. For this reason, I model firms as setting quantity.

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Table 2

Market Shares of Capacity, Generation, and Demand by Firm in Summer of 1999

Firm	Capacity (%)	Generation (%)	Peak Generation (%)	Demand Served (%)
Public Service Electric	18.1	14.0	16.8	17.3
Philadelphia Electric Company	16.7	17.8	19.9	8.8
GPU Energy	16.7	19.8	16.4	14.7
Pennsylvania Power & Light	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

Note. Summer is defined as April 1 to September 30. Data for generation are from EIA Form 759 (ftp://ftp.eia.doe.gov/pub/electricity/f906utilm1999.exe). I aggregate monthly generation for April through September. Data for peak generation are from U.S. Environmental Protection Agency, Clean Air Markets: Hourly Emissions Data (http://www.epa.gov/airmarkets/emissions/raw.index.html). Peak generation share is the share during hours with demand above 40,000 MW. 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 (Energy Information Administration, Form EIA-861 Database [http://www.eia.doe.gov/cneaf/electricity/page/eia861.html]). In 1999, many Pennsylvania customers switched to alternative providers, leaving GPU (3.4 percent of total market demand), PECO (5.6 percent), and PPL (2.5 percent). "Other" demand includes direct-access customers (Pennsylvania Office of Consumer Advocate, Pennsylvania Electric Shopping Statistics [http://www.oca.state.pa.us/Industry/Electric/elecstats/instat.htm]).

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. However, in Pennsylvania—where PECO, PPL, and parts of GPU Energy are located—some customers did change providers in 1999. As part of restructuring, Pennsylvanian regulators enacted an aggressive retail choice policy that rewarded customers for leaving their historic providers.[11] As mentioned in the Introduction, retail switching was short-lived because of higher prices in capacity markets. Decisions over generation capacity, historic service territory, and contracts were initially determined under a regulatory environment and are assumed to be exogenous to firms' incentives after restructuring.

For 1999, Table 2 reports each firms' market share of capacity, total generation, generation when demand exceeded 40,000 MW, and peak demand. On average, the generation of the three Pennsylvania companies—PECO, PPL, and GPU—exceeded their native load. However, GPU may have been less inclined to learn how to set high prices in this new environment because it was in the process

[11] On July 1, the percentages of customers who had switched from GPU Energy, Philadelphia Electric Company (PECO), and PPL were 5.5, 16.0, and 3.5. In particular, large customers switched. For these three firms, this was 39.9, 37.1, and 19.2 percent, respectively, of their initial load switch (Pennsylvania Office of Consumer Advocate, Pennsylvania Electric Shopping Statistics [http://www.oca.state.pa.us/Industry/Electric/elecstats/instat.htm]).

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of selling its assets.[12] In contrast, on average, the other firms either had close to a zero net position or were net buyers. Between the summers of 1998 and 1999, the market structure did not change substantially.[13]

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. In contrast, GPU offered only 14 percent of these bids. In a news article, Smith and Fialka (1999, p. A1) document the bidding behavior of PECO and PPL as making "the most of steamy conditions."[14]

Given these firms' incentives, I characterize PJM as having two quantity-setting, dominant firms that face a competitive, albeit large, fringe, and perfectly inelastic demand. This model implies that the aggregate output of the strategic firms will be less than the level in a competitive equilibrium, while the price-taking fringe firms will increase production to meet demand.

This model implies two testable hypotheses. First, actual prices exceed perfectly competitive price levels. Section 3 tests the hypothesis that prices exceeded competitive levels after restructuring. Second, firms will distort production decisions.[15] Section 4 tests whether firms distort production decisions from the competitive level.

3. Measuring Market Power

Unlike much of the recent industrial organization literature, where price-cost margin estimates tend to depend on 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 perfectly 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 common to the literature. This approach is useful as it is relatively straightforward to apply and allows comparisons with other markets where researchers have also used the technique. Wolfram (1999) develops a method of studying market imperfections

[12] It sold a 2,012-MW coal-fired plant to Edison in March and most the rest of its plants to Sithe, a transaction completed in November.

[13] Other than GPU's sale of the large coal plant, no other plant was sold or retired from 1998 through October 1999. Also there was no major construction in the period of study (less than 700 MW capacity were built; see forms 860a and 860b, Energy Information Administration, Form EIA-860 Database: Annual Electric Generator Report: Superseded Forms (with Data prior to 2001) [http://www.eia.doe.gov/cneaf/electricity/page/eia860.html]).

[14] Smith and Fialka (1999, p. A1) note, "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."

[15] Strategic firms with asymmetric costs, or firms with asymmetric strategies, distort production decisions from the competitive equilibrium (Borenstein and Farrell 2000).

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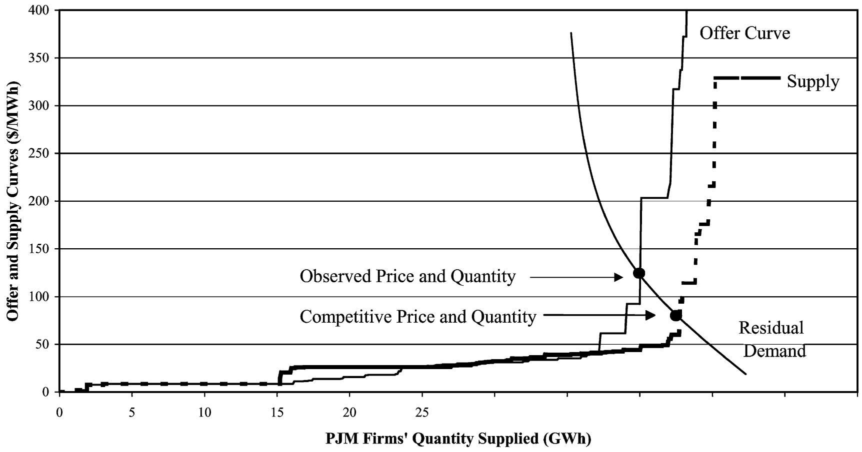

Figure 1. Determining the competitive equilibrium

in electricity markets. She calculates the marginal cost of each generating unit in the England-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 behavior.

Other studies have modified this method in applications to other electricity markets. In analyzing the California electricity market, Borenstein, Bushnell, and Wolak (2002) 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 this 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 this method and find that margin estimates are quite sensitive to their determination of the appropriate price to use in comparisons. The PJM Market Monitoring Unit examined firm behavior and found some evidence of market power being exercised as well.[16]

Figure 1 depicts a hypothetical example of how to solve for the competitive

[16] Bowring et al. (2000) and PJM Interconnection (2000a) center on 3 high-demand days and find that prices may have resulted from either a scarcity or firms exercising market power. However, the Market Monitoring Unit does not attempt to separate out these effects. A more expansive study, PJM Interconnection (2001a), compares units' bids and marginal costs between April 1999 and December 2000. By their measures, firms exercised a modest amount of market power. That study bases its 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. Prior to restructuring, Borenstein, Bushnell, and Knittel (1997) used a Cournot model and found that firms have the potential to exercise market power in PJM.

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equilibrium in a restructured electricity market using this common technique. The equilibrium depends on the offer curve of generating units in a market, their competitive supply curve, and their residual demand function (market demand less the supply function of imports). 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 firms in the market. I use this model to predict competitive prices and output decisions for each generating unit in PJM.

3.1. Method

The model focuses on those generating units capable of being used to exercise market power. These units are assumed to operate following an on-off strategy by producing at full capacity if and only if price equals or exceeds marginal costs. The competitive price equals the marginal cost of generating an additional unit of electricity, given that the least costly technologies are already producing to meet demand. As discussed below, my measure of marginal cost will account for scarcity rents and opportunity costs. To the degree that there are nonconvexities in production costs, my estimates may over- or understate the true costs. The impact of this potential bias is discussed at the end of this section.

Demand for energy services in the spot market, which does not depend on prices, comprises demand for electricity (q_t^d) and additional reserves (q_t^r) that are regulated to insure against blackouts.[17] 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. In contrast, nuclear power plants—which have low marginal costs, are expensive to start, 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 affect revenue from this inframarginal nuclear generation. Hydroelectric generation (q_t^h) could potentially be used to exercise market power. However, as I argue in Appendix A, 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

[17] Demand also includes energy lost in the process of transmission. Line losses equal approximately 4.5 percent of generation (http://www.pjm.com). PJM Interconnection requires regulation to insure against system-wide outages. The operators require 1.1 percent of the maximum of the predicted load during early morning hours (1–5 A.M.) and the rest of the day (PJM Interconnection 2000b). In addition, operators require reserves of 1,700 MW at all times. I define q_t^r as the sum of regulation and reserves.

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the surrounding regulated markets are competitive and, as described in Section 3, depend on P_t^*. In equilibrium, P_t^* clears the market:

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

3.1.1. Sample Period

In the summer following restructuring, from April through September 1999, PJM observed substantially higher prices than during most seasons since the market restructured.[18] I focus on this 6-month period when some firms began to make market-based offers. While prices averaged \$26/MW hour (MWh) in the summer of 1998, they increased to an average of \$38 in the following summer, reaching the market cap several times.[19] In general, during high-demand periods like that summer, generation and transmission capacity limits bind, which makes firms' residual demand inelastic and market power more likely. Furthermore, regulators may not have 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. Table 3 provides summary statistics of some market characteristics for the summers of 1998 and 1999. First, demand grew, in part because of higher temperatures.[20] While demand increased only 809 MW (2.7 percent) on average, matching the slow growth in generation capacity, peak demand increased by 3,245 MW (6.7 percent) over the previous summer.[21] 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 from \$2.33/mmBTU to \$2.60/mmBTU, respectively (data sources are discussed in Appendix A).

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 (SO_2) market, which then regulated 23 PJM units, climbed from approximately \$150 to \$200 per ton. For some power plants, the

[18] Since the summer of 1999, prices have been relatively low in the energy market (although high-price periods still occur occasionally). As mentioned, many retail customers returned to their incumbents. Furthermore, since 1999, changes in ownership resulted in less market concentration and increased the likelihood of some firms being net buyers.

[19] PJM reports a load-weighted average of all locational 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 with competitive price estimates. This price exceeded \$130/MWh, a value PJM Interconnection (2000a) deems the most expensive unit's marginal cost, almost three times as often in the summer of 1999 (96 hours) as in the previous summer (37 hours). As shown in Table 2, the load-weighted average price increased even more so over the summers of 1998 and 1999 than the unweighted average price.

[20] The mean of the daily temperature averages went from 73.3°F to 74.3°F, and the mean of the daily maximum temperature went from 82.5°F to 84.8°F (U.S. Department of Commerce, National Climatic Data Center, NOAA Satellite and Information Service [http://www7.ncdc.noaa.gov/IPS/getcoopstates.html]).

[21] PJM Interconnection, Hourly Load Data (http://www.pjm.com/markets/jsp/loadhryr.jsp).

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Table 3

Pennsylvania, New Jersey, and Maryland Market Summary Statistics during the Summers of 1998 and 1999

Variable	Units	Mean	SD	Min	Max
Summer of 1998:					
Quantity demanded hourly	MWh	29,650	6,482	17,461	48,469
Price ($):					
Electricity	$/MWh	26.04	43.46	0.00	999.00
Electricity (Q weighted)	$/MWh	29.82	53.45	0.00	999.00
Natural gas	$/mmBTU	2.33	0.25	1.80	2.81
Oil	$/Barrel	16.30	1.36	13.99	19.17
SO_2 pPermit	$/Ton	172.44	24.40	136.50	198.50
NO_x permit	$/Ton	N.A.	N.A.	N.A.	N.A.
Marginal cost ($):					
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	$/MWh	46.94	11.54	22.79	113.49
Summer of 1999:					
Quantity demanded (hourly)	MWh	30,459	7,156	17,700	51,714
Price ($):					
Electricity	$/MWh	37.97	100.99	.00	999.00
Electricity (Q weighted)	$/MWh	47.92	47.92	.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	$/Ton	2,406	1,756	0	5,244
Marginal cost ($):					
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

Note. Electricity price data are from PJM Interconnection, Monthly Locational Marginal Pricing (http://www.pjm.com/markets/jsp/lmpmonthly.jsp); quantity data are from PJM Interconnection, Hourly Load Data (http://www.pjm.com/markets/jsp/loadhryr.jsp). Natural gas prices at Transco Zone 6 non-New York are from Natural Gas Intelligence. Values for no. 2 heating oil sold at New York Harbor are from Energy Information Administration, NYMEX Futures Prices (http://tonto.eia.doe.gov/dnav/pet/pet_pri_rut_s1_d.htm). The Environmental Protection Agency reports monthly average trades of SO_2 permits at two brokerage firms (Cantor Fitzgerald and Fieldston). NO_x costs are from Cantor Fitzgerald's monthly price index. In addition to the above input costs, data from the PROSYM model (Kahn 2000) are used to determine marginal costs. N.A. = not applicable; SD = standard deviation.

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 1999, permit prices exceeded $5,000 per ton, increasing some units' marginal costs by 50 percent, but fell precipitously to $1,093 by summer's end. These input price shocks increased marginal costs of coal, natural gas, and oil units 23, 15, and 27 percent, respectively. As discussed below, my measure of competitive price accounts for demand and supply shocks.

For each firm, Table 4 describes the capacity factor (the fraction of capacity used in generating electricity) during the summers of 1998 and 1999. Over these summers, PECO and PPL reduced output by 8 and 19 percent, respectively. In

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Table 4
Capacity Factor for Fossil Units by Firm and Year

Firm	Summer 1998	Summer 1999	Percent Change
Public Service Electric	.142	.171	20.3
Philadelphia Electric Company	.230	.211	−8.1
GPU Energy	.604	.575	−4.7
Pennsylvania Power & Light	.546	.442	−19.0
Potomac Electric Power	.466	.490	5.1
Baltimore Gas & Electric	.515	.519	.9
Delmarva Power & Light	.371	.377	1.6
Atlantic City Electric	.233	.267	14.7
Other	.698	.636	−8.9
Fringe	.441	.442	.2

Source. U.S. Environmental Protection Agency, Clean Air Markets: Hourly Emissions Data (http://www.epa.gov/airmarkets/emissions/raw.index.html).
Note. Capacity factor is the fraction of total fossil-fuel-burning generation capacity being used in generating electricity for each large firm in Pennsylvania, New Jersey, and Maryland 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. Summer is defined as April 1 to September 30. "Other" includes the following utilities: Safe Harbor Water Power, Easton Utilities, UGI Development, Edison (Homer City), Allegheny Electric Coop, A&N Electric Coop, and the cities of Berlin, Dover, Lewes, Seaford, and Vineland. Fringe is the quantity-weighted average of all firms except PECO and PPL.

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 the PJM region 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 perfectly inelastic demand, PJM's more expensive units will operate in a competitive market. For each summer, I estimate net import supply.[22] 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.[23] Margin estimates will be understated if this assumption is incorrect.

[22] In contrast, Borenstein, Bushnell, and Wolak (2002) 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.

[23] At 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.

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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 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:*

$$\begin{aligned} q_t^{\mathrm{IMP}} &= \beta_1 \ln(P_t) \times \mathrm{Peak}_t + \beta_2 \ln(P_t) \times (1 - \mathrm{Peak}_t) \\ &\quad + \sum_{m=1}^{M} \alpha_m \mathrm{Month}_{\mathrm{mt}} + \delta \mathrm{Peak}_t + \sum_{s=1}^{S} \gamma_s \mathrm{Temp}_{\mathrm{st}} + \varepsilon_t, \end{aligned} \tag{4}$$

where Peak_t indicates hours between 11 A.M. and 8 P.M. on weekdays, $\mathrm{Month}_{\mathrm{mt}}$ is an indicator variable for each summer month, and $\mathrm{Temp}_{\mathrm{st}}$ measures temperature for bordering states.[24] For hour *t*, the idiosyncratic error term on net imports is ε_t. This error results from supply shocks not captured by the fixed effects (like forced outages) or demand shocks in other regions not captured by the temperature variables (like economic activity). This model is smooth, defined for all net imports, and accounts for the inelastic nature of imports nearing capacity.[25] The paper's results are robust to this specific functional form.[26]

Prices are endogenous to net imports: a positive shock to net imports will lower the price.[27] I address this endogeneity using two-stage least squares (2SLS).

[24] The temperature variables for bordering states are modeled as quadratic functions for cooling degree days (degrees daily mean above 65°F) and heating degree days (degrees daily mean below 65°F). As such, $\mathrm{Temp}_{\mathrm{st}}$ has four variables for each of the four states. These data are state averages from the National Oceanic and Atmospheric Administration's daily temperature data (U.S. Department of Commerce, National Climatic Data Center, NOAA Satellite and Information Service [http://www7.ncdc.noaa.gov/IPS/getcoopstates.html]).

[25] Other potential single-coefficient, 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, which makes a constant elasticity model inappropriate. A linear model would not account for the inelastic nature of supply (for example, transmission lines entering PJM occasionally bind and limit net imports).

[26] An alternative, more flexible model allows price to enter as a higher-order polynomial function. I estimate a cubic function of price using the same method as the main model. In the two-stage least squares (2SLS) estimates, the price variable (and the higher-order terms) are regressed on the exogenous variables and a set of instruments. These include the higher-order terms of load, as in the text, plus the squared terms of all exogenous variables. Finally, peak and off-peak hours are estimated separately to allow for more flexibility. All results of the paper are robust to this more flexible form and are available from the author on request.

[27] Prices are determined by the PJM operator ex post. Therefore, prices are a function of net imports. In addition, firms choose net imports on the basis of expectations of this price at the time of production. I assume that firms predict prices correctly. If they do not, then the ex post price variable used here will measure firms' expected price with error. This would be an additional reason to instrument price. A model of the ex post price on net imports would also be subject to endogeneity

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Table 5

Instrumental Variables Estimation of Net Import Supply Function, Summers of 1998 and 1999: First-Stage Dependent Variable Is Log of Hourly Pennsylvania, New Jersey, and Maryland (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* (.08)	.47* (.10)	2.72* (.09)	.50* (.10)
ln(Load) × Off Peak	.16* (.05)	2.18* (.06)	.15* (.06)	2.35* (.06)
R^2	.96	.94	.94	.93

Note. Two-stage least squares (2SLS) coefficients are presented. 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 $\Delta x = x(t) - \rho \times x(t-1)$ for all data. I reestimate the 2SLS results using these quasi-differenced data. Robust standard errors are given in parentheses. Regression includes month fixed effects, peak indicator (between 11 A.M. and 8 P.M. 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.

* Statistically significant at the 5% level.

Ignoring this endogeneity would result in attenuation bias. A valid instrument is uncorrelated with the error term, ε_t, and is excluded from the economic model. I argue that PJM load is a valid instrument. Importers into PJM may consider forecast load but only to the degree that it helps them predict price. Actual load does not directly affect firm profits, except through price, and is thus excluded from the net import regression. Typically, a shock to net imports could change price, which in turn would affect the quantity demanded and make load an invalid instrument. However, since the derived demand for wholesale electricity is perfectly inelastic, this unusual instrument choice is valid in this case. A shock to net imports is not correlated with PJM load. For both peak and off-peak hours, I instrument the log of hourly prices with the log of hourly load in PJM: $\ln(q_t^d) \times \text{Peak}_t$ and $\ln(q_t^d) \times (1 - \text{Peak}_t)$.

Tables 5 and 6 report 2SLS coefficient and standard error estimates that account for serial correlation and heteroskedasticity separately for 1998 and 1999.[28] Table 5 shows the coefficients on the instruments in the first stage, which suggest that the instruments are strong, while Table 6 displays $\hat{\beta}_1$ and $\hat{\beta}_2$ 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

concerns given that firms form expectations about the price. An error in the price that is unobserved by the econometrician but is observed by the firms would be correlated with net imports.

[28] I test the error structure for autocorrelation (Breusch-Godfrey Lagrange multiplier statistic p-value of .00) and heteroskedasticity (Cook-Weisberg test with a p-value of .00). First I estimate the instrumental variables (IV) coefficients assuming independent and identically distributed errors in order to calculate an unbiased estimate of ρ, the first-degree autocorrelation parameter. After quasi-differencing the data, I reestimate the IV coefficients while using the White technique to address heteroskedasticity. This feasible generalized least squares technique is used throughout the paper.

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Table 6

Instrumental Variables Estimation of Net Import Supply Function, Summers of 1998 and 1999: Second-Stage Dependent Variable Is Hourly Net Imports into PJM by Year

Variable	1998	1999
ln(Price) × Peak	295.7* (85.6)	1,110.2* (128. 8)
ln(Price) × Off Peak	484.1* (65.6)	1,717.2* (82.7)
R^2	. . .	. . .
AR(1) coefficient (ρ)	.89	.84
Sample size	4,330	4,341

Note. Two-stage least squares (2SLS) coefficients are presented. 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 $\Delta x = x(t) - \rho \times x(t-1)$ for all data. I reestimate the 2SLS results using these quasi-differenced data. Robust standard errors are given in parentheses. Regression includes month fixed effects, peak indicator (between 11 A.M. and 8 P.M. 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.

* Statistically significant at the 5% level.

elasticity of net imports on-peak equal to .79 at average imports, while off-peak the elasticity is 4.2.[29]

In the following section, I solve for the competitive equilibria—as shown in equation (3)—by using these estimates to predict net imports. While the economic model controls for economic conditions in other regions using month fixed effects and temperature variables, transmission lines may be constrained because of physical limitations. For a given summer, I assume that the observed bounds on net imports ($q^{\text{IMP}}_{\text{MIN}}$, $q^{\text{IMP}}_{\text{MAX}}$) represent capacity constraints on transmission lines into and out of PJM.[30] As in Figure 1, the quantity of net imports under competition $[q^{\text{IMP}}_t(P^*_t)]$ equals the actual net imports $q^{\text{IMP}}_t(P_t)$ plus the deviation in imports given that, under competition, price will be P^*_t, not the actual P_t:

$$\begin{aligned} q^{\text{IMP}}_t(P^*_t) &= \beta_1 \ln(P^*_t) \times \text{Peak}_t + \beta_2 \ln(P^*_t) * (1 - \text{Peak}_t) \\ &\quad + \sum_{m=1}^{M} \alpha_m \text{Month}_{\text{mt}} + \delta \text{Peak}_t + \sum_{s=1}^{S} \gamma_s \text{Temp}_{\text{st}} + \varepsilon_t \\ &= q^{\text{IMP}}_t(P_t) + [\hat{\beta}_1 \text{Peak}_t + \hat{\beta}_2 (1 - \text{Peak}_t)] \ln\left(\frac{P^*_t}{P_t}\right) \end{aligned} \tag{5}$$

[29] Elasticity equals $\hat{\beta}_i/\overline{q^{\text{IMP}}_t}$. In the summer of 1999, net imports averaged 1,404 on peak and 407 off-peak.

[30] The observed net imports for the summer of 1998 ranged from −5,882 to 3,194 MWh. In the summer of 1999, it ranged from −3,304 to 6,095 MWh. Given the infrequency of observations at these limits, I do not econometrically model censoring.

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subject to the constraint that

$$q_t^{\mathrm{IMP}}(P_t^*) \in (q_{\mathrm{MIN}}^{\mathrm{IMP}}, q_{\mathrm{MAX}}^{\mathrm{IMP}}).$$

Note that this specification assumes that hour t's error term, ε_t, would have occurred in the competitive model. This ensures that if the simulated competitive price equals the actual price, then the simulated net imports will exactly equal the actual net imports.

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}):

$$c_{it} = \mathrm{VOM}_i + \mathrm{HR}_i \times (W_{it}^{\mathrm{fuel}} + W_{it}^{\mathrm{SO_2}} r_i^{\mathrm{SO_2}} + W_{it}^{\mathrm{NO}_x} r_i^{\mathrm{NO}_x}), \tag{6}$$

where VOM_i is variable operating and maintenance cost, HR is an efficiency measure called heat rate, and W_{it}^{fuel}, $W_{it}^{\mathrm{SO_2}}$, and $W_{it}^{\mathrm{NO}_x}$ are daily prices for unit i's fuel usage, SO_2 emissions, and NO_x emissions. Emissions rates for SO_2 and NO_x equal $r_i^{\mathrm{SO_2}}$ and $r_i^{\mathrm{NO_x}}$. Appendix A 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 stepwise function. Therefore, scarcity rents may arise when the equilibrium price falls between the marginal production 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 perfectly inelastic demand in this market, scarcity rents only occur with positive probabilities in this latter, extreme case.

Two potentially important opportunity costs involve intertemporal and spatial trading. However, since electricity cannot be stored, intertemporal opportunity costs are irrelevant.[31] Pennsylvania, New Jersey, and Maryland 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, I account for arbitrage opportunities such that no addition trade opportunities exist in equilibrium. The competitive price, therefore, will account for import response and be determined by marginal costs from equation (6) or, if generation and transmission capacity are exceeded, by the market's $1,000/MWh price cap.

As well as computing the marginal costs of the units, the determination of competitive supply also requires knowing their production capability. Generating units cannot run constantly and must be shut off for routine maintenance, which limits available capacity. These scheduled outages primarily occur in the low-

[31] I discuss two notable exceptions, pumped storage and hydroelectric power, in Appendix A.

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demand spring and fall seasons. As this paper focuses on summer months, 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}):

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

where K_i is unit i's capacity. In each hour, the forced outage factor (FOF_i) states the probability a unit cannot produce electricity when called upon. If $\xi_{it} \leq \text{FOF}_i$, 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 to 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 $\tilde{q}_{it}(P_t^*) = K_i \times (1 - \text{FOF}_i)$ if $P_t^* \geq c_{it}$ and zero otherwise. However, the market's supply curve is convex with respect to price and outages are lumpy in capacity. Therefore, the expected costs will exceed the 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 Borenstein, Bushnell, and Wolak (2002), 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 on the basis of equation (7), I determine the equilibrium as the intersection of fossil supply and residual demand, which depends on price as given by equations (3) and (5). If residual demand intersects supply between operating units, then price is determined on the basis of the importer's supply curve. If residual demand exceeds fossil supply such that all generation and transmission capacity binds, scarcity rents exist and I set price to the $1,000 cap.

For each hour, I repeat the process 100 times and calculate the mean of these simulations of the equilibrium price $\overline{P}_t^*$. Given the assumptions above, this price is an unbiased estimate of the expected price under perfect competition (recall that this competitive price equals the marginal cost of producing an additional megawatt hour). I measure price-cost markups ($P_t - \overline{P}_t^*$) using these cost estimates. Section 3.2 discusses the results of this method. This method is also used to predict competitive production levels $q_{it}(P_t^*)$. Section 4 compares these output decisions with actual output of each PJM firm.

3.2. Price-Cost Margin Results

For each month in the summers of 1998 and 1999, Table 7 reports hourly averages for demand, actual price, and competitive price estimates. From April

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through September 1999, the competitive equilibrium price averaged \$32.33/MWh, about \$5.64 below the actual price average. In contrast, during the previous summer, the observed prices (\$26.04) only slightly exceeded marginal costs (\$25.93). Examining market performance in specific months, one notes substantial variation in price-cost markups. On the one hand, during June and July 1999, actual prices surpassed competitive price estimates by \$5.90 and \$40.06, respectively. In contrast, all other summer months of that year had small positive or 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 A.M. and 8 P.M. on weekdays, were nearly twice as great as costs in 1999, while I estimate negative margins during off-peak hours. I discuss the implications of negative margins at the end of this section.

I measure overall market performance by highlighting the economic significance of high-demand hours in measuring the cost of procuring electricity. This is important in an industry that lacks storage and has substantial intraday variation in quantity demanded. For a given set of hours (S), I define market performance, MP(S), in a manner similar to Borenstein, Bushnell, and Wolak (2002):

$$\mathrm{MP}(S) = \frac{\sum_{t\in S} (P_t - \overline{P}_t^{\star})\tilde{q}_t}{\sum_{t\in S} P_t\tilde{q}_t}, \tag{8}$$

where $\tilde{q}_t$ equals the quantity of electricity sold at price P_t. The PJM region'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 may 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.[32] Therefore, I define $\tilde{q}_t$ as energy actually purchased on the spot market or through bilateral contracts.[33]

Using this measure for the entire summer of 1999, I estimate MP = .24 (see

[32] The 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 PJM Interconnection (2000a, p. 54), "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."

[33] PJM Interconnection (2000a) summarizes actual average spot market purchases by month and time of day (disaggregating peak, 11 A.M. to 8 P.M., and off peak). Each hour, I assume contracts equal .3 times total quantity demanded plus regulated reserves: $.3 \times (q_t^d + q_t^r)$.

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Table 7

Demand, Actual Price, Competitive Price, and Market Performance

Month or Time of Day	Hourly Demand (MW)	Actual Price ($/MWh)	Competitive Price ($/MWh)	Market Performance
April 1998	25,427	19.20	20.23	−.04
May 1998	26,775	24.15	23.04	.10
June 1998	29,739	24.98	27.36	−.04
July 1998	32,863	34.23	35.49	.01
August 1998	33,183	29.58	25.88	.19
September 1998	29,780	23.53	23.33	.07
April 1999	25,612	21.44	22.19	−.02
May 1999	25,871	22.68	27.76	−.19
June 1999	31,542	37.10	31.20	.29
July 1999	36,957	91.67	51.61	.48
August 1999	33,461	31.77	33.44	.02
September 1999	29,140	22.06	27.24	−.21
Peak 1998	35,068	41.72	34.60	.20
Off peak	27,347	19.32	22.24	−.11
Overall	29,650	26.04	25.93	.06
Peak 1999	35,722	74.21	44.07	.45
Off peak	28,221	22.56	27.34	−.15
Overall	30,459	37.97	32.33	.24

Note. Competitive price is the average of Monte Carlo simulations of the competitive equilibrium price for a set of hours (for example, a month). Competitive prices and market performance are reported for the linear-log model of net import supply. For a given time period, market performance is the ratio of additional procurement costs (relative to the competitive estimates) over actual procurement costs. "Peak" indicates hours between 11 A.M. and 8 P.M. on weekdays.

Table 5). This reflects an increase in procurement costs through the spot market for $182 million above actual procurement costs. I estimate that this increase in procurement costs has a standard error of $40 million (see Appendix B for a discussion of the estimation method). My measure of total transfers associated with market power increases to $676 million if bilateral contracts exhibited similar margins (with a standard error of $121 million). To put these procurement cost increases in context, these estimates are 32 percent greater than those from a competitive market (namely, $\sum_{t\in S}\overline{P}_t^{*}\tilde{q}_t$). In contrast, during the previous summer, procurement costs were only weakly significantly different from those of the competitive model.[34]

The total cost to retailers could have been much higher if firms were not vertically integrated. Given the observed prices, the procurement costs for the summer of 1999 would have exceeded those of a competitive wholesale market by $1.6 billion.[35] Since most of these transfers were from one division of a firm

[34] Using similar calculations, the increase in overall procurement costs equals $95 million (standard error, $52 million), while increases to the spot market costs alone total $28 million (standard error, $15 million). The corresponding *t*-statistics, 1.83 and 1.87, are significant at the 10 percent level (*p*-values of .078 and .072).

[35] In 1998, they would have been $223 million above the competitive level.

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to another, the distributional impacts of market power were limited by vertical integration.

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/MWh. As regulators did not require compliance of firms until year's end, some firms may have ignored this new market's high costs.[36] In these months, cost estimates ignoring NO_x permits result in competitive price estimates similar to actual prices.[37]

In general, off-peak hours also display negative margins. However, plants do actually operate when price falls below their marginal costs. 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 unit commitment problems during off-peak hours, the method overstates marginal costs.

In contrast, during peak hours, start-up costs may delay firms from operating even when expected prices exceed marginal costs; firms may expect the price-cost differences to be temporary and insufficient to cover their unit commitment costs. By ignoring these nonconvexities in cost during peak hours, those most subject to the exercise of market power, the method biases marginal cost estimates downward. While the overall implications of ignoring start-up costs and other cost nonconvexities may be ambiguous, Borenstein, Bushnell, and Wolak (2002) argue that the overall effect is negligible when including margins from peak and off-peak hours.

4. Vertical Integration and Firm Conduct

4.1. Difference-in-Differences Model

This section examines whether PJM firms' behavior changed after restructuring. Using a difference-in-differences model, I test whether output from two firms, PECO and PPL, differed after the PJM market restructured relative to the other firms. I isolate these firms because, relative to others, they offered unreg-

[36] Furthermore, Kolstad and Wolak (2003) find that, in the California electricity market, firms do not account for tradable permits to the full extent as for 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 Borenstein, Bushnell, and Wolak (2002), in comparison with relative behavior in 1998 and 1999.

[37] Prices are $2.33 above costs in May and $3.35 below costs in September. This suggests that some firms may have either disregarded or discounted current NO_x prices when determining marginal production costs.

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ulated, market-based bids (Section 2), had net selling positions (Table 1), and reduced output from 1998 to 1999 (Table 4).

Since market conditions may asymmetrically affect competitive firms, I control for estimates of competitive production decisions. For each firm $j \in \{1, \ldots, N\}$ in Table 1, I define q^{*}_{jt} as the estimated competitive production for hour t. The unit level estimates of competitive production (q^{*}_{it}) from Section 3 are aggregated by firm:[38]

$$q^{*}_{jt} = \sum_{i \in j} q^{*}_{it} \quad \text{for all firms} \quad j = 1, \ldots, N. \tag{9}$$

Recall that the q^{*}_{it} estimates account for cost and demand shocks.

An indicator variable measures the unobserved shock common to all firms in the summer after the policy of restructuring is enacted (Policy_t). Firm fixed effects (η_j) are also included. In addition, regressors include a vector of exogenous variables ($\boldsymbol{Z}_t$) with indicators for hour of day and day of week, as well as a piecewise linear function of demand that is separated by decile.

The log of actual firm output, q_{jt}, is modeled as follows:

$$\ln(q_{jt}) = \phi \ln(q^{*}_{jt}) + \zeta \text{Policy}_t + \gamma \text{Policy}_t \times \text{Olig}_j + \boldsymbol{Z}'_t \Pi + \eta_j + v_{jt}, \tag{10}$$

where v_{jt} is the error term. In this difference-in-differences approach, I estimate behavioral changes following restructuring for oligopolists PECO and PPL (Olig_j) 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 likely to have neither incentives nor the ability to affect prices. As Policy_t is equal to one for all firms after restructuring, $\zeta + \gamma$ measures the impact of restructuring on the oligopolists. In contrast, ζ measures the impact of restructuring for the other firms. Therefore, the impact of restructuring on the oligopolists relative to the other firms is measured by the difference γ. As with any difference-in-differences approach, there are numerous caveats.[39]

Table 8 reports the results with six different specifications of equation (10).[40] Column 1 is a difference-in-differences regression with no controls. The coefficients on competitive production (ϕ) and the other controls (Π) in equation (10) are set to zero. Here, the $\hat{\gamma}$ coefficient measuring the change in production by oligopolists after restructuring relative to other firms is $-.32$. This implies

[38] All small firms are aggregated as "other" since none of them would be large enough to exercise significant market power.

[39] Besley and Case (2000) note that policies may be endogenous and that it is incorrect to treat them as natural experiments. Restructuring was a response to inefficient historic investments in nuclear and renewable energies. Abadie (2005) points out that the control group may not have the same range of exogenous regressors. The only regressor varying by firm is $\ln(q^{*}_{jt})$. The variance of this measure for PECO and PPL is within the range observed by other firms. Blundell and MaCurdy (2000) review difference-in-differences estimation and discuss whether it can ever isolate a specific behavioral parameter.

[40] As mentioned in footnote 28, a feasible generalized least squares technique is used throughout this paper. I use the Prais-Winsten method to estimate equation (10) and calculate the White standard errors using the robust function in Stata.

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Table 8

Test of Firm Behavior Based on Hourly Firm-Level Production

	(1)	(2)	(3)	(4)	(5)	(6)
Restructuring	−. 039	.009	.113*	.097*	.139*	.148*
	(.059)	(.038)	(.033)	(.027)	(.017)	(.017)
Oligopolist × Restructuring	−.322*	−.289*	−.388*	−.351*	−.127*	−.132*
	(.155)	(.098)	(.121)	(.089)	(.035)	(.037)
ln(Estimated Production)	. . .	. . .	.184*	.073*	. . .	. . .
			(.004)	(.004)		
Other controls	No	Yes	No	Yes	No	Yes
AR(1) coefficient	.97	.96	.96	.96	.88	.88
R^2	.04	.35	.58	.71	.01	.04

Note. Dependent variables in columns 1–4 are the ln(actual production) by firm and hour. Dependent variables in columns 5–6 are ln(actual production) − ln(estimated production) by firm and hour. The values presented are feasible generalized least squares coefficients estimated using the Prais-Winsten methodology. Robust standard errors are in parentheses. Regressors include firm fixed effects. Other controls are indicator variables for hour of day and day of week and a piece-wise linear function of demand that is separated by decile. The sample includes 78,766 firm-hour observations.

* Statistically significant at the 5% level.

that these two firms reduced output by 32 percent, on average, in the summer of 1999 relative to other firms. In column 2, I control for the control variables that vary by time ($\boldsymbol{Z}_t$) and find a similar result. In column 3, I control for competitive output estimates but not for $\boldsymbol{Z}_t$. Here, $\hat{\gamma}$ equals −.39 and the coefficient on the log of the estimated production, $\hat{\phi}$, is .18. Column 4 controls for both competitive production and the other controls, and the production by oligopolists is still 35 percent below that of other firms. In this case, some of the predictive power of q^*_{jt} has been absorbed by the $\boldsymbol{Z}_t$ vector, and in this regression $\hat{\phi}$ is .07.

However, columns 3 and 4 may be biased. 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 ϕ equal to one. In columns 5 and 6, the dependent variable is the difference between the log of actual output and the log of the estimated competitive output. As above, I do not control for $\boldsymbol{Z}_t$ in column 5 but do in column 6. Both models suggests that oligopolists reduced output by 13 percent after restructuring relative to other firms. The other firms increased production by approximately 15 percent.

Given the potential biases from including regressors with measurement error ($\hat{q}_{it}$), I find the results of column 6 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.

4.2. Robustness Test with Alternative Model

This section uses an alternative model to explore firm behavior after restructuring as a robustness check of the difference-in-differences model's results. As a benchmark, I write the first-order condition in equation (2) assuming firms

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optimize in a static game setting by choosing quantities.[41] 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). I modify equation (2) to include a parameter of firm conduct for each firm and year (θ_{ij}). This approach is similar to Genesove and Mullin's (1998) study of firm conduct in the sugar industry, Wolfram's (1999) paper on the England-Wales electricity market, and Puller's (2007) work on the California electricity market.

For firm *i*, year *j*, and hour *t*, the modified equation (2) is

$$P_{jt} + \theta_{ij} P'_{jt} \times (q_{ijt} - q^{d}_{ijt} - q^{c}_{ijt}) = c_{ijt}, \tag{11}$$

where the notation is defined in Section 2. In a Nash equilibrium, all firms take other strategic firms' behavior as given. Therefore, the slope of residual demand is the same for all firms. A firm's marginal cost (c_{ijt}) equals its most expensive unit that is operating below capacity.[42] As shown in equation (11), a strategic firm ($\theta_{ij} = 1$) will determine output as a function of price, marginal cost, the slope of the inverse residual demand facing firm *i*, and the net position of production ($q_{ijt} - q^{d}_{ijt} - q^{c}_{ijt}$). In contrast, the first-order condition of a firm behaving competitively ($\theta_{ij} = 0$) will be $P_{jt} = c_{ijt}$. The overall amount a price-taking firm generates does not affect its decision on the margin.

For purpose of estimation, I write equation (11) as $\text{PCM}_{ijt} = \alpha_{ij} + \beta_{ij} q^{\text{net}}_{ijt} + \varepsilon_{ijt}$, where ε_{ijt} is an idiosyncratic shock. The price-cost markup (PCM_{ijt}) is the difference between the market price and marginal cost. I define net position (q^{net}_{ijt}) 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. The β_{ij} coefficient on the net position equals $-\theta_{ij} P'_{jt}$, which is nonnegative. As all strategic firms face the same slope of residual demand, differences in β_{ij} across firms indicate variation in θ_{ij}. If a firm is a price taker, then α_{ij} and β_{ij} equal zero. As P'_{ijt} and contract specifications may differ by time of day, I allow α to vary for peak (Peak_t) and off-peak hours. I test whether firm behavior changed after restructuring by allowing (α_{ij}, β_{ij}) to differ in 1999. A positive shock to the firm's price-cost margin, such as a drop in costs, will increase firm production. Therefore, q^{net} is endogenous. I estimate the model with 2SLS using instruments of daily temperatures for both states in PJM and those bordering the region.[43] Appendix A discusses data sources.

[41] 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.

[42] That is, $c_{ijt} \geq c_{ljt}, \forall l \neq i : q_{ljt} \in (0, K_l)$. As with Puller (2007), 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.

[43] Temperatures are likely to be correlated with load in PJM and surrounding regions, which in turn will be correlated with firm production and a firm's native load (the two components of q^{net}). Furthermore, a price shock, ε_{ijt}, has no impact on temperature, and, conditional on q^{net}, the two are likely to be uncorrelated. Finally, a firm's first-order condition does not directly depend on temperature, only on net output. Temperature variables are modeled as quadratic functions for daily

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Table 9

Test of Firm Behavior Based on Price-Cost Markups

	Net Q All Observations		Net Q > 0 Sample	
Firm	(1)	(2)	(3)	(4)
Public Service Electric	−.138* (.026)	.247* (.052)	.040 (.024)	−.083 (.061)
Philadelphia Electric Company	−.176* (.021)	.491* (.068)	−.193* (.024)	.323* (.051)
GPU Energy	−.021* (.005)	−.035* (.017)	−.018* (.005)	−.060* (.014)
Pennsylvania Power & Light	−.044* (.010)	.131* (.021)	−.046* (.011)	.089* (.012)
Potomac Electric Power	.045* (.009)	−.077* (.019)	−.194* (.052)	−.046 (.041)
Baltimore Gas & Electric	.056* (.018)	−.202* (.039)	.013 (.011)	−.084* (.010)
Delmarva Power & Light	.174* (.035)	−.472* (.084)		
Atlantic City Electric	.364* (.093)	−1.013* (.212)		
Other	.090* (.028)	−.290* (.064)		

Note. The dependent variable is price-cost markup by firm and hour. For each firm, I separately estimate these coefficients using two-stage least squares (2SLS). I correct for serial correlation by estimating an AR(1) coefficient (ρ) and quasi-differencing the data, namely, by calculating $\Delta x = x(t) - \rho^* x(t-1)$ for all data. Then, I estimate the 2SLS results using these quasi-differenced data. Robust standard errors are given in parentheses. Columns 1 and 2 examine the entire sample. Columns 3 and 4 are conditioned on positive net output positions. Delmarva Power & Light, Atlantic City Electric, and "other" firms always have negative net positions. The independent variable, Net Q, is firm net output (in MWh). In columns 1 and 3, the coefficients are for both summers, while in columns 2 and 4, the coefficients are the incremental effect for the summer of 1999. Regression includes a constant (a) and an indicator of restructuring (α). In the first stage, I regress net quantity on the instruments of daily temperatures for both states in Pennsylvania, New Jersey, and Maryland and those bordering the region. Temperatures are modeled as quadratic functions for cooling degree days (degrees daily mean above 65°F) and for heating degree days (degrees daily mean below 65°F).

* Statistically significant at the 5% level.

For each firm, Table 9 reports the coefficients and robust standard errors.[44] Column 1 reports the impact of net position on markups during 1998. Relative to this baseline, column 2 reports the additional impact in 1999. Recall that regardless of net position, a positive coefficient is consistent with exercising market power. Two net sellers, PECO and PPL, have significant and positive coefficients in 1999, which implies 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 coefficient in 1999; 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. For Potomac, Baltimore, Delmarva, Atlantic, and "other" firms, I estimate a negative coefficient for 1999. In columns 3 and 4, 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,

means, with coefficients allowed to vary above and below 65°F (cooling and heating degree days, respectively).

[44] I model the idiosyncratic shock as a heteroskedastic, first-order autoregressive error term. I 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 the robust standard errors estimated using the Huber-White sandwich estimator of variance.

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during these hours, only PECO and PPL have positive coefficients in 1999. These firms seem the most culpable for the wealth transfers previously measured.

The results of this section support those of the difference-in-differences model. Note that while the difference-in-differences model uses the results of Section 3, this method does not depend on results from the previous section. Nevertheless, in both cases, PECO and PPL are found to have behaved differently than other firms after restructuring.

5. Conclusions

This paper examines how vertical integration affects wholesalers' behavior in restructured electricity markets. In contrast to other electricity markets, most firms in PJM remained vertically integrated the summer after restructuring occurred. However, because of variation in state retail policies during a brief period, some firms had the capacity to produce substantially more energy than their customers demanded. These net sellers had incentives to set high prices.

I find that these firms, PECO and PPL, reduced output by approximately 13 percent relative to the other firms after the market was restructured. Furthermore, these findings are supported by another test of firm behavior. After restructuring, these two firms changed their behavior in a manner that is consistent with profit maximization for a Cournot-Nash equilibrium. While restructuring PJM led to an increase in anticompetitive behavior by these two large net selling firms, the others continued to act like price takers. These findings can be explained by differences in the scope of vertical integration.

To the degree that some firms did exploit market power, wholesale prices exceeded those of a competitive market. Using a technique based on Wolfram (1999), this paper estimates prices for a competitive market in determining estimates of price-cost margins and finds some wealth transfers from retailers to wholesalers. Since most of the transfers associated with higher prices occurred within a firm, the distributional impacts were relatively small.

I conclude that vertical integration both mitigates market power in the upstream market and limits its distributional effects, issues that have plagued other electricity markets. In contrast to PJM, policies requiring divestiture, such as in California and the United Kingdom, may partially explain the performance of these markets. This paper's results do not necessarily imply that divesting power plants is always a poor decision. However, it does caution regulators that, if they do require divestiture, then they also should enable firms to sign contracts that will limit incentives to exercise market power.[45]

[45] For an examination of whether these long-term contracts mitigate market power, see Wolak (2000), Bushnell and Saravia (2002), and Bushnell, Mansur, and Saravia (2005).

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Appendix A

Data Sources

The PJM energy market uses a nodal pricing system in order to accommodate transmission constraints and may have thousands of different locational prices at a given time.[46] 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 instead of 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 Interconnection 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.

1. 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 forfeit the opportunity of receiving a higher price.[48] Firms optimize subject to constraints of minimum flow rates of rivers, 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 Borenstein, Bushnell, and Wolak (2002).

[46] Each node is a point where energy is supplied, demanded, or transmitted. The PJM energy market can have over 2,000 prices every 5 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.

[47] Loop 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.

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

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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.[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. There 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 (that is, they are inframarginal). When firms do shut down nuclear 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.

2. Fossil Fuel Data Sources

To determine PJM fossil units' marginal costs, I use publicly available PROSYM model output (Kahn 2000) that provides 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

[49] Energy Information Administration, Form EIA-906 Database: Monthly Utility Powerplant Database (http://www.eia.doe.gov/cneaf/electricity/page/eia906u.html). 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 Interconnection reports all of the zero-priced bids for the entire system by hour.

[50] For EIA Form 759, see Energy Information Administration, Form EIA-906 Database: Monthly Utility Powerplant Database (http://www.eia.doe.gov/cneaf/electricity/page/eia906u.html). 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.

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operating and maintenance costs, SO_2 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] The 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.[52] To calculate SO_2 regulation costs, I use the mean of two monthly price indices of SO_2 permit prices that brokerage firms Cantor Fitzgerald and Fieldston report to the Environmental Protection Agency (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 1 (including substituting units). Plants in Pennsylvania, New Jersey, and Delaware had NO_x regulatory compliance obligations in 1999.

3. Firm Conduct Tests Data Sources

Calculating firms' hourly net position requires data on production, demand, and contract positions. The EPA's Continuous Emissions Monitoring System (CEMS) provides hourly production data for the fossil units. The CEMS records hourly gross production of electricity, heat input, and three pollutants—sulfur dioxide, nitrogen oxides, and carbon dioxide—for most fossil units in the country.[53] I convert the CEMS gross production to net production by comparing the total plant production from April through September 1998 of the CEMS gross output with the EIA net production. The ratio between net and gross production is assumed to be constant. I aggregate the CEMS fossil 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 on 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 from the Pennsylvania Office of Consumer Advocate.[54]

[51] While 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 model each plant's coal costs, I impose constant prices for delivery of coal.

[52] Federal Energy Regulatory Commission, FERC Form 423 Database: Monthly Cost and Quality of Fuels for Electric Plants Data (http://www.eia.doe.gov/cneaf/electricity/page/ferc423.html).

[53] Gross 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 90–95 percent of gross generation.

[54] Pennsylvania Office of Consumer Advocate, Pennsylvania Electric Shopping Statistics (http://www.oca.state.pa.us/Industry/Electric/elecstats/instat.htm).

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Appendix B

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 that 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, emissions rates, and input prices, from differences between realized outages and those in the Monte Carlo simulation, and from unit commitment problems.

I note that for each hour t the markup equals

$$P_t - \overline{P}_t^{*} = E(P_t - \overline{P}_t^{*}) + \varepsilon_t. \tag{B1}$$

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 independent and identically distributed 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

$$\mathrm{Var}\sum_{t=1}^{T}(P_t - \overline{P}_t^{*})\tilde{q}_t = \mathrm{Var}\Big(\sum_{t=1}^{T}\varepsilon_t\tilde{q}_t\Big) = \frac{\sigma_u^2}{1-\rho^2}\sum_{i=1}^{T}\sum_{j=1}^{T}q_i q_j \rho^{|i-j|}. \tag{B2}$$

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 feasible generalized least square regressions—using the Prais-Winsten method—to express markup $(P_t - \overline{P}_t^{*})$ 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 for $\hat{\sigma}_u$ and $\hat{\rho}$ are 40 and .70, respectively.

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