

Knittel, Christopher R.; Kim, Dae-Wook

Working Paper

Biases in static oligopoly models? Evidence from the California electricity market

Working Paper, No. 05-26

Provided in Cooperation with:

University of California Davis, Department of Economics

Suggested Citation: Knittel, Christopher R.; Kim, Dae-Wook (2005) : Biases in static oligopoly models? Evidence from the California electricity market, Working Paper, No. 05-26, University of California, Department of Economics, Davis, CA

This Version is available at:

<https://hdl.handle.net/10419/31312>

Standard-Nutzungsbedingungen:

Die Dokumente auf EconStor dürfen zu eigenen wissenschaftlichen Zwecken und zum Privatgebrauch gespeichert und kopiert werden.

Sie dürfen die Dokumente nicht für öffentliche oder kommerzielle Zwecke vervielfältigen, öffentlich ausstellen, öffentlich zugänglich machen, vertreiben oder anderweitig nutzen.

Sofern die Verfasser die Dokumente unter Open-Content-Lizenzen (insbesondere CC-Lizenzen) zur Verfügung gestellt haben sollten, gelten abweichend von diesen Nutzungsbedingungen die in der dort genannten Lizenz gewährten Nutzungsrechte.

Terms of use:

Documents in EconStor may be saved and copied for your personal and scholarly purposes.

You are not to copy documents for public or commercial purposes, to exhibit the documents publicly, to make them publicly available on the internet, or to distribute or otherwise use the documents in public.

If the documents have been made available under an Open Content Licence (especially Creative Commons Licences), you may exercise further usage rights as specified in the indicated licence.

Department of Economics

Working Paper Series

Biases in Static Oligopoly Models?: Evidence from the California Electricity Market

Christopher Knittel
University of California, Davis

Dae-Wook Kim
UC Davis

September 14, 2005

Paper # 05-26

Estimating market power is often complicated by a lack of reliable marginal cost data. Instead, policy-makers often rely on summary statistics of the market, thought to be correlated with price cost margins? such as concentration ratios or the HHI. In many industries, these summary statistics may be only weakly correlated with deviations from marginal cost pricing. Beginning with Gollop and Roberts (1979), a number of empirical studies identify industry competition and marginal cost levels by estimating the first order condition within a conjectural variations framework. Despite the prevalence of such New Empirical Industrial Organization (NEIO) studies, Corts (1999) illustrates the estimated mark-ups may be biased, since the estimated conjectural variations model forces the supply relationship to be a ray through the marginal cost intercept, whereas this need not be true in dynamic games. In this paper, we use direct measures of marginal cost for the California electricity market to measure the extent to which estimated mark-ups and marginal costs are biased. Our results suggest that the NEIO technique poorly estimates mark-ups and the sensitivity of marginal cost to cost shifters

UCDAVIS

Department of Economics
One Shields Avenue
Davis, CA 95616
(530)752-0741

http://www.econ.ucdavis.edu/working_search.cfm

Biases in Static Oligopoly Models?: Evidence from the California Electricity Market

Dae-Wook Kim and Christopher R. Knittel*

September 14, 2005

Abstract

Estimating market power is often complicated by a lack of reliable marginal cost data. Instead, policy-makers often rely on summary statistics of the market, thought to be correlated with price cost margins—such as concentration ratios or the HHI. In many industries, these summary statistics may be only weakly correlated with deviations from marginal cost pricing. Beginning with Gollop and Roberts (1979), a number of empirical studies identify industry competition and marginal cost levels by estimating the firms’ first order condition within a conjectural variations framework. Despite the prevalence of such “New Empirical Industrial Organization” (NEIO) studies, Corts (1999) illustrates the estimated mark-ups may be biased, since the estimated conjectural variations model forces the supply relationship to be a ray through the marginal cost intercept, whereas this need not be true in dynamic games. In this paper, we use direct measures of marginal cost for the California electricity market to measure the extent to which estimated mark-ups and marginal costs are biased. Our results suggest that the NEIO technique poorly estimates mark-ups and the sensitivity of marginal cost to cost shifters.

*We thank Severin Borenstein, Jim Bushnell, Erin Mansur, Steve Puller, Victor Stango and Catherine Wolfram for helpful comments. We also thank Severin Borenstein, Jim Bushnell and Frank Wolak for providing us with their marginal cost data. Kim gratefully acknowledges support from the California Energy Commission, while Knittel gratefully acknowledges support from the University of California Energy Institute. *Kim*: Korea Institute for Industrial Economics and Trade. *Email*: daekim@kiet.re.kr. *Knittel*: Department of Economics, University of California, Davis, University of California Energy Institute and NBER. *Email*: crknittel@ucdavis.edu.

1 Introduction

Estimating market power is often complicated by a lack of reliable marginal cost data. Instead, policy-makers often rely on summary statistics of a market, thought to be correlated with price cost margins—such as concentration ratios or the HHI. In many industries, these summary statistics may be only weakly correlated with deviations from perfectly competitive pricing.¹

Beginning with Gollop and Roberts (1979), “New Empirical Industrial Organization” (NEIO) studies estimate price-cost margins by estimating the firms’ first order condition within a conjectural variations framework. Marginal costs are treated as a function of observable cost shifters and a set of unknown parameters. By observing fluctuations in demand over time (or cross-sectionally), marginal costs are identified through the firms’ first order conditions, which relate prices to marginal costs, the “conduct parameter” and the elasticity of demand. While the use of these models has been extensive,² Corts (1999) illustrates the estimated conduct parameter may be biased, since the estimated conduct parameter forces the supply relationship to be a ray through the marginal cost intercept, whereas this need not be true in dynamic games.

Because policy can often hinge on these estimates, it is important to understand the extent of this bias, and, if possible, its direction. For example, perceived market power in California’s electricity industry prompted a number of policy changes and lawsuits; many antitrust actions are also based on the level of market power in an industry.

In this paper, we take advantage of unique data that allow us to quantify the accuracy of NEIO estimates. We analyze NEIO methods using a number of metrics. First, we use direct measures of marginal cost to calculate the average elasticity-adjusted Lerner index and compare this to the NEIO estimate. Second, we calculate hourly NEIO estimates of marginal cost and compare these to direct marginal cost levels. Third, we compare the sensitivity of the estimated marginal cost to cost shifters with the sensitivity of the direct marginal cost measure to the same set of cost shifters. Finally, to test the robustness of the NEIO results,

¹Borenstein, Bushnell and Knittel (1999) show that these measures may actually be negatively correlated with market power levels in restructured electricity markets.

²See, for example, Appelbaum (1983), Porter (1983), Roberts (1984), Spiller and Favaro (1984), Gelfand and Spiller (1987), Brander and Zhang (1990 and 1993), Ellison (1994), Berg and Kim (1994), Graddy (1995), Nebesky, McMullen, Lee (1995), Kadiyali (1996 and 1999), Kadiyali, Vilcassim, Chintagunta (1999), Raper, Love and Shumway (2000).

we estimate a number of demand and marginal cost functional forms. Our results suggest that the NEIO technique does a poor job of estimating market power levels. In general, we find that NEIO estimates overstate market power. We also find that despite direct measures of market power levels being robust to changes in the functional form of demand, NEIO results vary widely. Furthermore, the NEIO estimates of marginal cost do not measure the sensitivity of marginal cost to cost shifters well.

Our empirical setting is the restructured California electricity market. Concerns regarding market power levels in restructured electricity markets are especially high, as many industry observers argue prices far exceed marginal costs. Fortunately, as a result of the long history of regulation and the transparency of the production technology, detailed cost data for electricity markets are currently available. These data have been used to calculate the level of market power, measured as Lerner and elasticity-adjusted Lerner indexes, in the UK and California markets. Wolfram (1999) compares UK wholesale electricity prices with marginal costs. Her results suggest the average elasticity-adjusted Lerner index is small. Borenstein, Bushnell and Wolak (2002) and Joskow and Kahn (2001) estimate hourly marginal cost for the California market and compare these estimates to wholesale prices. They find that, in certain time periods, prices substantially exceeded marginal cost.

While reliable marginal cost data for the electricity industry are currently available, this is unlikely to continue. Entrants into these markets—independent power producers—do not face the same data requirements as investor owned utilities. In addition, there is evidence that existing firms are lobbying policy-makers to make cost data unavailable to the public. The absence of reliable data in the future increases the importance of evaluating methods that infer price-cost margins without cost data. In our analysis, we employ only data that are likely to be available in the future: market level prices, quantities and demand and cost shifters. As such our focus is not on individual firm conduct, but instead on the ability to estimate the efficiency of the market as a whole without detailed cost data.

Our work adds to a small literature examining the accuracy of NEIO techniques. Genesove and Mullin (1998) use data from the sugar industry during the late 19th and early 20th centuries; the transparency of sugar's cost technology and its heavy reliance on the price of cane sugar allow them to accurately estimate marginal costs. They find that the direct measure of the elasticity-adjusted Lerner index falls outside the 95 percent confidence interval of the NEIO estimate, and that the NEIO estimate understates margins; however, in economic terms, the difference is not large. Clay and Troesken (2003) perform a similar

analysis for the whiskey industry during the late nineteenth century. They also find that the direct elasticity-adjusted Lerner index falls outside of the 95 percent confidence interval of the NEIO estimate. Unlike Genesove and Mullin, they find that the NEIO technique overstates mark-ups for each of the estimated functional forms. Finally, Wolfram (1999) studies the deregulated UK electricity market and finds that the NEIO technique provides a noisy estimate of market power; neither perfect competition nor equality to the direct level of mark-ups can be rejected.

2 Empirical Framework

The typical empirical implementation of the NEIO technique uses data on industry level prices, quantities and demand and cost determinants. The technique begins by characterizing market i 's equilibrium price within a conjectural variations model:

$$P(Q_i, X_i; \beta) + \theta Q_i P'(Q_i, X_i; \beta) = C'(Q_i, K_i; \gamma) \quad (1)$$

where $P(Q_i, X_i; \beta)$ is the market inverse demand function, $C'(Q_i, K_i; \gamma)$ is the market marginal cost function, Q_i is the market quantity, X_i is a vector of variables that affect demand, K_i is a vector of variables that affect costs and β and γ are vectors of unknown parameters associated with demand and costs, respectively.

Solving for θ , we see that θ represents the elasticity-adjusted Lerner index:

$$\theta = \frac{P_i - MC_i}{P_i} \eta \quad (2)$$

Identification of θ relies on variation in demand across time or across markets. The model nests joint profit maximization ($\theta = 1$), perfect competition ($\theta = 0$) and the Cournot equilibrium ($\theta = 1/N$).

Given equation (1) and functional form assumptions for demand and marginal costs, P_i can be solved for as a function of some measure of the responsiveness of demand and marginal cost shifters. Once isolated, P_i becomes the dependent variable for estimation purposes.

2.1 Potential Weaknesses

The relevance of equation (1) has been questioned on a number of fronts. For one, because the pricing rule is the result of a conjectural variations model, it need not represent a Nash

equilibrium. Taking the conjectural variation model literally, the parameter represents firms’ beliefs regarding how competitors will react to changes in a firm’s quantity. Unfortunately, the theoretical literature has shown that the behavioral parameter represents a consistent equilibrium only under very specific information assumptions. (Lindh [1992]) A number of authors have defended the method on this front, however. The basis of the defense is that the conjectural variations model is only proxying for a dynamic model, and the Folk theorem tells us that a range of conducts are Nash equilibria in a dynamic game. Therefore, one can view θ not as an estimate from a theoretical model, but a measure of the elasticity-adjusted Lerner index, measuring the “static-equivalent” level of an industry’s competitiveness. Provided the technique yields accurate estimates of the elasticity-adjusted Lerner index, it is a useful exercise.

A second criticism comes from Corts (1999). Corts illustrates that the conduct parameter estimated from equation (1) can be biased even if the econometrician views θ as an “as-if” estimate of behavior. The intuition is simple. The pricing rule in equation (1) is the solution to the firms’ static first order conditions. If firms are competing in a dynamic setting, then the firms’ first order conditions may also depend on the incentive compatibility constraints associated with collusion. If the incentive compatibility constraints are a function of demand shocks, then the estimated θ may be biased.

Finally, Bresnahan (1982 and 1989), Lau (1982) and Reiss and Wolak (2005) point out that identification of θ hinges on demand and costs functional form assumptions; the estimates of θ may vary widely depending on functional form assumptions. Empirical evidence of this is mixed. While the results of Genesove and Mullin (1998) and Clay and Troesken (2003) are robust across functional form assumptions, Wolfram (1999) and Bettendorf and Verboven (2000) find that their results vary widely.

3 Empirical Setting

3.1 Institutional Detail

The restructured California wholesale electricity market began operation in April of 1998. Prior to 2001, wholesale electricity was primarily traded in two markets. The now defunct Power Exchange (PX) organized a day-ahead market and was one of many “Scheduling Coordinators” (SCs). The PX had an advantage over other SCs because California’s

three IOUs—Pacific Gas and Electric, Southern California Edison and San Diego Gas and Electric—were initially required to trade through the PX. Electricity that was not traded through a scheduling coordinator, was traded through the Independent System Operator (ISO), which operated an “imbalance market” designed to instantaneously equate supply and demand.

For system reliability reasons, the vast majority of energy was traded in the PX market; the ISO was designed to meet only unforeseen shocks to supply or demand.³ Trading the bulk of electricity in the day prior to delivery allowed market organizers sufficient time to plan the use of the state’s transmission grid.

The PX worked as follows: At 7am each morning, suppliers and demanders submitted hourly supply and demand curves for the following day (beginning at 12am). The PX aggregated these bids into one hourly supply bid and one hourly demand bid. The intersection of these bids determined the “unconstrained” PX price for each hour of the day. The PX then submitted its “preferred” prices and quantities to the ISO. Provided the preferred schedule did not result in any transmission congestion, the unconstrained PX price became the market clearing price. If the preferred schedule (along with the schedules of other scheduling coordinators) resulted in congestion, another round of bidding was used to reduce the demand (or increase the supply) in certain areas. In our analysis, we follow the existing literature and use the unconstrained PX price as the market clearing price.⁴

3.2 Measuring Marginal Cost

In many ways, the California electricity industry is an ideal setting for analyzing NEIO techniques. The bulk of electricity generated is produced using fossil fuel generation plants; furthermore fossil-fuel plants are predominantly the marginal plants operating. Accurate estimates of the short-run marginal cost of fossil-fuel electricity plants can be calculated since their thermal efficiencies at different output levels are currently available, as are spot market prices for natural gas. In particular, for each plant, a heat rate is available measuring

³During the PX’s operation, over 80% of energy was traded in the PX, but there is evidence that the IOUs underscheduled demand in the PX as a means of reducing PX prices. See Borenstein, Bushnell, Knittel and Wolfram (2001) for an analysis of this.

⁴The results do not qualitatively change if we use the ISO price or constrained PX prices.

the efficiency in which the plant converts fuel to electricity.⁵ The heat rate coupled with fuel prices allows the component of marginal cost attributed to fuel to be computed. The remaining components of marginal cost are operation and maintenance costs. Borenstein, Bushnell and Wolak (2002) calculate hourly marginal costs in the California electricity market; we make use of their marginal cost data and refer the reader to their work for additional details of the process.

We make one adjustment to their measure of marginal cost. In 45 percent of the hours price is below their measure of marginal cost. Since short-run profit maximizing firms would not price below marginal cost, this likely reflects either (a) estimation error in the marginal cost measures, or (b) inter-temporal constraints to shutting down power plants.⁶ Consistent with both of these explanations, this occurs predominantly in low demand hours. To control for this, we define marginal cost as:

$$\min (P_t, MC_t^{BBW}) \tag{3}$$

By doing this, we set the Lerner index to zero in these hours, thereby understating market power during low demand periods, since we know only that marginal cost is, at most, equal to the price. We note, however, while we make this adjustment in a significant number of the hours, for many of the hours, this reflects a small change in the Borenstein, Bushnell and Wolak (BBW) marginal cost estimates. Marginal cost is above price by more than ten percent in only 19 percent of the hours. Nevertheless, in section 5 we analyze the robustness of this assumption.

Figure 1 is a scatterplot of system-wide marginal cost on quantity; a Lowess non-parametric regression line is also plotted. It is apparent that the market faces a capacity constraint, although the regression line does not appear to become vertical only steeper as quantity increases. To capture this feature of marginal cost we initially assume that marginal costs are quadratic in quantity; we also estimate an endogenous spline model in section 5.

⁵Specifically, the heat rate is defined as the the number of BTUs required to produce one KWh of electricity.

⁶Plants face non-trivial start up costs, implying a firm may be willing to run a plant when the price is below the plants static marginal costs if price is expected to rise in the coming hours.

3.3 Estimation of Demand

The demand for electricity is extremely inelastic. Compounding the inelastic nature of demand is the fact that only a small percentage of demand faces wholesale prices. During the time period analyzed in this paper, retail consumers faced a fixed price, that was, at least in the short run, independent of wholesale prices. Barbose, Goldman and Neenan (2004) report that only one percent of demand faced wholesale prices during our sample period. This feature of the market suggests that short run demand is best viewed as being perfectly inelastic. However, for issues of market power, the relevant elasticity measure is the elasticity faced by “strategic” firms in the market, since some firms may not possess unilateral market power. Following Borenstein, Bushnell and Wolak (2002) and Puller (2002), we define a set of firms as “non-strategic” and a set of firms as “strategic.” Non-strategic firms are price takers and bid their marginal cost curves. Strategic firms, in contrast, price according to equation (1).

As an initial step in classifying firms, Table 1 reports the in-state firms’ generation capacities in July of 1999 by fuel type. Seven firms held significant amounts of generation assets, with the “Other” category representing many small firms, many of which were “Qualifying Facility” units that were paid outside of the auction. PG&E and SCE differed from the other large firms. For the majority of hours, PG&E and SCE were net *buyers* of electricity. Therefore, these firms did not have an incentive to increase prices and would therefore not act on any market power they possess. Given these considerations, we treat supply from PG&E, SCE and “Other” as non-strategic.

California also receives a significant amount of electricity from out-of-state firms; we treat these firms as non-strategic. The bulk of out-of-state supply comes from regulated utilities and quasi-governmental entities (*e.g.*, Bonneville Power Administration). Out-of-state utilities are regulated via rate-of-return regulation and must first meet their native demand requirements, leaving only excess generation capacity for exporting to California. This reduces the size of any single firm. For entities such as BPA, it is unclear that their objective function would be improved from exercising any market power that they possess.

Therefore, we define the strategic group of firms as AES, Duke, Dynegy, Reliant and Mirant. To estimate the hourly residual demand for these firms, we first estimate the non-strategic firms’ inverse supply equation, given as:

$$Q_{ns} = f(P, X, Z, \beta, \varepsilon_{ns}) \quad (4)$$

where P is the wholesale price, X is a vector of cost variables, Z is a vector of variables that capture the native demand of out-of-state firms, β is a vector of unknown parameters and ε_{ns} is an error term that captures unobserved components of non-strategic supply.

Letting Q_{tot} be the total amount of electricity demanded, the residual demand faced by strategic firms can be expressed as:

$$\begin{aligned} Q_s &= Q_{tot} - Q_{ns} \\ &= Q_{tot} - f(P, X, Z, \beta, \varepsilon_{ns}) \end{aligned} \tag{5}$$

4 Results

4.1 Non-Strategic Functional Form, Variables and Results

In this section we discuss functional form assumptions for non-strategic supply as well as the variables included in X and Z . Table 2 reports the summary statistics for these variables and their correlations with non-strategic supply.

We allow the wholesale price to affect non-strategic supply differently during peak, off-peak and weekend periods and in each of the three years of our data.⁷ This yields nine coefficients associated with the wholesale price. We instrument for wholesale prices since shocks to non-strategic supply decisions will be correlated with the wholesale price. Fortunately, good demand instruments are available. Specifically, we instrument for price using the ISO’s forecast for demand, which is independent of the error term since these forecasts do not take non-strategic supply into consideration. Given the interaction terms associated with price, we create nine instruments by interacting forecasted demand with the peak/off-peak/weekend/year indicator variables. Although we estimate non-strategic supply within a GMM framework, the results of the “first stage” regressions of the PX price on forecasted demand are presented Table 3; forecasted demand is highly significant in each of the specifications.⁸

The vector X includes variables that capture the marginal cost of non-strategic supply. The bulk of non-strategic supply is generated using natural gas and hydroelectric resources. P_N^{NG} and P_S^{NG} are the daily city-gate price of natural gas for northern and southern Califor-

⁷We define the peak period as those hours between 12pm and 6pm.

⁸The results with the variables in logs are qualitatively similar.

nia, respectively. While many of the non-strategic suppliers are out-of-state firms, regional natural gas prices are highly correlated. We control for the availability of hydroelectric resources using year/month indicator variables (a total of 28).

A key determinant of an out-of-state firm’s ability to export power to California is their native demand requirements. To capture out-of-state native demand requirements, Z includes the average of the daily minimum and maximum temperatures in Phoenix and Tucson, AZ; Portland and Pendleton, OR; Ely Yelland Field and Las Vegas, NV; Salt Lake City, UT; Seattle and Spokane, WA.⁹ We also interact this variable with a summer indicator variable, since native demand is positively correlated with temperature during the summer—because of air conditioning—and negatively correlated with temperature during the winter—because of heating.

Finally, in addition to the year/month indicator variables, we include three sets of indicator variables to capture temporal changes in supply. We include day of week, hour/weekday and hour/weekend indicator variables.

We estimate three functional forms for non-strategic supply: a linear model, a log-log model and a linear-log model.¹⁰ The results for the three models are reported in Table 4. We estimate the equation using GMM and report Newey-West corrected standard errors that account for the serial correlation in the residuals.¹¹

The results are largely consistent with economic intuition. In each of the three models, non-strategic supply is more responsive to price changes during the off-peak and weekend periods; this is likely because out-of-state firms have more excess capacity available throughout the different regions of their marginal cost curves. The sensitivity to price is not statistically different between 1998 and 1999, but decreased during 2000. This decrease is dramatic for the linear model. The results also suggest that higher natural gas prices reduce the supply of non-strategic generators; this effect is stronger for southern California natural gas prices. This may be because many of the out-of-state non-strategic natural gas plants are located in Arizona. Finally, lower out-of-state temperatures decrease non-strategic supply in the fall, winter and spring months, while this effect is reversed in the summer.

⁹The results are robust to a number of alternatives to simple averaging the maximum and minimum temperatures. In particular, we included each of the high and low temperatures separately and included the average of the high temperatures and the average of the low temperatures.

¹⁰That is, $y = \log(X)\beta + \varepsilon$. Because the log of price enters the log-log and linear-log models, we delete the 110 observations where price is zero. We do this for all three models to be consistent.

¹¹We include 24 lags.

The non-strategic supply curve estimates define the residual demand faced by strategic firms. Table 5 reports the mean, median and standard deviation of the residual demand elasticity estimates. The log-log and linear-log models yield similar results while the linear demand model implies a more inelastic residual demand curve.

4.2 Direct Measures of Mark-ups

Using the residual demand estimates and the BBW marginal cost numbers, we calculate the hourly Lerner index and elasticity-adjusted Lerner index for the three models; the descriptive statistics are reported in Table 6. For the entire sample, the average Lerner index is 0.13. Interestingly, while the linear demand model yields elasticity estimates that contrast with the other two models, the elasticity-adjusted Lerner indexes widely agree across the three models. Among the three models, the hourly linear and linear-log elasticity-adjusted Lerner indexes are the least correlated; yet, this correlation is still .82. The average elasticity-adjusted Lerner index ranges from 0.070 to 0.073, which is equivalent to a static equilibrium with 14 symmetric Cournot firms, far more than the five strategic firms that operate in California, suggesting the industry is more competitive than what a Cournot model would imply.

To see if there are temporal changes in mark-ups, Table 6 also reports the Lerner index and elasticity-adjusted Lerner index separately for weekday peak, weekday off-peak and weekend periods and for each of the three years. Both adjusted and non-adjusted Lerner indexes are higher during peak hours. The average Lerner index during weekday off-peak periods is higher than weekend periods; for the elasticity-adjusted Lerner index in the linear and linear-log models, this relationship is reversed. The average Lerner index increased significantly in 2000, compared to 1998 and 1999. Interestingly, however, the average adjusted Lerner index shows little variation across the three years. The log-log and linear-log models suggest that market power levels increased slightly in 2000, but not nearly as much as the unadjusted Lerner index.

4.3 Strategic Supply

Given residual demand estimates, the strategic supply relationship is estimated from the first order condition in equation (1). Marginal costs are parameterized as:

$$MC = \gamma_0 + \gamma_1 P^{NG} + \gamma_4 P^{NOx} + \gamma_5 Crisis \times P^{NOx} + \gamma_6 q_{st} + \gamma_7 q_{st}^2 \quad (6)$$

where P^{NG} is the average daily price of natural gas paid by IOUs, P^{NOx} is the price of NO_x permits and q_{st} is the quantity of strategic firms.¹² For much of the sample period NO_x emission permit prices were low. During the California electricity crisis, however, NO_x prices increased dramatically and became a significant component of marginal cost. To allow for non-linearities associated with the NO_x permit prices, we interact the permit price with a crisis indicator variable.¹³ Because the quantity variables are likely to be endogenous, we instrument for them using total demand and the square of total demand, which will be uncorrelated with shocks to price because it is perfectly inelastic.

Table 7 reports the strategic supply estimates for the three demand models. The standard errors account for serial correlation and the first stage estimation of demand.¹⁴ Despite the consistency of the direct elasticity-adjusted Lerner indexes across functional forms, the NEIO estimates vary widely. The linear model produces the most accurate estimate of the direct market power level: 0.123 compared to the direct measure of 0.070. The log-log and linear-log models overstate market power levels, 0.229 and 0.188, respectively, compared to the direct measures of .073 and .071, respectively. In each of the models, the direct measure falls outside of the 95 percent confidence interval of the NEIO estimate. These results provide an initial test of the NEIO method.

In the linear and linear-log models, marginal costs are estimated to be convex in quantity. The sensitivity of marginal cost to natural gas prices varies across the models, ranging from 5.60 in the log-log model to 8.02 in the linear-log model. The coefficients with respect to the price of NO_x permits are puzzling. For the linear model, increases in the price of permits are estimated to reduce marginal costs. During the crisis period this effect subsides, but remains negative.

To further test the accuracy of the NEIO technique in estimating marginal costs, Figure 2 is a density estimate of the difference between direct measure of marginal costs and the

¹²These prices include transportation costs. While they are at the IOU level, not the strategic firm level, these prices are likely to be strongly correlated. We include the weighted average of the natural gas prices for PG&E, SCE and SDG&E (weighted by monthly generation by natural gas units). The estimates of θ are robust to this assumption.

¹³We define the crisis period as after May of 2000.

¹⁴The standard errors report Newey West standard errors accounting for the first stage estimation using McFadden's (1999) GMM correction.

NEIO marginal costs from the linear model.¹⁵ On average, the NEIO technique overstates marginal costs; however this is not symmetric.¹⁶ A regression of the NEIO estimates on the direct measure of marginal cost yields:

$$MC_t^{NEIO} = 5.36 + .79MC_t^{Direct} + \varepsilon_t \quad (7)$$

Thus, the NEIO technique tends to overstate marginal cost when marginal cost is low, but understate marginal cost when it is high. Figure 3 is a scatterplot of the direct measure of marginal cost and the NEIO marginal cost estimates plotted against strategic quantity. The NEIO estimates fail to capture the high marginal costs during high demand periods.

As a second metric for the NEIO marginal cost estimates, we regress the direct measure of marginal cost on the cost shifters included in equation (6) and compare these parameter estimates to those obtained from the NEIO estimates. These results are reported in the final column of Table 7. Comparing these to the NEIO technique, we find that the NEIO technique does a poor job of estimating the sensitivity of marginal cost to cost shifters. The direct measure implies marginal costs are more sensitive to natural gas price changes. The direct measure of marginal cost suggests that NO_x permit prices have a positive effect on marginal costs. This is not the case in the NEIO results. Finally, the direct measure of marginal cost is estimated to be linear in quantity.

The next thought experiment we conduct is the following: suppose the econometrician knew the sensitivity of marginal cost to a specific input, possibly because of engineering estimates, would the estimate of market power become more accurate? We do this for each of the models estimated. Tables 8 through 10 report the results. For variables denoted as “known” we replace the unknown marginal cost parameter with the marginal cost parameter estimated using the direct measures of marginal cost listed in the final column of Table 7. In general, this does not improve the accuracy of the NEIO estimates or the estimates of the remaining marginal cost parameters.¹⁷

¹⁵We chose the linear model since this yields the most accurate estimate of market power. We truncate observations above \$20 (1.9%) so that the figure is easier to interpret.

¹⁶The mean difference (actual minus NEIO) is -1.95 with a standard deviation of 8.11.

¹⁷In a similar exercise, Genesove and Mullin (1998) find that replacing the marginal cost parameter associated with the price of raw sugar does not improve their estimate of market power, but does improve their estimate of the marginal cost intercept.

4.3.1 Time-Varying Mark-Ups

We next analyze the NEIO technique’s ability to accurately reflect temporal changes in mark-ups. As in Table 6, we allow for mark-ups to vary across years and throughout the day. The NEIO estimates of mark-ups for the different years are reported in Table 11; the results contrast with the direct measures of mark-ups. The estimates of θ suggest that market power existed only in 2000, despite the consistency of the direct measure across years.

Table 12 reports the NEIO estimates allowing for a different θ during the peak hours of a weekday, the off-peak hours of a weekday and during weekends. Each of the NEIO models suggests that market power levels are highest during the weekend, at odds with the direct measures which imply market power is greatest during peak hours.

The inability of the NEIO technique to accurately estimate *changes* in market power is important, since it could be the case that it does not estimate market power levels accurately, but policy makers can still learn about *changes* in market power levels. Unfortunately, this does not appear to be the case.

5 Robustness Checks

As noted, one shortcoming of our data is that in a substantial number of hours our marginal cost measure is above the market clearing price. In the previous analysis we adjusted the hourly marginal cost numbers to be the minimum of the BBW measure and price. In this section, we adjust our sample so that this is less of an issue. In doing so, our goal is to use selection criteria that are simple enough to be used when marginal cost data are *not* available.¹⁸

We look at two sub-samples of the data. The first selects observations based on the time of day and time of year, using only weekday-peak hours in the months between May and October observations. Because price is higher during peak times and summer months, the dynamic marginal cost is more likely to be equal to the static marginal cost measure. In this sample, marginal cost exceeds price in 14 percent of the hours, but exceeds price by more than ten percent in only six percent of the hours. The second sub-sample uses only

¹⁸We have also analyzed samples that are based on our direct marginal cost data and the results do not qualitatively change. For example, we have used only those observations where price is above the direct measure of marginal cost and estimated a probit to predict when price will be above marginal cost based on forecasted demand.

observations where demand is expected to be high, using hours in which forecasted demand is above the median. In this sample, marginal cost exceeds price in 19 percent of the hours, but it exceeds price by more than ten percent in only four percent of the hours. Focusing on these sub-samples has the additional advantage that market power concerns are highest during high demand periods when supply constraints begin to bind. If the NEIO technique can accurately reflect market power levels during these times, but not during all hours, then it may still be useful for policy analysis.

Tables 13 and 14 report the direct measures of market power and the NEIO estimates for the two sub-samples. The results are mixed. For both sub-samples, the NEIO technique provides accurate “entire sample” estimates of market power for two of the three functional forms; unfortunately the two functional forms vary. In the weekday peak sample, the linear and log-log models provide accurate estimates, whereas the linear and linear-log results are accurate for the forecasted-demand sample. The linear model continues to yield the most accurate results.

The estimation of temporal changes in market power is also mixed. As with the full sample, the NEIO estimates fail to capture the existence of market power in the 1998 and 1999. Again, given that the direct measures of market power vary little across functional forms, we would hope that the NEIO would also be consistent. Using the forecasted-demand sample, within day changes in market power are accurately reflected for the linear demand model, but the other two demand models overstate market power.

One possible explanation for the poor performance of the NEIO technique is that the market in 2000 was very different compared to 1998 and 1999, thus combining all of the years into one sample may lead to erroneous conclusions. In support of this, Kolstad and Wolak (2004) present evidence that during certain periods of 2000, firms were able to use their market power in the *NOx* permit market to increase the costs of their rivals. This would imply that *NOx* permit prices may be endogenous. To account for this, we estimate market power using data only for 1998 and 1999 and report these results in Table 15. This does little to increase the accuracy of the NEIO estimates.

In the previous specifications, marginal costs are assumed to be quadratic in quantity. Our last robustness check alters the functional form for marginal cost. We assume that marginal costs are a linear spline with one knot. We endogenously determine the knot by using the method in Andrews (1993). We estimate the endogenous spline model under the linear non-strategic supply model since this model provided the most accurate estimates

of market power. The results are listed in Table 16 and are consistent with the quadratic marginal cost model.

6 Conclusion

In this paper, we compare direct measures of mark-ups and marginal costs to estimates based on the static conjectural variations first-order conditions of an industry. We take advantage of unique data that allow us to directly measure marginal costs in the restructured California electricity market. Our results suggest that, in this setting, the NEIO technique does a poor job of estimating market power.

Admittedly, it is difficult to extend our results to other industries, but our results suggest that policy makers should be cautious when relying on NEIO techniques to diagnose industry performance. Furthermore, these results underline the importance of data collection requirements in restructured electricity markets. Given that the NEIO does a poor job in this setting, future policy based on market power concerns will require actual marginal cost data.

References

- [1] Andrews, D. W. K. "Tests for Parameter Instability and Structural Change With Unknown Change Point." *Econometrica* 61(4), July 1993, pp. 821-856.
- [2] Appelbaum, E. "The Estimation of the Degree of Oligopoly Power." *Journal of Econometrics* 19(2-3), August 1982, pp. 287-99.
- [3] Barbose, G., Goldman, C. and Neenan, B. "A Survey of Utility Experience with Real Time Pricing." Lawrence Berkeley National Laboratory Working Paper, LBNL-54238, 2004.
- [4] Berg, S. A. and Kim, M. "Oligopolistic Interdependence and the Structure of Production in Banking: An Empirical Evaluation." *Journal of Money, Credit, and Banking* 26(2), May 1994, pp. 309-322.
- [5] Bettendorf, L. and Verboven, F. "Incomplete Transmission of Coffee Bean Prices: Evidence from the Netherlands." *European Review of Agricultural Economics* 27(1), 2000, pp. 1-16.
- [6] Brander, J. A. and Zhang, A. "Market Conduct in the Airline Industry: An Empirical Investigation." *Rand Journal of Economics* 21(4), Winter 1990, pp. 567-583.
- [7] Brander, James A. and Zhang, A. "Dynamic Oligopoly Behaviour in the Airline Industry." *International Journal of Industrial Organization* 11(3), September 1993, pp. 407-435.
- [8] Bresnahan, T.F. "The Oligopoly Solution Concept is Identified." *Economic Letters* 10(1/2), 1982, pp. 87-92.
- [9] Bresnahan, T. F. "Empirical Studies of Industries with Market Power." In R. Schmalensee and R.D. Willig, eds., *The Handbook of Industrial Organization*. New York: North-Holland, 1989, pp. 1011-57.
- [10] Borenstein, S., Bushnell, J. B., and Knittel, C. R. "Market Power in Electricity Markets: Beyond Concentration Measures." *The Energy Journal* 20(4), October 1999, pp. 65-88.

- [11] Borenstein, S., Bushnell, J. B., Knittel, C. R., and Wolfram, C. D. "Trading Inefficiencies in California's Electricity Markets." POWER working Paper PWP-086, University of California, 2001.
- [12] Borenstein, S., Bushnell, J. B. and Wolak, F. "Measuring Market Inefficiencies in California's Restructured Wholesale Electricity Market." *American Economic Review* 92(5), December 2002, pp. 1376-1405.
- [13] Clay, K. and Troesken, W. "Further Tests of Static Oligopoly Models: Whiskey, 1882-1898." *Journal of Industrial Economics* LI(2), June 2003, pp. 151-166.
- [14] Corts, K.S. "Conduct Parameters and the Measurement of Market Power." *Journal of Econometrics* 88(2), February 1999, pp. 227-50.
- [15] Diewert, W. E. and Wales, T. J. "Flexible Functional Forms and Global Curvature Conditions." *Econometrica* 55(1), January 1987, pp. 43-68.
- [16] Ellison, G. "Theories of Cartel Stability and the Joint Executive Committee." *RAND Journal of Economics* 25(1) Spring 1994, pp. 37-57.
- [17] Gelfand, M. D. and Spiller, P. T. "Entry Barriers and Multiproduct Oligopolies: Do They Forebear or Spoil?" *International Journal of Industrial Organization* 5(1). March 1987, pp. 101-13
- [18] Genesove, D. and Mullin, W. "Testing Static Oligopoly Models: Conduct and Cost in the Sugar Industry, 1890-1914." *Rand Journal of Economics* 29(2), Summer 1994, pp. 355-377.
- [19] Gollop, F. and Roberts, M. "Firm Interdependence in Oligopolistic Markets." *Journal of Econometrics* 1(3), August 1979, pp. 313-31.
- [20] Graddy, K. "Testing for Imperfect Competition at the Fulton Fish Market." *RAND Journal of Economics* 26(1), Spring, 1995, pp. 75-92
- [21] Joskow, P. and Kahn, E. "A Quantitative Analysis of Pricing Behavior in California's Wholesale Electricity Market during Summer 2000." *Energy Journal* 23(4), October 2002, pp. 1-35.

- [22] Kadiyali, V. "Exchange Rate Pass-through for Strategic Pricing and Advertising: An Empirical Analysis of the U.S. Photographic Film Industry." *Journal of International Economics* 43(3-4), November 1997, pp. 437-461.
- [23] Kadiyali, V., Vilcassim, N., and Chintagunta, P. "Product Line Extensions and Competitive Market Interactions: An Empirical Analysis." *Journal of Econometrics* 89(1-2), March-April 1999, pp. 339-363.
- [24] Kolstad, C. and Turnovsky, M. "Cost Functions and Nonlinear prices: Estimating a Technology with Quality-Differentiated Inputs." *Review of Economics and Statistics* 80(3), August 1998, pp. 444-453.
- [25] Kolstad, J. T. and Wolak, F. A. "Using Environmental Emissions Permit Prices to Raise Electricity Prices: Evidence from the California Electricity Market." mimeo, Stanford University, 2003.
- [26] Lau, L.J. "On Identifying the Degree of Competitiveness from Industry Price and Output Data." *Economic Letters* 10(1/2), 1982, pp. 93-99.
- [27] Lindh, T. "The Inconsistency of Consistent Conjectures: Coming Back to Cournot." *Journal of Economic Behavior and Organization* 18(1), June 1992, pp. 69-90.
- [28] McFadden, D. "Chapter 3. Generalized Method of Moments," UC Berkeley Lecture Notes, available at: http://emlab.berkeley.edu/users/mcfadden/e240b_f01/ch3.pdf.
- [29] Nebesky, W., McMullen, B. S., and Lee, M. "Testing for Market Power in the U.S. Motor Carrier Industry." *Review of Industrial Organization* 10(5), October 1995, pp. 559-576.
- [30] Natural Gas Intelligence, "NGI's Daily Gas Historical Data. 1998-2000."
- [31] Parker, P. and Röller, L. "Collusive Conduct in Duopolies: Multimarket Contact and Cross-Ownership in the Mobile Telephone Industry." *Rand Journal of Economics* 28(2), Summer 1997, pp. 304-322.
- [32] Porter, R. H. "A Study of Cartel Stability: The Joint Executive Committee, 1880-1886." *BELL Journal of Economics* 14(2) Autumn 1983, pp. 301-314

- [33] Puller, S. "Pricing and Firm Conduct in California Deregulated Electricity Market." POWER Working Paper PWR-080, University of California, 2001.
- [34] Raper, K. C., Love, A. H., and Shumway, R. C.. "Determining Market Power Exertion between Buyers and Sellers." *Journal of Applied Econometrics* 15(3), May-June 2000, pp. 225-252.
- [35] Reiss, P. and Wolak, F. "Structural Econometric Modeling: Rationales and Examples From Industrial Organization." mimeo, Stanford University.
- [36] Roberts, M. J. "Testing Oligopolistic Behavior: An Application of the Variable Profit Function." *International Journal of Industrial Organization* 2(4), December 1984, pp. 367-383.
- [37] Röller, L. "Proper Quadratic Cost Function with an Application to the Bell System." *Review of Economics and Statistics* 72(2), May 1990, pp. 202-210.
- [38] Rotemberg, J. J. and Saloner, G. "A Supergame-Theoretic Model of Price Wars during Booms." *American Economic Review* 76(3), June 1986, pp. 390-407.
- [39] Rubinovitz, R. "Market Power and Price Increases for Basic Cable Service Since Deregulation." *RAND Journal of Economics* 24(1), Spring 1993, pp. 1-18.
- [40] Spiller, P. T., and Favaro, E. "The Effects of Entry Regulation on Oligopolistic Interaction: The Uruguayan Banking Sector." *Rand Journal of Economics* 15(2). Summer 1984, pp. 244-54.
- [41] Wolak, F. "Identification and Estimation of Cost functions Using Observed Bid Data: an Application to Electricity Markets." Working Paper 8191, National Bureau of Economic Research (2000).
- [42] Wolfram, C. D. "Measuring Duopoly Power in the British Electricity Spot Market." *American Economic Review* 89(4), September 1999, pp. 805-826.

A Tables

Table 1: In-state Capacity during July 1999

Firm	Fossil	Hydro	Nuclear	Renewable
AES	4,071	0	0	0
Duke	2,950	0	0	0
Dynegy	2,856	0	0	0
PG&E	580	3,878	2,160	793
Reliant	3,531	0	0	0
SCE	0	1,164	1,720	0
Mirant	3,424	0	0	0
Other	6,617	5,620	430	4,888

Source: California Energy Commission

Table 2: Summary Statistics of Non-Strategic Supply Variables

	Mean	Std Dev	Min	Max	$Corr(X, Q_{ns})$
<i>Price</i>	45.580	58.328	0.0001	749.996	0.204
<i>NaturalGas^N</i>	2.998	1.093	1.810	6.840	-0.182
<i>NaturalGas^S</i>	2.893	1.177	1.650	7.260	-0.176
<i>Temperature</i>	60.233	13.581	21.056	86.667	0.182
<i>Temperature</i> \times <i>Sum</i>	75.018	5.076	58.722	86.667	0.114

Table 3: First Stage Regressions

	<i>Price</i>	$P \times WDay \times Pk$	$P \times Wday \times OPk$	$P \times Wend$
Full Sample				
<i>Constant</i>	-104.899 (10.692)	-341.787 (55.836)	-69.569 (10.249)	-73.353 (12.398)
<i>Forecast</i>	0.006 (0.000)			
<i>Forecast</i> \times <i>WDay</i> \times <i>Pk</i>		0.013 (0.002)		
<i>Forecast</i> \times <i>WDay</i> \times <i>OPk</i>			0.004 (0.000)	
<i>Forecast</i> \times <i>Wend</i>				0.005 (0.001)
-N-	21104	4340	10474	6290
Adj R ²	0.274	0.398	0.215	0.285
1999 Sample				
<i>Constant</i>		-79.308 (15.796)	-12.785 (1.755)	-21.669 (3.052)
<i>Forecast</i> \times <i>WDay</i> \times <i>Pk</i>		0.004 (0.001)		
<i>Forecast</i> \times <i>WDay</i> \times <i>OPk</i>			0.002 (0.000)	
<i>Forecast</i> \times <i>WEnd</i>				0.002 (0.000)
-N-		1792	4344	2612
Adj R ²		0.430	0.356	0.368
2000 Sample				
<i>Constant</i>		-673.504 (76.773)	-136.659 (19.183)	-140.453 (20.642)
<i>Forecast</i> \times <i>WDay</i> \times <i>Pk</i>		0.024 (0.003)		
<i>Forecast</i> \times <i>WDay</i> \times <i>OPk</i>			0.008 (0.001)	
<i>Forecast</i> \times <i>WeekEnd</i>				0.008 (0.001)
-N-		1498	3638	2183
Adj R ²		0.655	0.339	0.444
<i>Notes:</i> All estimates are significant in 1% level.				

Table 4: Estimates of the Non-Strategic Supply Relationship

	Linear	Log-log	Linear-log
$P \times Wday \times Pk$	66.543*** (7.813)	0.159*** (0.011)	3976.5*** (266.0)
$P \times Wday \times OffPk$	104.522*** (13.602)	0.195*** (0.017)	4471.5*** (385.1)
$P \times Wend$	147.298*** (15.382)	0.216*** (0.016)	4923.9*** (370.8)
$P \times Wday \times Pk \times Yr99$	13.656 (8.735)	-0.008 (0.012)	-41.824 (270.2)
$P \times Wday \times OffPk \times Yr99$	14.876 (11.034)	-0.011 (0.013)	-111.133 (289.5)
$P \times Wend \times Yr99$	7.138 (13.355)	0.010 (0.012)	-102.861 (287.4)
$P \times Wday \times Pk \times Yr00$	-51.101*** (7.675)	-0.014 (0.012)	-426.561* (257.8)
$P \times Wday \times OffPk \times Yr00$	-81.156*** (12.237)	-0.026** (0.012)	-632.1** (279.3)
$P \times Wend \times Yr00$	-108.425*** (13.754)	-0.030** (0.012)	-724.899*** (282.2)
P_N^{NG}	-901.744** (471.4)	-0.178** (0.090)	-4393.13** (2080.5)
P_S^{NG}	-775.013* (429.3)	-0.195** (0.085)	-4142.07** (1948.7)
<i>Temperature</i>	39.155*** (10.770)	0.044** (0.022)	970.954* (523.7)
<i>Temperature</i> \times <i>Sum</i>	-75.232*** (23.000)	-0.295*** (0.085)	-6646.07*** (1963.1)

Day, year \times month, hour \times weekday and hour \times weekend monthly indicator variables not reported.

Table 5: Estimates of Residual Demand Elasticities

	Linear			Log-Log			Linear-Log		
	Mean	Median	Std Dev	Mean	Median	Std Dev	Mean	Median	Std Dev
Entire Sample	0.695	0.581	0.486	1.250	1.004	0.870	1.344	1.011	1.037
1998	0.739	0.663	0.376	1.279	1.133	0.693	1.364	1.155	0.856
1999	0.996	0.895	0.494	1.493	1.246	0.921	1.622	1.254	1.123
2000	0.304	0.270	0.178	0.938	0.633	0.817	0.998	0.655	0.935
Weekday Peak	0.388	0.395	0.216	0.713	0.621	0.412	0.713	0.614	0.414
Weekday Offpeak	0.648	0.612	0.407	1.263	1.058	0.798	1.347	1.044	0.956
Weekend	0.983	0.917	0.578	1.599	1.368	1.019	1.775	1.466	1.226

Table 6: Direct Measures of Lerner and Elasticity-Adjusted Lerner Indexes

	Linear Model		Log-log Model	Linear-Log Model	
	LI	Adj LI	Adj LI	Adj LI	N
Entire Sample	0.128 (0.191)	0.070 (0.139)	0.073 (0.096)	0.071 (0.090)	21104
1998	0.099 (0.164)	0.066 (0.147)	0.068 (0.101)	0.063 (0.091)	5037
1999	0.088 (0.139)	0.072 (0.140)	0.066 (0.094)	0.064 (0.089)	8748
2000	0.196 (0.237)	0.072 (0.131)	0.085 (0.094)	0.085 (0.090)	7319
Weekday Peak	0.228 (0.243)	0.097 (0.148)	0.103 (0.094)	0.099 (0.085)	4340
Weekday Offpeak	0.108 (0.168)	0.058 (0.122)	0.066 (0.092)	0.064 (0.086)	10474
Weekend	0.093 (0.162)	0.074 (0.154)	0.064 (0.099)	0.064 (0.097)	6290

Numbers in parentheses represent standard deviations.

Table 7: Strategic Pricing Relationship Estimates

	Linear Model	Log-log Model	Linear-log model	Direct MC
<i>Constant</i>	26.798*** (6.449)	6.531** (2.783)	-1.480 (3.253)	-7.020*** (0.759)
\bar{P}^{NatGas}	6.501*** (1.798)	5.599** (2.550)	8.023*** (0.797)	8.792*** (0.273)
P^{NO_x}	-2.942*** (0.966)	0.405 (0.502)	-0.134 (0.438)	0.265*** (0.105)
$P^{NO_x} \times Crisis$	2.618*** (0.794)	-0.571 (0.421)	0.160 (0.369)	-0.048 (0.093)
<i>Quantity</i>	-0.015*** (0.002)	-0.002 (0.004)	-0.001 (0.001)	0.002*** (0.000)
$Quantity^2$	1.556×10^{-6} *** (2.048×10^{-7})	3.724×10^{-7} (4.461×10^{-7})	2.932×10^{-7} * (1.635×10^{-7})	1.035×10^{-8} (1.526×10^{-8})
θ	0.123*** (0.017)	0.229*** (0.053)	0.188*** (0.022)	

Notes: * denotes significant at the .1 level, ** at the .05 level, and *** at the .01 level
Quantity and $Quantity^2$ are instrumented for using Forecasted Demand and Forecasted Demand².

Standard Errors account for the first stage estimation of non-strategic supply.

Table 8: Supplemental Information and Estimates of Market Power
Linear Model. For variables marked as known, their estimate from the Direct MC
equation are used and treated as fixed.

	Direct MC	NEIO 1	NEIO 2	NEIO 3	NEIO 4
<i>Constant</i>	-7.020*** (0.759)	26.798*** (6.449)	20.923*** (4.604)	34.359*** (6.930)	-4.378 (5.287)
\bar{P}^{NatGas}	8.792*** (0.273)	6.501*** (1.798)	known	2.888** (1.264)	4.748** (2.184)
P^{NO_x}	0.265*** (0.105)	-2.942*** (0.966)	-3.187*** (0.877)	known	-6.184*** (0.972)
P^{NO_x} $\times Crisis$	-0.048 (0.093)	2.618*** (0.794)	2.678*** (0.779)	known	5.431*** (0.786)
<i>Quantity</i>	0.002*** (0.000)	-0.015*** (0.002)	-0.015*** (0.002)	-0.015*** (0.002)	known
$Quantity^2$	-1.035×10^{-8} (1.526×10^{-8})	1.556×10^{-6} *** (2.048×10^{-7})	1.567×10^{-6} *** (2.069×10^{-7})	1.614×10^{-6} *** (2.105×10^{-7})	known
θ	0.070 (0.139)†	0.123*** (0.017)	0.116*** (0.018)	0.120*** (0.017)	0.225*** (0.025)

* denotes significant at the .1 level, ** at the .05 level, and *** at the .01 level

† This represents the standard deviation.

Table 9: Supplemental Information and Estimates of Market Power
Log-log Model. For variables marked as known, their estimate from the Direct MC
equation are used and treated as fixed.

	Direct MC	NEIO 1	NEIO 2	NEIO 3	NEIO 4
<i>Constant</i>	-7.020*** (0.759)	6.531** (2.783)	2.027 (3.616)	13.816*** (3.918)	-3.148 (4.174)
\bar{P}^{NatGas}	8.792*** (0.273)	5.599** (2.550)	known	3.231* (1.974)	5.555*** (1.524)
P^{NO_x}	0.265*** (0.105)	0.405 (0.502)	-0.077 (0.512)	known	0.238 (0.532)
P^{NO_x} $\times Crisis$	-0.048 (0.093)	-0.571 (0.421)	-0.276 (0.439)	known	-0.458 (0.400)
<i>Quantity</i>	0.002*** (0.000)	-0.002 (0.004)	-0.004** (0.002)	-0.003 (0.005)	known
$Quantity^2$	1.035×10^{-8} (1.526×10^{-8})	3.724×10^{-7} (4.461×10^{-7})	6.195×10^{-7} *** (2.270×10^{-7})	4.415×10^{-7} (5.383×10^{-7})	known
θ	0.073 (0.096)†	0.229*** (0.053)	0.192*** (0.036)	0.220*** (0.060)	0.240*** (0.017)

* denotes significant at the .1 level, ** at the .05 level, and *** at the .01 level

† This represents the standard deviation.

Table 10: Supplemental Information and Estimates of Market Power Linear-Log Model. For variables marked as known, their estimate from the Direct MC equation are used and treated as fixed.

	Direct MC	NEIO 1	NEIO 2	NEIO 3	NEIO 4
<i>Constant</i>	-7.020*** (0.759)	-1.480 (3.253)	-2.976 (2.641)	1.983 (2.067)	-8.523*** (2.102)
\bar{P}^{NatGas}	8.792*** (0.273)	8.023*** (0.797)	known	6.733*** (0.731)	8.072*** (0.807)
P^{NO_x}	0.265*** (0.105)	-0.134 (0.438)	-0.268 (0.403)	known	-0.305 (0.374)
$P^{NO_x} \times Crisis$	-0.048 (0.093)	0.160 (0.369)	0.224 (0.364)	known	0.298 (0.331)
<i>Quantity</i>	0.002*** (0.000)	-0.001 (0.001)	-0.002 (0.001)	-0.001 (0.001)	known
$Quantity^2$	1.035×10^{-8} (1.526×10^{-8})	$2.932 \times 10^{-7*}$ (1.635×10^{-7})	$3.223 \times 10^{-7*}$ (1.763×10^{-7})	$3.218 \times 10^{-7**}$ (1.577×10^{-7})	known
θ	0.071 (0.090) [†]	0.188*** (0.022)	0.184*** (0.024)	0.186*** (0.023)	0.198*** (0.006)

* denotes significant at the .1 level, ** at the .05 level, and *** at the .01 level

† This represents the standard deviation.

Table 11: Strategic Pricing Relationship Estimates—Yearly Variation in θ

	Linear Model	Log-log Model	Linear-log Model
<i>Constant</i>	28.089*** (7.369)	15.214*** (4.122)	17.676*** (5.508)
\bar{P}^{NatGas}	3.677** (1.873)	4.460*** (1.062)	4.962*** (1.106)
P^{NO_x}	-3.173*** (1.017)	0.828* (0.509)	-0.005 (0.467)
$P^{NO_x} \times Crisis$	3.396*** (0.819)	-1.045*** (0.419)	0.039 (0.388)
<i>Quantity</i>	-0.009*** (0.002)	-0.005** (0.002)	-0.006*** (0.002)
$Quantity^2$	$1.275 \times 10^{-6***}$ (1.923×10^{-7})	$7.604 \times 10^{-7***}$ (3.006×10^{-7})	$9.917 \times 10^{-7***}$ (2.304×10^{-7})
$\theta \times Yr98$	-0.027 (0.049)	0.069 (0.081)	-0.043 (0.056)
$\theta \times Yr99$	0.014 (0.054)	0.111* (0.066)	0.015 (0.049)
$\theta \times Yr00$	0.066*** (0.017)	0.197*** (0.037)	0.135*** (0.025)

* denotes significant at the .1 level, ** at the .05 level, and *** at the .01 level

Table 12: Strategic Pricing Relationship Estimates—Intra-day Variation in θ

	Linear Model	Log-log Model	Linear-log Model
<i>Constant</i>	38.277*** (6.869)	13.245*** (3.454)	1.053 (1.823)
\overline{P}^{NatGas}	2.077 (2.078)	3.661 (3.256)	4.599*** (0.566)
P^{NO_x}	-2.987*** (0.961)	0.935 (0.618)	0.328 (0.302)
$P^{NO_x} \times Crisis$	2.698*** (0.793)	-1.067** (0.522)	-0.201 (0.260)
<i>Quantity</i>	-0.015*** (0.002)	-0.004 (0.004)	0.002*** (0.001)
<i>Quantity</i> ²	1.599×10^{-6} *** (2.014×10^{-7})	4.711×10^{-7} (4.302×10^{-7})	-1.570×10^{-7} (1.116×10^{-7})
$\theta \times Wday \times Pk$	0.139*** (0.018)	0.219*** (0.053)	0.241*** (0.015)
$\theta \times Wday \times OffPk$	0.159*** (0.020)	0.252*** (0.069)	0.260*** (0.018)
$\theta \times Wend$	0.263*** (0.034)	0.278*** (0.070)	0.298*** (0.017)

* denotes significant at the .1 level, ** at the .05 level, and *** at the .01 level

A.1 Robustness Checks

A.1.1 Weekday Peak Hours

Table 13: Weekday Peak Sample (from May to October)

	Linear Model		Log-log Model		Linear-Log Model		N
	Direct	Estimated	Direct	Esitimated	Direct	Estimated	
Entire Sample	0.134 (0.165)	0.161** (0.074)	0.131 (0.093)	0.129 (0.149)	0.123 (0.078)	0.238*** (0.018)	2583
1998	0.122 (0.165)	-0.196 (0.333)	0.123 (0.105)	-0.141 (0.356)	0.111 (0.087)	0.234 (0.548)	770
1999	0.134 (0.154)	-0.125 (0.425)	0.121 (0.084)	-0.072 (0.275)	0.116 (0.075)	0.233 (0.452)	903
2000	0.146 (0.176)	0.122 (0.160)	0.147 (0.087)	0.116 (0.145)	0.140 (0.070)	0.235 (0.167)	910

Numbers in parentheses for Direct measures represent standard deviations and for Estimated represent standard errors.

A.1.2 Selecting on Forecasted Demand

Table 14: Selecting on Forecasted Demand

	Linear Model		Log-log Model		Linear-Log Model		N
	Direct	Estimated	Direct	Esitimated	Direct	Estimated	
Entire Sample	0.110 (0.167)	0.085*** (0.025)	0.112 (0.101)	0.217*** (0.027)	0.105 (0.090)	0.149*** (0.044)	10607
1998	0.111 (0.178)	-0.082 (0.061)	0.113 (0.107)	0.123 (0.084)	0.103 (0.092)	-0.042 (0.123)	2442
1999	0.117 (0.168)	-0.001 (0.073)	0.107 (0.101)	0.166*** (0.057)	0.102 (0.094)	0.034 (0.087)	4079
2000	0.102 (0.158)	0.039* (0.023)	0.115 (0.096)	0.207*** (0.043)	0.109 (0.085)	0.141*** (0.049)	4086
Weekday Peak	0.102 (0.151)	0.104*** (0.029)	0.107 (0.094)	0.214*** (0.052)	0.103 (0.084)	0.228*** (0.037)	4101
Weekday Offpeak	0.094 (0.152)	0.119*** (0.037)	0.105 (0.098)	0.251*** (0.065)	0.097 (0.086)	0.247*** (0.042)	4873
Weekend	0.178 (0.222)	0.209*** (0.065)	0.143 (0.118)	0.282*** (0.062)	0.136 (0.106)	0.284*** (0.037)	1633

Numbers in parentheses for Direct measures represent standard deviations and for Estimated represent standard errors.

* denotes significant at the .1 level, ** at the .05 level, and *** at the .01 level

A.1.3 1998 and 1999 Only

Table 15: Direct and Estimated Measures of Adjusted Lerner Indexes—1998 and 1999 only

	Linear Model		Log-log Model		Linear-Log Model		N
	Direct	Estimated	Direct	Estimated	Direct	Estimated	
Entire Sample	0.070 (0.143)	0.132*** (0.034)	0.067 (0.096)	0.254*** (0.024)	0.064 (0.090)	0.146*** (0.030)	13785
1998	0.066 (0.147)	0.134*** (0.040)	0.068 (0.101)	0.222*** (0.026)	0.063 (0.091)	0.144*** (0.032)	5037
1999	0.072 (0.140)	0.148*** (0.043)	0.066 (0.094)	0.228*** (0.023)	0.064 (0.089)	0.154*** (0.030)	8748
Weekday Peak	0.100 (0.145)	0.171*** (0.059)	0.101 (0.095)	0.274*** (0.029)	0.097 (0.087)	0.287*** (0.023)	2842
Weekday Offpeak	0.058 (0.129)	0.181** (0.080)	0.059 (0.091)	0.316*** (0.040)	0.055 (0.085)	0.303*** (0.030)	6836
Weekend	0.069 (0.159)	0.249*** (0.102)	0.056 (0.100)	0.370*** (0.042)	0.055 (0.095)	0.366*** (0.035)	4107

Numbers in parentheses for Actual measures represent standard deviations and for Estimated represent standard errors.

* denotes significant at the .1 level, ** at the .05 level, and *** at the .01 level

A.1.4 Endogenous MC Spline

Table 16: Strategic Pricing Relationship Estimates (Spline Function)

	Model 1	Model 2	Model 3
<i>Constant</i>	-7.301 (4.553)	-0.322 (4.441)	3.608 (5.385)
\bar{P}^{NatGas}	7.912*** (1.864)	5.874*** (1.820)	3.146 (2.237)
P^{NO_x}	-3.932*** (0.979)	-4.038*** (1.099)	-4.183*** (0.977)
$P^{NO_x} \times Crisis$	3.547*** (0.791)	4.247*** (0.896)	3.801*** (0.787)
<i>Spline1</i>	0.001*** (0.000)	0.003*** (0.001)	0.001** (0.000)
<i>Spline2</i>	0.025*** (0.003)	0.023*** (0.002)	0.024*** (0.002)
θ	0.139*** (0.021)		
$\theta \times Yr98$		-0.011 (0.045)	
$\theta \times Yr99$		0.054 (0.050)	
$\theta \times Yr00$		0.075*** (0.018)	
$\theta \times Wday \times Pk$			0.163*** (0.023)
$\theta \times Wday \times OffPk$			0.181*** (0.026)
$\theta \times Wend$			0.302*** (0.043)

* denotes significant at the .1 level, ** at the .05 level,
and *** at the .01 level

B Figures

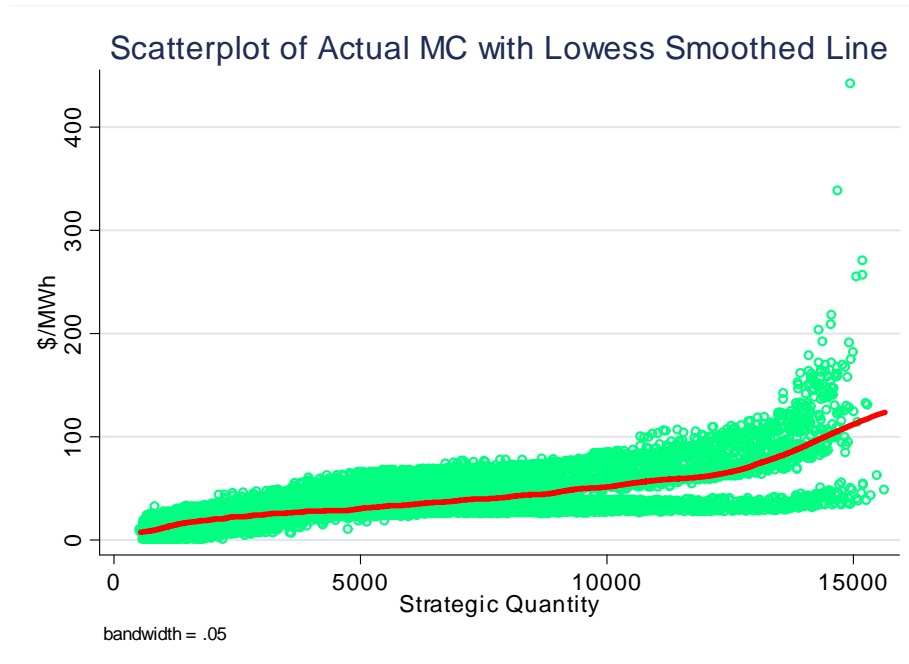


Figure 1: Scatterplot of Actual MC versus Strategic Quantity

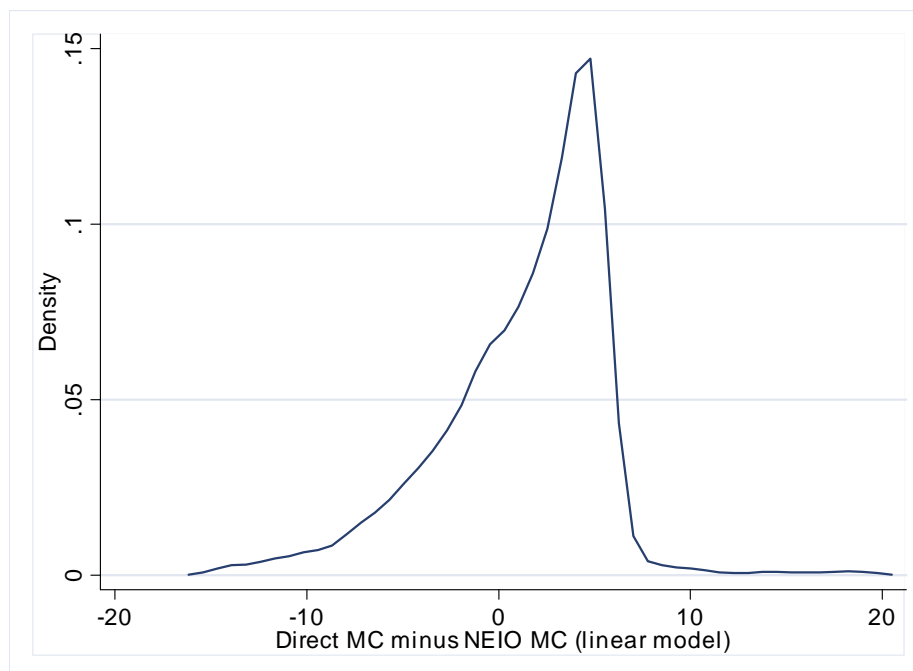


Figure 2: Kernel Density Estimate of Actual MC minus NEIO MC

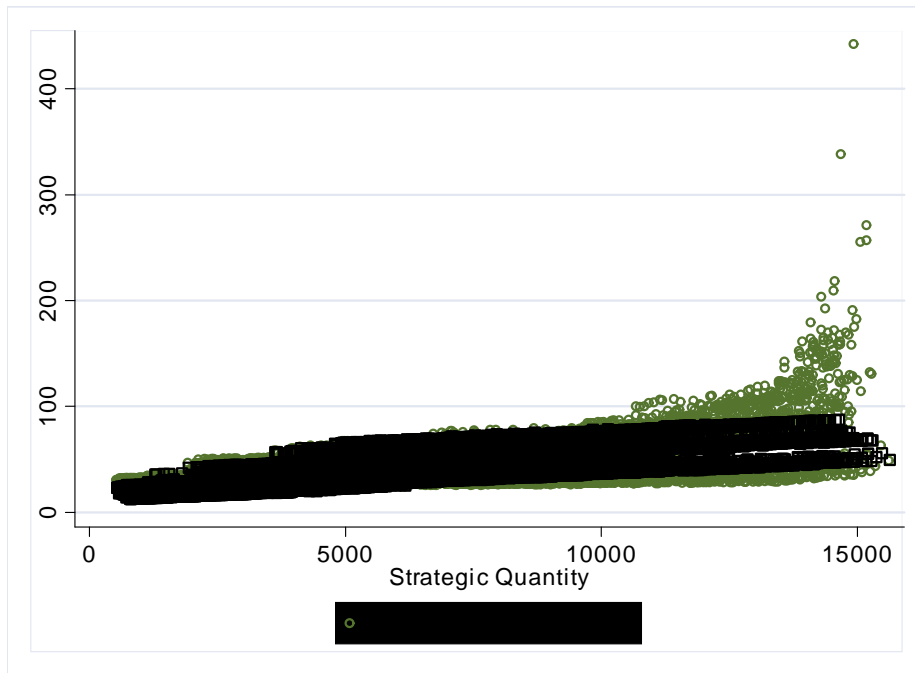


Figure 3: Scatterplot of Actual MC and NEIO MC Estimates versus Strategic Quantity

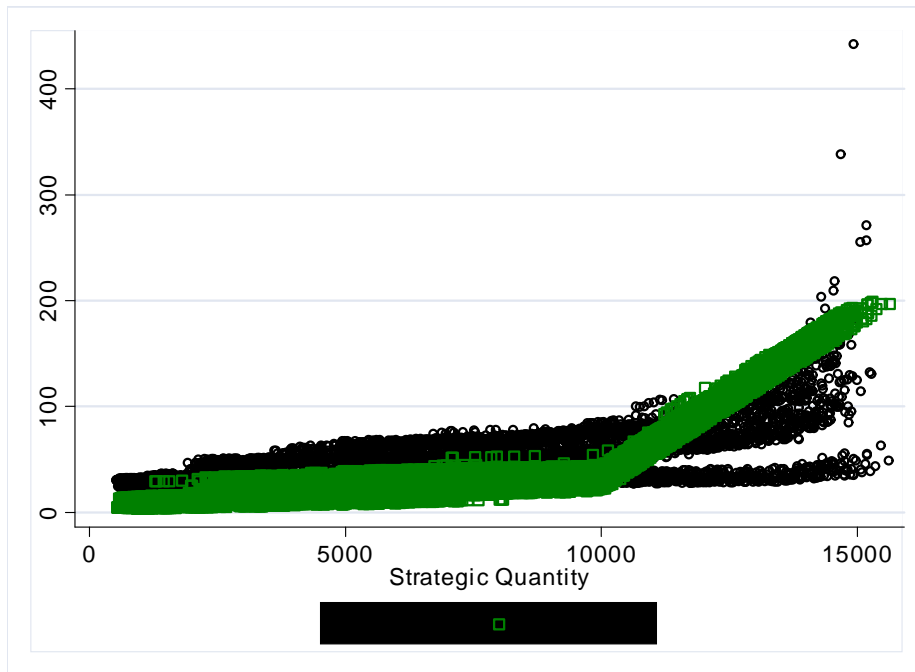


Figure 4: Scatterplot of Actual MC and Endogenous Spline NEIO MC Estimates