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ABSTRACT
This paper contains a dynamic conduct parameter model to look at the pricing behavior of five power marketers in the California Power Exchange (CalPX) on daily data for 2000. Only our previous paper Hodge and Dahl (2012) specifically focused on just the electric power marketers. In this paper we compare a dynamic conduct parameter with that of our earlier static model to test whether the static estimates are biased downwards or towards not rejecting the null hypothesis of no market power. We estimate the model using generalized methods of moments on data for each marketer. We find more evidence of collusive behavior with the dynamic than the earlier static model estimates.

JEL **codes: L10, L94, Q40, Q41**

Keywords: Electricity, Conduct Parameter, Dynamic, Marketer.

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Introduction

Electricity market restructuring, which began with Chile in 1982, has spawned liberalization of electricity markets in dozens of countries. However, with suspected price manipulation in some of these reformed markets, numerous industrial organization studies have been conducted to investigate whether evidence suggests the pricing changes arose from market power abuse.

In the U.S., numerous studies have focused on the California Power Exchange (Cal PX) because of its extraordinary failure in 2001 along with copious amounts of available trading data. Previous investigations of this failure have found statistical evidence of price manipulation for merchant generating firms. See for example, Joskow & Kahn (2002), Wolak (2003), and Puller (2007). However, only our earlier paper -- Hodge and Dahl (2012)--has focused specifically on the behavior of power marketers that buy electricity and sell it directly into the wholesale market or to industrial consumers. In our earlier paper, we looked at the pricing behavior of five largest power marketers in the Cal PX. Using a static conduct parameter model, we only found statistical evidence that the largest two marketers --Duke (38% of nonutility sales) and Reliant (15% of nonutility sales)--were exercising market power, while we found no statistical evidence that the smaller marketers -- Enron (8.5 % of nonutility sales), Dynergy (8 % of nonutility sales), and Williams (5 % of nonutility sales)—were exercising market power. We were somewhat surprised by this result, since the Federal Energy Regulatory Commission (FERC) concluded that the flawed and complex market design allowed price manipulation by Enron and other companies, Enron was actually convicted of market manipulation, while all the trading companies studied here agreed to pay refunds in California without admitting guilt. (FERC (2005)).

Corts (1999) demonstrated that static models can produce biased results if the firms use dynamic pricing strategies and Kim and Knittel (2006) found the static conjectural variation model did not measure market power well in the California context. Therefore, we extend our earlier paper to determine whether the traditional static model for detecting market power can be improved by incorporating dynamic behavior. To provide a comparison, we again focus on the behavior of the same five largest power marketers in the Cal PX. In Section 2, we describe the econometric model of dynamic pricing; in section 3, we describe the generalized method of moments two-stage estimation technique; Section 4 contains the results of the model estimation with a summary of findings and implications for further research in Section 5.

2. DYNAMIC MODEL

We analyze pricing conduct in the California Power Exchange during 2000 using a dynamic version of the model based on the traditional conjectural variations approach. We begin with the static model based on Bresnahan (1989) developed in Hodge and Dahl (2012):

$$
\begin{aligned}
\text{(Demand)}\quad & P_t = \alpha_0 + \alpha_1 D_t^H + \alpha_2 D_t^C + \alpha_3 W_t + \alpha_4 Y_t \\
& \qquad + \alpha_5 R_t + \alpha_6 H_t + \gamma_0 Q_t^D + \gamma_1 Q_t^D D_t^C + \varepsilon_t^D \\
\text{(Supply)}\quad & P_t = \beta_0 + \left(\beta_1 - \theta\gamma_0\right) q_{it} - \theta\gamma_1 D_t^C q_{it} + \beta_2 C_{it} + \beta_3 T_t + \beta_4 G_t + \varepsilon_{it}^S \\
\text{(Equilibrium)}\quad & Q_t^D \equiv q_{it} + \sum_{j\neq i} q_{jt}
\end{aligned}
$$

Variables in the model are on daily data unless otherwise indicated. Variable definitions along with expected sign of coefficient for right hand side variables in parenthesis are:

Endogenous variables

P_t = California PX price

C_{it} (+) = firm i's wholesale purchase cost of electricity

Q_t^D (-) = Cal PX market demand

$Q_t^D D_t^C$ (+) = interaction terms between the market demand and cooling-degrees

q_{it} (-) = quantity supplied by firm i.

$D_t^C q_{it}$ (-) = interaction terms between firm quantity variable and cooling-degrees

$\sum_{j\neq i} q_{jt}$ = the quantity sold by all firms but firm i

Exogenous variables used as instruments

D_t^C (+)= cooling degrees measured as mean temperature – 65°, if mean is above 65°, otherwise $D_t^C = 0$.

D_t^H (+)= heating degrees measured as 65° minus mean temperature, if mean is below 65°, otherwise $D_t^H = 0$

ε_t^D = random errors in the demand equation

ε_t^S = random errors in the supply equation

G_t (+)= monthly heat rate of affiliated generator as a proxy for self generation cost

H_t (-)= Shasta Dam hydropower releases as a proxy for shifting municipal power purchases on the Cal PX

R_t (+) = weekly refinery production of gasoline as a proxy for industrial activity

T_t (+) = daily hours of transmission constraint as proxied by the number of hours the price in California's northern (NP-15) and southern (SP-15) control zones were not equal

W_t (-) = weekend dummy variable to proxy lower weekend industrial and commercial consumption

Y_t (+) = California monthly employment as a proxy for California income

In addition we use two other instrumental variables for the wholesale purchase cost variable. They are (1) the daily marginal fuel cost from Arizona as measured by the maximum hourly system lambda (the most expensive unit dispatched in a transmission control area during any given hour) in the Arizona Public Service Control Area (FERC 2003a) and (2) hydropower releases from Bonneville Dam in Oregon.

The conduct parameter to test whether firms are exercising market power is θ = $\sum_{j=1}^{n} \frac{\partial q_j}{\partial q_i}$, θ = 0 if the firm is competitive, θ = 1 if n equal sized firms are Cournot pricing, and θ = n, if the firms are colluding and behaving as a monopolist. Hodge (2006) also shows that $\theta = -\left(\frac{P - MC}{P}\right)\left(\frac{\gamma}{s}\right)$ or that θ is related to the degree of price (P) markup over marginal cost (MC) where γ is the market demand elasticity and s is the individual firm's market share. Thus, any value for θ greater than 0 measures some degree of market power.

Corts (1999) argues that the above static models underestimates θ, if the firms behave dynamically. Our study addresses Corts' criticism of the standard static models applied to electricity markets such as above. The model that we develop adds a dynamic aspect of supply behavior, which allows us to estimate a more accurate conduct parameter.

In our dynamic extension of Hodge and Dahl (2012), we hypothesize that the level of market power in the California PX, as measured by θ, varies with the level of expected market demand if firms are colluding. This approach is similar to the empirical model outlined in Borenstein and Shephard (1996), which attempts to explain the level of market power in retail gasoline, as measured by a price-cost margin, based on shocks to expected demand and cost. An important distinction between our approach and their approach is that they measure market power directly with a price-cost margin, whereas we measure market power through an estimated conduct parameter (which can be interpreted as an elasticity-weighted price-cost margin, as discussed above). We use the conduct parameter, θ, instead of directly calculating a price-cost margin because we only have data on average not marginal costs (the relevant cost when measuring market power).

As Borenstein and Shephard (1996) discuss, this approach is derived from the theoretical model developed by Rotemberg and Saloner (1986) in which they reason that colluding firms (behaving as a monopolist whether organized as a cartel or tacitly colluding) require an incentive to encourage compliance with the pricing arrangement. Specifically, the group of firms chooses the price which will maximize total profits while also making sure that any individual firm considering deviation from the pricing arrangement realizes that the present value of current and future profits from "cooperating" exceeds the sum of the current period profit the firm may obtain from deviating and the present value of all future profit realized after the arrangement falls apart. Under such an arrangement, Rotemberg and Saloner illustrate that maintaining high prices under a collusive regime is easier when demand is expected to increase. This result occurs because firms realize higher future demand corresponds with higher future collusive profits. Conversely, the current gain from deviating is higher and the future loss is relatively smaller when demand is expected to decline. Colluding firms should be able to more easily maintain excessively higher prices when demand is growing. Thus, changes in the level of market power should be positively related to changes in expected demand.

As in Borenstein and Shephard's (1996) analysis, we model this argument by assuming that market power, measured in our case by the conduct parameter, varies depending on the level of expected demand in the next period, $E\left(Q_{t+1}^{D}\right)$, while also controlling for the current level of demand, Q_t^D:

$$\theta = \theta_0 + \theta_1 E\left(Q_{t+1}^{D}\right) + \theta_2 Q_t^D \tag{2}$$

We substitute the conduct parameter specification into the static model (1) to get the following system of equations:

$$\begin{aligned}
\text{(Demand)} \quad P_t &= \alpha_0 + \alpha_1 D_t^H + \alpha_2 D_t^C + \alpha_3 W_t + \alpha_4 Y_t \\
&\quad + \alpha_5 R_t + \alpha_6 H_t + \gamma_0 Q_t^D + \gamma_1 Q_t^D D_t^C + \varepsilon_t^D \\
\text{(Supply)} \quad P_t &= \beta_0 + \left[\beta_1 - \left(\theta_0 + \theta_1 E\left(Q_{t+1}^{D}\right) + \theta_2 Q_t^D\right)\gamma_0\right] q_{it} \\
&\quad - \left(\theta_0 + \theta_1 E\left(Q_{t+1}^{D}\right) + \theta_2 Q_t^D\right)\gamma_1 D_t^C q_{it} \\
&\quad + \beta_2 C_{it} + \beta_3 T_t + \beta_4 G_t + \varepsilon_{it}^S \\
\text{(Equilibrium)} \quad Q_t^D &\equiv q_{it} + \sum_{j \neq i} q_{jt}
\end{aligned} \tag{3}$$

In this dynamic model, demand is still determined myopically, but supply (and the level of market power) depends on future expected market conditions.[2] The estimated coefficient θ_1 in our model is expected to take on a positive value if the firms are indeed colluding. Furthermore, Corts' (1999) criticism implies that the dynamic θ calculated from Eq. (3) should be larger than the θ estimated in the static model, if the group of firms is indeed colluding. We compare our earlier static model results to the results from this expanded model that captures firms' dynamic market demand expectations.

[2] Puller (2007) notes that a full structural model would require a much more complicated but empirically intractable model that incorporates a forward market, two sequential auctions, and a host of regulatory uncertainties.

3. Estimation Methodology

Obtaining accurate measures of the conduct parameter coefficients in the static model (θ) and the dynamic model (θ_0, θ_1, and θ_2) requires an appropriate estimation technique. The endogeneity of price and quantity in both the demand equation and the supply relation require a system's estimation technique since the error term for each individual equation is correlated with a regressor variable. Furthermore, the supply relation coefficients θ_i and β_1 require estimates of the parameters, γ_0 and γ_1, from the demand equation in order to be identified. Coefficients that appear in both equations must be restricted to take on identical values during estimation so that the conduct parameter can be separately estimated.

The conduct parameter coefficients appear multiplicatively in the supply relation of both models, excluding the possibility of using a linear estimator, and OLS would produce biased coefficient estimates due to the existence of endogenous variables on the right-hand side of the equations. Instead we must directly minimize a least-squares objective function. One popular method of constructing the objective function is the generalized method of moments (GMM). This technique for calculating estimated parameters when confronted with a nonlinear model is popular because the estimators are asymptotically consistent as long as the model is correctly specified. With daily data over twelve months, the relatively large sample size should ensure fairly accurate estimates.

For both the static model (1) estimated earlier by Hodge and Dahl (2012) and the dynamic model (3), we can represent the supply equation and the demand equation as a system of two equations (i = 1, 2) in the following compact form:

$$\mathbf{y}_i = h_i(\boldsymbol{\beta}\mathbf{X}_i) + \boldsymbol{\varepsilon}_i$$

where $\mathbf{y}_i$ is the vector of left-hand side variables for each of the two equations. These variables are shown as a generalized function of the regressor variables, $\mathbf{X}_i$, in each equation and the common set of parameters, $\boldsymbol{\beta}$. Some of the variables in $\mathbf{X}_i$ are endogenous, so we will primarily be working with the related matrix of instruments, $\mathbf{Z}$. As Greene (1997) describes, the GMM method is derived from the following standard econometric assumption that regressor variables are uncorrelated with the error term:

$$E(\mathbf{z}_t \varepsilon_{it}) = \mathbf{0}$$

where $\mathbf{z}_t$ is the vector of instrument values for observation t and ε_{it} is the associated observation-specific residual. The corresponding sample moment condition for equation i is:

$$\frac{1}{T}\sum_{t=1}^{T}\mathbf{z}_t\left[y_{it} - h_i(\boldsymbol{\beta}, \mathbf{x}_t)\right] = \mathbf{0}$$

where, in place of the residual, we now have y_{it} as a nonlinear function of the parameters, $\boldsymbol{\beta}$, and the regressor variables, $\mathbf{x}_t$.

If we were estimating a single equation or each equation in the system individually, the sample moment condition would yield a single set of estimated parameters (in the case of a single linear equation, the sample moment condition results in the standard OLS system of normal equations). When estimating a system of equations with cross-equation parameter restrictions, the goal is to fulfill an assumption similar to the single equation case:

$$E\left[\left(\mathbf{Z}'\boldsymbol{\varepsilon}_i\right)'\mathbf{Z}'\boldsymbol{\varepsilon}_j\right]=0$$

where **Z** is the matrix of instrumental variables, which are common for both equations *i*, *j* = 1, 2, and the prime symbol indicates the transpose of a particular matrix. However, if the system is over-identified with more instruments than endogenous variables (as our system is), these sample moment conditions will likely yield multiple solution estimates. Instead of equating each one to zero, the GMM method attempts to minimize an objective function, Q, similar to the sample moment conditions:

$$\begin{aligned}\text{Min } Q &= \left(\mathbf{Z}'\boldsymbol{\varepsilon}_i\right)'\boldsymbol{\Sigma}_{ij}^{-1}\mathbf{Z}'\boldsymbol{\varepsilon}_j \\ &= \sum_{i=1}^{2}\sum_{j=1}^{2}\left[\boldsymbol{\varepsilon}_i(\boldsymbol{\beta})'\mathbf{Z}\right]\boldsymbol{\Sigma}_{ij}^{-1}\left[\mathbf{Z}'\boldsymbol{\varepsilon}_j(\boldsymbol{\beta})\right] \\ &= \sum_{i=1}^{2}\sum_{j=1}^{2}\left[(\mathbf{y}_i-\mathbf{h}_i(\boldsymbol{\beta},\mathbf{X}))'\mathbf{Z}\right]\boldsymbol{\Sigma}_{ij}^{-1}\left[\mathbf{Z}'(\mathbf{y}_j-\mathbf{h}_j(\boldsymbol{\beta},\mathbf{X}))\right]\end{aligned}$$

where $\boldsymbol{\Sigma}_{ij}$ is the ij^{th} partition of the error variance-covariance matrix. This matrix is calculated using the residuals obtained from an initial two-stage least squares estimation. Note that this is a general covariance matrix that allows for any heteroscedasticity and autocorrelation in the data.

An additional variable for expected demand, $E\left(Q_{t+1}^{D}\right)$, in now included in the dynamic supply relation. Electricity suppliers likely base their demand expectations on forecasted weather conditions—however, historical data on weather forecasts is not readily available. Instead, we follow the example of Borenstein and Shephard (1996) and assume that firms base their expectations of future demand on historical trends. We use an ARIMA modeling procedure to obtain predicted values for next-period's expected market demand by estimating the following AR equation for quantity demanded in the California PX:

$$Q_{t+1} = \alpha_0 + \sum_{i=0}^{L} \alpha_i Q_{t-i} + \varepsilon_t \tag{4}$$

The specific value for the total number of lags L (i.e., how many prior periods are used to form expectations) is determined empirically by selecting the number of lags that best fits the data based on the Schwartz Criterion (Enders 1995). We estimated autoregressive models (4) for the quantity demanded using lags ranging from 1 to 28. The model with the lowest Schwarz Criterion statistic was selected as the best fitting model. The formula for this statistic is given by (Enders 1995):

$$SC = T \ln \frac{\sum e_t^2}{T} + k \frac{\ln T}{T}$$

where e_t are the individual estimated residual terms, T is the number of observations, and k represents the number of parameters estimated in the particular model. The SC model selection procedure indicated that a model with L = 8 lags (just over one week of observations) was most appropriate for modeling market demand expectations. The variable for next-period expected demand was calculated as the fitted values from this model shifted back one day (i.e., $E\left(Q_t^D\right) = \hat{Q}_{t+1}$).

All of the statistical and econometric analysis for this paper was completed using SAS software. SAS first obtains GMM parameter estimates using two-stage least squares. These estimates act as starting values for the GMM estimation process, which uses the Gauss-Newton method to search for the minimum objective function value. Each iteration in this minimization process consists of changing those parameter estimates that have the largest (negative) impact on the objective function. These iterations continue until the improvement in the objective is smaller than 0.001. Given the nonlinear characteristics of our model, there is the possibility that a given solution provided by SAS may not represent the global optimum set of parameter estimates. However, we experimented with manually selecting various parameter starting values with various versions of the model and always obtained estimates very close to the estimates from SAS's default GMM process.

We perform hypothesis tests on the dynamic conduct parameter in order to describe the market structure within which the five firms are operating and to test for any pricing abuses. If the firms are acting competitively then the conduct parameters in both the static and dynamic models should not be significantly different from zero. Any level of market power should cause us to reject the null hypothesis that the firms act competitively (i.e., calculated $\theta = 0$). If so, we next test for the possibility that each firm is behaving as a Cournot firm ($\theta = 1$). In addition, as Rotemberg and Saloner (1986) argue, we should expect a positive relationship between expected demand and the conduct parameter (i.e., a positive value for θ_1 in the supply relation).

4. **Empirical Results**

We estimate the equations in model (3) above using daily data from January 1, 2000 – December 31, 2000 that was used in Hodge and Dahl (2012). Figure 1 shows the price volatility during this period.

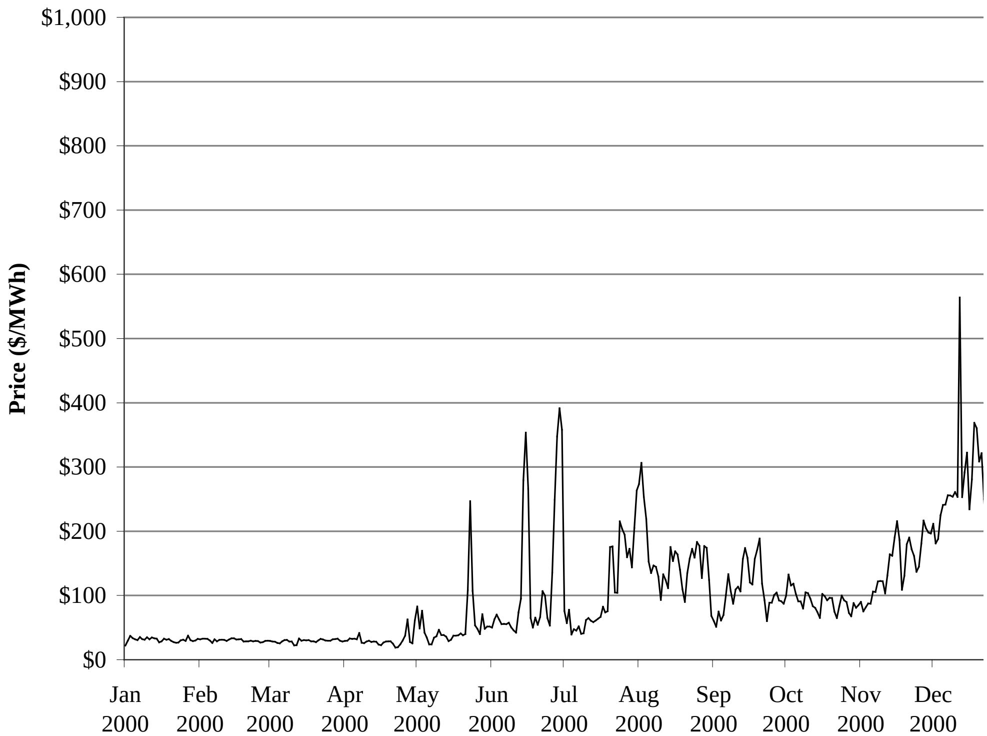

Figure 1 Daily California Power Exchange Prices
(Source: University of California Energy Institute, 2006)

Table 1 gives descriptive statistics for the model variables.

Table 1 Descriptive Statistics

	# of Obs	Mean	Standard Deviation
Quantity Supplied (Mwh/day)			
Duke	309	44,056	27,920
Dynegy	364	7,862	5,909
Enron	365	8,303	5,017
Reliant	366	15,062	7,560
Williams	344	4,742	4,203
All five firms	366	73,018	35,252
Price ($/MWh)			
Duke	309	76.55	73.14
Dynegy	360	101.58	93.57
Enron	365	88.14	75.52
Reliant	365	89.18	73.72
Williams	344	84.41	65.72
All five firms	366	80.02	65.78
Cost ($/MWh)			
Duke	308	108.72	124.90
Dynegy	337	97.08	75.40
Enron	366	102.20	106.32
Reliant	328	94.46	73.34
Williams	321	114.62	113.56
All five firms	366	101.71	92.48
Quantity Demanded (MWh/day)	366	514,334	54,271
Expected Demand (MWh/day)	359	513,685	51,735
Employment (thousands)	366	16,035	147
Refinery Production (bbls/day)	366	7,361	605.87
Shasta Dam Releases (cubic feet/sec)	365	9,638	8,466
Cooling Degrees	366	1.98	3.04
Heating Degrees	366	3.92	4.45
Hours of Transmission Constraint	366	12.31	7.03
Bonneville Dam Releases (cfs)	366	13,891	4,882
Arizona Public Service Lambda ($/Mwh)	366	36.65?	15.63

We analyze of the dynamic extension of the conduct parameter model by estimating the demand and supply equations (3) for each of the five power marketers. The results are shown in Table 2 along with the results from the earlier static model taken from Hodge and Dahl (2012). The shaded cells are the p values for the coefficient.

Table 2. Static and Dynamic Model Estimation Results

	Residual Demand	Duke		Dynegy		Enron		Reliant		Williams	
	Independent Variable = Price	Static	Dynamic	Static	Dynamic	Static	Dynamic	Static	Dynamic	Static	Dynamic
α_0	Constant	-5582.83	-5347.44	-3770.90	-4118.60	-4942.70	-5050.53	-4805.57	-5126.46	-3904.76	-4496.78
		0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
α_1	Heating Degrees	5.13	6.21	4.01	4.93	3.54	4.93	2.53	3.90	3.66	5.62
		0.00	0.00	0.00	0.00	0.00	0.00	0.03	0.00	0.00	0.00
α_2	Cooling Degrees	-130.41	-7.25	-36.34	-99.62	-151.48	-69.92	-164.55	-97.76	-153.93	-42.27
		0.06	0.76	0.61	0.01	0.00	0.02	0.03	0.03	0.07	0.40
α_3	Weekend Transaction	6.87	-17.92	-33.76	-7.20	-0.72	-9.35	-7.55	-9.30	-6.50	-11.66
		0.64	0.00	0.01	0.28	0.92	0.11	0.62	0.09	0.67	0.09
α_4	Employment	3.52E-04	3.37E-04	2.48E-04	2.53E-04	3.19E-04	3.17E-04	3.13E-04	3.24E-04	2.60E-04	2.84E-04
		0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
α_5	Refinery Production	0.01	0.01	0.01	0.01	0.01	0.01	0.02	0.01	0.01	0.01
		0.01	0.00	0.09	0.00	0.04	0.02	0.00	0.00	0.00	0.00
α_6	Hydropower Releases	-8.00E-04	-6.70E-04	-4.40E-04	-5.20E-04	-6.30E-04	-5.30E-04	-3.90E-04	-3.80E-04	-8.50E-04	-6.40E-04
		0.00	0.00	0.07	0.00	0.00	0.01	0.20	0.09	0.00	0.01
γ_0	Quantity Demanded	-1.70E-04	-2.00E-04	-4.10E-04	6.10E-05	-3.60E-04	-7.00E-05	-5.00E-04	-2.00E-04	-6.10E-04	-1.70E-04
		0.39	0.02	0.15	0.46	0.05	0.50	0.08	0.28	0.00	0.32
γ_1	Quantity Demanded X Cooling Degrees	2.27E-04	1.70E-05	9.70E-05	1.98E-04	2.82E-04	1.38E-04	3.06E-04	1.85E-04	2.85E-04	8.70E-05
		0.00	0.67	0.44	0.00	0.00	0.01	0.02	0.02	0.05	0.33

Continued on next page

Table 2. Model Estimation Results, *continued*											
	Supply Relation										
	Independent Variable = Price	Duke		Dynegy		Enron		Reliant		Williams	
	Model	Static	Dynamic	Static	Dynamic	Static	Dynamic	Static	Dynamic	Static	Dynamic
β_0	Constant	96.66	142.55	-33.27	-29.90	-8.85	4.42	-15.44	-24.23	62.45	-2.96
		0.08	0.02	0.03	0.04	0.39	0.70	0.14	0.05	0.12	0.96
β_1	Quantity Supplied	1.43E-04	-8.10E-04	5.16E-03	7.36E-04	8.16E-04	-6.50E-04	1.16E-03	1.45E-03	4.83E-04	3.60E-03
		0.64	0.65	0.17	0.55	0.35	0.61	0.00	0.00	0.75	0.32
β_2	Cost of Electricity	0.79	0.74	0.91	0.89	0.86	0.76	0.92	0.89	0.64	0.72
		0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
β_3	Hours Constrained	0.36	0.55	-0.91	-0.29	0.38	0.60	-0.56	-0.77	-0.10	-0.59
		0.30	0.09	0.03	0.54	0.25	0.08	0.05	0.01	0.81	0.34
β_4	Generation Heat Rate	-10.70	-15.66	2.76	3.80	NA	NA	0.90	1.69	-4.49	0.04
		0.03	0.00	0.03	0.00			0.42	0.19	0.12	0.99
θ_o	Conduct Parameter	0.54	15.02	-7.59	66.89	0.07	45.93	0.48	9.82	-0.29	-1.80
		0.07	0.19	0.44	0.00	0.85	0.04	0.07	0.12	0.50	0.98
θ_1	Expected Quantity Demanded	NA	-4.00E-06	NA	-3.00E-05	NA	-6.00E-05	NA	-7.05E-06	NA	1.42E-04
			0.92		0.48		0.35		0.49		0.68
θ_2	Quntitity Demanded	NA	-1.00E-05	NA	-9.00E-05	NA	-3.00E-05	NA	-9.18E-06	NA	-1.40E-04
			0.72		0.00		0.55		0.36		0.62
	Minimum Objective Function	23.1242	43.5241	50.0871	49.055	16.7403	12.6308	8.3872	12.6404	17.3223	30.7928
	Number of Observations	308	308	333	333	365	365	328	328	323	323

In many cases, both the static and dynamic models conform to our preconceived expectations. In the inverse residual demand equation, the coefficients for heating degree days, employment, and refinery production are always positive and all are significant at better than a 10% level. The coefficients for weekend transaction, hydropower releases, and quantity are almost always negative but the significance levels aren't always as strong as for the previous three variables. The coefficient on cooling degree days times quantity demanded is positive but is not significant in three cases. A puzzling result is the universal negative coefficient on cooling degree days. It is significant for 70% of the coefficients but more often significant for the static model. The total coefficient on cooling degree days is $\alpha_2+\gamma_1 Q_t^D$. If we compute this total effect, it is negative for half of the estimates, whether we only include coefficients at the 10% level or better or not, but most of the negative values are on the static model. In general, the dynamic model performs somewhat better in terms of the number of expected significant coefficients.

In the inverse supply equation, the coefficient on cost is always positive and significant. However, only for a couple of firms do transmission constraints have a positive effect on price, and only in the dynamic model is the effect significant at better than a 10% level. The heat rates for affiliated generators are also mixed. With no affiliated generator, we do not include the heat rate for Enron. For the other firms, it is only positive and significant for Dynegy.

The supply relation is where we observe the dynamic pricing adjustments to the Bresnahan (1989) model. For the static model, we only found significant evidence rejecting competitive behavior (θ=0) for the two largest marketers: Duke and Reliant. Both had conduct parameters near 0.5 that were significant at a 7% level. For these two marketers, only for Duke could we not reject that it was behaving as a Cournot player (θ=1). See Table 3, columns 3 and 4 for these hypothesis tests.

Table 3: Hypothesis Tests for the Conduct Parameters for the Static and Dynamic Models

Power Marketer	Static Conduct Parameter	t for H_0: $\theta = 0$	t for H_0: $\theta = 1$	Dynamic Conduct Parameter	χ^2 for H_0: $\theta^{Dyn} = 0$	χ^2 for H_0: $\theta^{Dyn} = 1$	Non_util* Market Share
Duke Energy	0.54	1.810	-1.51	7.79	4.98	0.91	0.380
Dynegy Power Mktg.	-7.59	-0.760	-0.87	51.47	7.01	4.31	0.080
Enron Power Mktg.	0.07	0.190	-2.43	-0.34	2.56	1.10	0.085
Reliant Energy	0.48	1.800	-1.96	1.45	4.14	0.27	0.150
Williams Energy	-0.29	-0.670	-3.02	-1.25	0.57	0.38	0.050

Notes: Critical t value is 1.96 for 5% significance and 1.645 for 10% significance. Critical $\chi^2[1]$ value is 3.84 for 5% significance and 2.71 for 10% significance. *California non-utility sales comprised less than 25% of total electricity sales in 2000. N/A indicates tests for Cournot behavior are not conducted where competitive behavior is not rejected.

For the dynamic model, we compute the dynamic conduct parameter: $\theta^{Dyn} = \theta_0 + \theta_1 E(Q_{t+1}^D) + \theta_2 Q_t^D$ shown in Table 3, column 5. In order to check whether or not each linear combination is statistically significant, we apply the Wald test to our estimation results. The Wald statistic is calculated as:

$$W = (\mathbf{R}\hat{\boldsymbol{\theta}})' \left[\mathbf{R}s^2 \left(\mathbf{X}'\mathbf{X}\right)^{-1} \mathbf{R}'\right] (\mathbf{R}\hat{\boldsymbol{\theta}}) \sim \chi^2(1)$$

where $\mathbf{R} = \left(1,\ E(Q_{t+1}^D),\ E(Q_t^D)\right)$, $\hat{\boldsymbol{\theta}} = \left(\hat{\theta}_0,\ \hat{\theta}_1,\ \hat{\theta}_2\right)$, **X** is the matrix of observations, and s^2 is the square of the model standard error. This statistic follows the Chi-square distribution with one degree of freedom. The Wald statistics are shown in the sixth and seventh columns of Table 3.

As Corts predicted, the dynamic model shows more evidence of non-competitive behavior than the static model. While we still see no statistical evidence that Enron and Williams, who are among the smaller marketers, are behaving non-competitively, now we can reject the null of competitive behavior for Duke, Reliant, and Dynegy. In particular, Dynegy has the largest, and most significant, dynamic conduct parameter, in contrast to the negative conduct parameter estimated with the static model. For each of these three, their conduct parameter is larger, and for Duke and Reliant, we cannot reject Cournot behavior.

Another indicator that can be used to check for collusion is a positive sign on the estimated θ_1 coefficient as argued by Rotemberg and Saloner (1986). However, we find no statistical evidence that θ_1 is positive.

Joskow and Kahn (2002) suggest "overwhelming evidence" of pricing power for generators in California in 2000 from their simulation work and the several other comprehensive studies with varying techniques that they reviewed. Similarly, Wolak (2003) computes inverse price elasticities from proprietary hourly bid data by the 5 largest generators on CAISO and concludes it was in the generator's interest to exercise market power during this period. Although we do not find "overwhelming" evidence of market power for generators associated marketing companies, we find stronger evidence with a dynamic than our earlier static pricing model. It could be that affiliated marketers are not exercising as much pricing power with more of the rents being takend by the generators. Alternatively, since we do not have hourly but daily transaction data for the marketers, aggregating peak with with off-peak periods when market power is low may be masking some of the pricing power behavior.

Our results are fairly consistent with Puller (2007), who considered behavior for 5 large non-utility generators in California for daily data from 6 - 7 p.m. for three different periods from 1998-2000. He estimated residual demands and combined them with marginal cost to simulate various market structures for California 18 including competition, Cournot, and monopoly behavior data as well as estimating conduct parameters. For four of his generating companies, we have estimates for their marketing companies. He concluded that Duke and Reliant pricing were consistent with a Cournot model, which we could not reject for their marketing companies. He found Dynegy displayed the most aggressive market power with a conduct parameter statistically greater than 1 as did we for their marketing company. The only inconsistency between the two studies is that Puller could not reject Cournot behavior for AES, while we did not reject competitive behavior for their marketer - Williams.

5. CONCLUSION

In this paper, we were interested in determining whether the five largest power marketers selling electricity to the California Power Exchange in 2000 were manipulating prices above competitive levels. Our previous research using a static conduct parameter found some evidence of market power but less than expected given the strong conclusions from studies considering market power for non-utility generators. Since earlier work suggested that estimation using a static model might bias the estimates for the conduct parameter, we developed a dynamic model to re-estimate the conduct parameter with dynamic expectations.

As in the static case, Williams and Enron were classified as competitive firms with conduct parameters not significantly different from zero, while Duke and Reliant appeared to be pricing in a Cournot fashion. The calculated dynamic conduct parameter for Dynegy was now significantly greater than one suggesting the most aggressive pricing behavior of the five. Our results were supportive of the Corts (1999) conjecture that static models underestimate the conduct parameter

Policymakers such as the Federal Energy Regulatory Commission (FERC) could use this type of econometric analysis to provide “red-flags” indicating the need for a more intensive investigation of pricing practices. In fact, FERC has improved its collection of wholesale electricity transactions through its Electric Quarterly Report data collection system, which evolved out of its original investigation of manipulation of prices in the California energy markets. This system now allows power marketers to report transactions online, and the data include more detail about the type of transaction and its delivery location. Knowing the time of day of the transaction would also be helpful as market power should vary considerably over the load cycle.

The model developed in this paper and the associated empirical results offer a number of avenues for future research. Wolak (2003) and Puller (2007) did not find evidence of collusion but rather concluded that generators were individually taking advantage of market conditions to exercise market power. Future work could explore whether groups of marketers were colluding or not.

This paper limited pricing strategies to the standard strategies examined in a conduct parameter model: perfect competition, Cournot behavior, or monopoly. However, alternative models could also be developed to examine whether a Stackelberg or dominant firm-competitive fringe market structure might have been more relevant for power marketers in the California PX.

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