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Estimating Market Power in Homogenous Product Markets Using a Composed Error Model: Application to the California Electricity Market*

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Abstract

This study contributes to the literature on estimating market power in homogenous product markets. We estimate a composed error model, where the stochastic part of the firm's pricing equation is formed by two random variables: the traditional error term, capturing random shocks, and a random conduct term, which measures the degree of market power. Treating firms' conduct as a random parameter helps solving the issue that the conduct parameter can vary between firms and within firms over time. The empirical results from the California wholesale electricity market suggest that realization of market power varies over *both* time and firms, and reject the assumption of a common conduct parameter for all firms. Notwithstanding these differences, the estimated firm-level values of the conduct parameter are closer to Cournot than to static collusion across all specifications. For some firms, the potential for realization of the market power unilaterally is associated with lower values of the conduct parameter.

Keywords: market power, random conduct parameter, composed error model, asymmetric distributions, California electricity market.

JEL codes: C34, C51, L13, L94

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1. Introduction

Starting from seminal research works of Iwata (1974), Gollop and Roberts (1979), and Appelbaum (1982), measuring the degree of competition in oligopolistic markets has become one of key activities in empirical industrial organization. A large and growing economic literature in New Empirical Industrial Organization (NEIO) relies on structural models to infer what types of firm behaviour ("conduct") are associated with prices that exceed marginal costs.[1] A typical structural model based on the conduct parameter approach for homogenous product markets starts with specifying a demand function and writing down the first-order condition of firm's profit-maximization problem:

$$P(Q_t) - mc(q_{it}) + P'(Q_t)q_{it} \cdot \theta_{it} = 0, \tag{1}$$

where $P(Q_t)$ is inverse demand, $Q_t=\Sigma_i^N q_{it}$ is total industry's output, q_{it} is the firm's output in period t, $mc(q_{it})$ is the firm's marginal cost, and θ_{it} is a "conduct" parameter that parameterizes the firm´s profit maximization condition. Under perfect competition, θ_{it}=0 and price equals marginal cost. In equilibrium, when $\theta_{it}=1/s_{it}$ (where s_{it} denotes firm's market share of output) we face a perfect cartel, and when $0<\theta_{it}<1/s_{it}$ various oligopoly regimes apply. [2] In these models the (firm or industry) degree of market power is measured by a conduct parameter θ that is jointly estimated with other cost and demand parameters.[3]

[1] For an excellent survey of other approaches to estimating market power in industrial organization literature, see Perloff *et al.* (2007).

[2] In a symmetric equilibrium, the upper bound of inequality $0<\theta_{it}<1/s_{it}$ would be equal to the number of firms, N.

[3] Some studies interpret estimated conduct parameter as a 'conjectural variation', i.e., how rivals' output changes in response to an increase in firm *i*'s output. It is also sometimes argued that the conjectural variation parameter results from the reduced form of a more complex dynamic game, such as a tacit collusion game (see e.g., Itaya and Shimomura 2001, Itaya and Okamura 2003, Figuieres *et al*. 2004, and references therein). Other studies (Bresnahan 1989, Reiss and Wolak 2007) argue that with an exception of limited number of special cases (e.g., perfect competition, Cournot-Nash, and monopoly) there is there is no satisfactory economic interpretation of this parameter as a measure of firm behaviour. Sorting out between these theoretical complications is beyond the scope of this study. We therefore interpret this parameter as a simple descriptive measure of firm's degree of market power.

The conduct parameter θ_{it} may vary across time as market conditions change, and firms change their own pricing strategies.[4] Moreover, the conduct parameter may also vary across firms as "there is nothing in the logic of oligopoly theory to force all firms to have the same conduct" (Bresnahan, 1989, p. 1030).[5] Obviously, allowing the conduct parameter to vary both by firms and time-series results in an overparameterized model. To avoid this problem, empirical studies in structural econometric literature always impose some *restrictions* on the way the value of conduct parameter varies across firms and time. The overparameterization is typically solved by estimating the average of the conduct parameters of the firms in the industry (Appelbaum 1982), reducing the time variation into a period of successful cartel cooperation and a period of price wars or similar breakdowns in cooperation (Porter 1983a), allowing for different conduct parameters between two or more groups of firms (Gollop and Roberts 1979), or assuming firm-specific, but time-invariant, conduct parameters in a panel data framework (Puller 2007).

This study proposes a new econometric approach that deals with overparameterization problem and helps obtaining the values of firm's conduct that vary across *both* time and market participants. Instead of estimating the firm's conduct as a common parameter together with other parameters defining cost and demand, we propose treating firms' behaviour θ_{it} as a random variable. Our approach is based on composed error model, where the stochastic part is formed by two random variables - traditional error term, capturing random shocks, and a random conduct term, which

[4] As the problem of repeated oligopoly interaction has received greater attention, the estimation of time-varying conduct parameters that are truly dynamic has become an issue. Indeed, the Stigler's (1964) theory of collusive oligopoly implies that, in an uncertain environment, both collusive and price-war periods will be seen in the data. Green and Porter (1984) predict a procyclical behaviour pattern for mark-ups because of price reversion during a period of low demand. Hence the conduct parameter changes from collusive value to competitive value when there is an unanticipated negative demand shock. On the contrary, Rotemberg and Saloner (1986) predict that prices and mark-ups are countercyclical, and hence the conduct parameter will decrease when demand is high. Moreover, Abreu et al. (1986) find that in complex cartel designs the length of price wars (i.e., changes in conduct parameter) is random because there are "triggers" for both beginning a price war and for ending one. It is therefore difficult to impose plausible structural conditions and estimate firms' conduct over time.

[5] In many treatments of oligopoly as a repeated game, firms expect deviations from the collusive outcome. Firms expect that if they deviate from the collusive arrangement, other will too. This expectation deters them from departing from their share of the collusive output. Because these deviations are unobserved in an uncertain environment, each firm might have its own expectation about what would happen if it deviates from collusive output.

measures market power. The model is estimated in three stages.[6] In the first stage, all parameters describing the structure of the pricing equation (1) are estimated using appropriate econometric techniques. In the second stage, distributional assumptions on random conduct term are invoked to obtain consistent estimates of the parameters describing the structure of the two error components. In the third stage, market power scores are obtained for each firm by decomposing the estimated residual into a noise component and a market-power component.

The main contribution of the proposed approach is about the way the asymmetry of the composed error term is employed to get firm-specific market power estimates. While the first stage of our model is standard, the following stages take advantage of the fact that the distribution of conduct term is truncated and is likely to be positively or negatively skewed. Though the idea of identification of structural econometric models through asymmetries in variance of error term is not new in applied econometric literature, [7] to our knowledge skewness of conduct parameter in oligopolistic industry settings is not examined explicitly in most (if any) of the previous studies.

The proposed approach can be viewed as belonging to the same family as Porter (1983b), Brander and Zhang (1993), and Gallet and Schroeter (1995) who estimate a regime-switching model where market power enters in the model as a supply shock. As in our model, the identification of market power in these studies relies on making assumptions about the structure of unobservable error term. However, while previous papers estimated the pricing relationship (1) assuming $\theta_{it}=\theta_t$ to be a *discrete* random variable that follows a bimodal distribution ("price wars" vs. "collusion"), here θ_{it} varies both across firms and over time and is treated as a *continuous* random term. Therefore, while the switching regression models can only be estimated when there are discrete "collusive" and "punishment" phases that are either observable or could be inferred from the data, our model can be estimated in absence of regime switches.[8] The

[6] As in Porter (1983b), Brander and Zhang (1993), and Gallet and Schroeter (1995), Maximum Likelihood techniques can be used to estimate all parameters of the model in a unique stage. However this does not allow us to address the endogeneity issues that appear when estimating the pricing equation (1).
[7] See Rigobon (2003), and references therein.
[8] The regime switches only occur when a firm´s quantity is never observed by other firm and, hence, deviations cannot be directly observed. This is not the case in the electricity generating industry analyzed in the empirical section as market participants had access to accurate data on rivals' real-time generation.

continuous nature of our conduct random term thus allows us to capture *gradual* changes in firm behaviour.[9]

Another feature that distinguishes our paper from previous studies is the attempt to estimate a double-bounded distribution that imposes both lower and upper theoretical bounds (i.e., $0 \leq \theta_{it} \leq 1/s_{it}$) to a continuous random conduct term. To achieve this objective we have explored the stochastic frontier literature,[10] and adapted the doubly truncated normal distribution recently introduced by Almanidis *et al.* (2011) to our framework. To our knowledge, this is the first time the stochastic frontier models are used to measure market power. Because our model relies on distributional assumptions on the stochastic part, firm-specific market power estimates can be obtained just using cross-sectional data sets, unlike in previous papers that used a fixed effect treatment to estimate firm average conduct in a panel data framework. Therefore, our approach is especially useful when: *i*) no panel data sets are available;[11] *ii*) the time dimension of the data set is short;[12] *iii*) the available instruments are valid when estimating a common pricing equation to all observations, but not when we try to estimate separable pricing equations for each firm; or *iv*) the assumption of time-invariant conduct is not reasonable.

While economic theory imposes both lower and upper theoretical bounds to the random conduct term, the skewness of its distribution is an empirical issue. We argue, however, that the skewness assumption of the distribution of conduct term is reasonable because oligopolistic equilibrium outcomes often yield skewed conduct random terms where large (collusive) conduct values are either less or more probable than small (competitive) conduct values. For instance, the dominant firm theory assumes that one (few) firm(s) has enough market power to fix prices over marginal cost. This market

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[9] Kole and Lehn (1999) argue that for many firms the decision-making apparatus is slow to react to changes in the market environment within which it operates, due to the costs to reorient decision-makers to a new "game plan". In particular, the existing culture or the limited experience of the firm in newly restructured markets may be such that strategies to enhance market power may not be immediately undertaken. In addition, we would also expect gradual changes in firms conduct in a dynamic framework if firms are engaging in efficient tacit collusion and are pricing below the static monopoly level, and when there is a high persistence in regimes (Ellison, 1994).

[10] For a comprehensive survey of this literature, see Kumbhakar and Lovell (2000), and Fried *et al*. (2008).

[11] In particular, our approach is useful in cross-section applications when there is not prior information about the identities of suspected cartel members and hence a benchmark of non-colluding firms is not available.

[12] The fixed-effect treatment is only consistent when long panel data sets are available (i.e., as $T \rightarrow \infty$). In addition, the incidental parameter problem appears, i.e., the number of parameters grows with sample size (i.e., as $N \rightarrow \infty$).

power is, however, attenuated by a fringe of (small) firms that do not behave strategically.[13] The most important characteristic of this equilibrium is that the modal value of the conduct random term (i.e., the most frequent value) is close to zero, and higher values of θ_{it} are increasingly less likely (frequent). In other markets *all* firms might be involved in perfect cartel scheme. In such a cartel-equilibrium, firms usually agree to sell "target" quantities, and the resulting market price is the monopoly price, which is associated with the maximum conduct value, e.g., $\theta_{it} = 1/s_{it}$. Smaller values of θ_{it} are possible due, for instance, to cheating behaviour.[14] This means that the modal value of the conduct random term in this equilibrium is one, with smaller values of θ_{it} increasingly less likely. That is, firm-conduct is negatively skewed. In general, similar equilibria that yield asymmetric distributions for the firm-conduct parameter with modal values close to zero or to the number of colluding firms may also arise.

We illustrate the model with an application to the California electricity generating market between April 1998 and December 2000. This industry is an ideal setting to apply our model because there were high concerns regarding market power levels in California restructured electricity markets during that period, and detailed price, cost, and output data are available as a result of the long history of regulation and the transparency of the production technology. This data set allows us to compute directly hourly marginal cost and residual demand elasticities for each firm. We can therefore avoid complications from estimating demand and cost parameters and focus our research on market power, avoiding biases due inaccurate estimates of marginal cost and residual demand.[15] Hence, this data set provides a proper framework to discuss methodological issues and to apply the empirical approach proposed in the present paper. In addition, these data have been used in previous papers to evaluate market power in California electricity market. In particular, Borenstein et al. (2002) and Joskow and Kahn (2001) calculate hourly marginal cost for the California market and compare

[13] This partial collusion equilibrium is reasonable in markets with many firms where coordination among all firms is extremely difficult to maintain as the number of firms in the collusive scheme is too high or other market characteristics make coordination too expensive, e.g., markets with differentiated products.

[14] It is well known that secret price cuts (or secret sales) by cartel members are almost always a problem in cartels. For instance, Ellison (1994) finds that secret price cuts occurred during 25% of the cartel period and that the price discounts averaged about 20%. See also Borenstein and Rose (1994).

[15] See Kim and Knittel (2006) using data from the California electricity market. See also Genesove and Mullin (1998) and Clay and Troesken (2003) for applications to the sugar and whiskey industries respectively.

these estimates to wholesale prices. They find that, in certain time periods, prices substantially exceeded marginal cost. Wolak (2003) calculates the residual demand based on bidding data in California Independent System Operator’s (CAISO) real-time energy market. He concludes that the increase in market power in summer 2000 can be attributed to firms’ exercise of unilateral market power. Puller (2007) analyses the pricing behaviour of California electricity generating firms and finds that price-cost margins varied substantially over time.

Our first-stage results are generally similar to previous findings of Puller (2007). The estimated market power values are closer to Cournot (θ_{it} =1) than to static collusion ($\theta_{it}=1/s_{it}$). We find an increase in collusive behavior of all firms above Cournot levels during the period of price run-up in June – November 2000, using the residual demand elasticities based on Puller (2007) but not using the residual demand elasticities based on PX data. The analysis of firm-specific conduct parameters suggests that realization of market power varies over *both* time and firms, and rejects the assumption of a common conduct parameter for all firms. Estimated firm-specific conduct parameters generally tend to move in the same direction across time, suggesting that firms pursue similar market strategies as market conditions change.

Finally, we use the estimates of firm-specific conduct parameters to clarify the extent to which firms’ potential for exercising market power unilaterally affects their market conduct. Similar to Wolak (2003) we compute the residual demand elasticities facing each firm individually on the California PX market, and use their reciprocals (Lerner indices) as a measure of the firms’ potential to exercise unilateral market power. We find strong negative correlation between Lerner indices and estimated conduct parameters for 3 out of 4 firms during the first period of our sample (before entry of Southern) and for 2 out of 5 firms during the second period of our sample. This result indicates that, for some firms the potential for realization of the market power unilaterally is associated with lower values of the conduct parameter.

The rest of the paper is structured as follows. In Section 2 we describe the empirical specification of the model. In Section 3 we discuss the three-stage procedure to estimate the model. The empirical illustration of the model using California electricity data is described in Section 4. Section 5 concludes.

2. Empirical Specification

The traditional structural econometric model of market power is formed by a demand function and a pricing equation. Because we are interested in the estimation of industry or firm-specific market power scores, we only discuss here the estimation of the pricing equation (1), conditional on observed realization of residual demand.[16] If the demand function parameters are not known, they should be estimated jointly with cost and market power parameters.

In this section we develop a simple model where firms sell homogenous products (e.g., kilowatt-hours of electricity) and choose individual quantities each period so as to maximize their profits. Our model is static as we assume that firms maximize their profits each period without explicit consideration of the competitive environment in other periods.[17] Firm *i*'s profit function in period *t* can be written as:

$$\pi_{it} = P(Q_t)\cdot q_{it} - C(q_{it}, \alpha), \tag{2}$$

where $\hat{\beta}$ is a vector of previously estimated demand parameters, and α is a vector of cost parameters to be estimated. We assume that firms choose different quantities each period and their marginal cost varies across firms and over time.

In a static setting, the firm's profit maximization problem is

$$\max_{q_{it}} \quad P(Q_t, \hat{\beta})\cdot q_{it} - C(q_{it}, \alpha) \ . \tag{3}$$

The first order conditions (FOC's) of the static model are captured by equation (1), that is:

$$P_t = mc(q_{it}, \alpha) + g_{it}\cdot\theta_{it},$$

[16] This is the strategy followed, for instance, by Brander and Zhang (1993), Nevo (2001) and Jaumandreu and Lorences (2002).

[17] Corts (1999) argues that traditional approaches to estimating the conduct parameter from static pricing equations yield inconsistent estimates of the conduct parameter if firms are engaged in an effective tacit collusion. The robustness of the conduct parameter approach depends, in addition, on the discount factor and the persistency of the demand. Puller (2009) derives and estimates a more general model that addresses the Corts critique. The results from estimating the more general model for the California market yielded estimates very similar to the static model. This similarity comes from the fact that "California market [can be] viewed as an infinitely repeated game with a discount factor between days very close to 1" Puller (2007, p.84). Our empirical application to California electricity market as a static model is therefore sufficient for estimating market power consistently.

where $mc(q_{it}, \alpha)$ stands for firm's marginal cost, $g_{it} = P_t q_{it} / Q_t \eta_{it}^D$, and $\eta_{it}^D = P'(Q_t) P_t / Q_t$ is the (observed) elasticity of product demand. The stochastic specification of the above FOC´s can be obtained by adding the error term, capturing measurement and optimization errors:

$$P_t = mc(q_{it}, \alpha) + g_{it} \cdot \theta_{it} + v_{it} . \tag{4}$$

Instead of viewing firm's behaviour as a structural parameter to be estimated we here treat firms' behaviour as a random variable. While retaining standard assumption that the error term v_{it} is *i.i.d.* and symmetric with zero mean, we also assume that θ_{it} follows a truncated distribution that incorporates the theoretical restriction that $0 \leq \theta_{it} \leq 1/s_{it}$. The distinctive feature of our model is that the stochastic part is formed by two random variables - the traditional *symmetric* error term, v_{it}, and an *asymmetric* random conduct term, $g_{it} \cdot \theta_{it}$, that reflects the market power. The restriction that the composed error term is asymmetric allows us obtaining separate estimates of θ_{it} and v_{it} from an estimate of the composed error term.

Our static model can be easily adapted to a dynamic framework following Puller (2009). He notices that the dynamic part of the FOC's is common to all firms and, hence, Corts' critique can be avoided by estimating the pricing equation (4) with a set of time-dummy variables. Because firm's dynamic behaviour is affected by current demand, expected future demand, and expected future costs (Borenstein and Shephard, 1996), consistent estimates can be also obtained by replacing the set of dummy variables by a function of expected demand and cost shocks measured relative to current demand and costs.[18]

Challenges are greater if we want to estimate a general specification of the pricing equation that explicitly includes conduct determinants.[19] If conduct determinants affect both the shape and magnitude of the asymmetric random conduct term, their coefficients must be estimated using maximum likelihood (ML) techniques. However, a

[18] Kim (2006) proposes a similar solution to address Corts' critique. He suggests modelling the conduct parameter as a *core* time-invariant conduct parameter, and a (linear) function of dynamic behaviour´s determinants, i.e., demand and cost shocks.

[19] Because estimating the pricing equation does not require any distributional assumptions on either error component, this issue can be easily handled later on (see next section) once distributional assumptions are invoked to estimate the structure of the two error components, provided first-stage parameters are consistently estimated.

method-of-moments (MM) estimator can still be used if θ_{it} satisfies the so-called *scaling property,* which implies that changes in conduct determinants affect the scale but not the shape of θ_{it}.[20] Whether or not the scaling property should hold is an empirical question, but if this property cannot be rejected, some attractive features arise (see Wang and Schmidt, 2002).

3. Estimation strategy

We now turn to explaining how to estimate the pricing relationships presented in the previous section. Two estimation methods are possible: a method-of-moments (MM) approach and maximum likelihood (ML). The MM approach involves three stages. In the *first* stage, all parameters describing the structure of the pricing equation (i.e., cost, demand and dynamic parameters) are estimated using appropriate econometric techniques. In particular, because some regressors are endogenous, a generalized method of moments (GMM) method should be employed to get consistent estimates in this stage.[21] This stage is independent of distributional assumptions on either error component. In the *second* stage of the estimation procedure, distributional assumptions are invoked to obtain consistent estimates of the parameter(s) describing the structure of the two error components, conditional on the first-stage estimated parameters. In the *third* stage, market power scores are estimated for each firm by decomposing the estimated residual into an error-term component and a market-power component.

The ML approach uses maximum likelihood techniques to obtain second-stage estimates of the parameter(s) describing the structure of the two error components, conditional on the first-stage estimated parameters. It can be also used to estimate simultaneously both types of parameters, if the endogenous regressors in the pricing

[20] The scaling property corresponds to a multiplicative decomposition of θ_{it} into a scaling function $h(z_{it},\varphi)$ times a random variable u_{it} that does not depend on z_{it}, where z_{it} is a vector are of firms' behaviour covariates. An alternative that has sometimes been proposed in the literature on frontier production functions (Huang and Liu, 1994; Battese and Coelli, 1995) is an additive decomposition of the form $\theta_{it}(z_{it},\varphi) = h(z_{it},\varphi) + \tau_{it}$. However, this can never actually be a decomposition into independent parts, because $\theta_{it}(z_{it},\varphi) \geq 0$ requires $\tau_{it} \leq h(z_{it},\varphi)$.

[21] The GMM estimator has the additional advantage over ML in that it does not require a specific distributional assumption for the errors, which makes the approach robust to nonnormality and heteroskedasticity of unknown term (Verbeek, 2000, p. 143).

equation are previously instrumented. In this case, the ML approach combines the two first stages of the method of moments approach into one.

While the first-stage is standard in the NEIO literature, the second and third stages take advantage of the fact that the conduct term is likely positively or negatively skewed, depending on the oligopolistic equilibrium that is behind the data generating process. Models with both symmetric and asymmetric random terms of the form in Section 2 have been proposed and estimated in the stochastic frontier analysis literature.[22]

3.1. First Stage: Pricing Equation Estimates

Let us rewrite the pricing equation (4) as:

$$P_t = mc(q_{it},\alpha) + g_{it} \cdot \theta + \varepsilon_{it}\,, \tag{5}$$

where α is the vector of cost parameters,[23] $\theta = E(\theta_{it})$ can be interpreted as a measure of the industry market power, and

$$\varepsilon_{it} = v_{it} + g_{it} \cdot \{\theta_{it} - \theta\}. \tag{6}$$

The possible endogeneity of some regressors will lead to least squares being biased and inconsistent. This source of inconsistency can be dealt with by using GMM. Though first-step GMM parameter estimates are consistent, they are not efficient by construction because the v_{it}'s are not identically distributed. Indeed, assuming that θ_{it} and v_{it} are distributed independently of each other, the second moment of the composed error term can be written as:

$$E(\varepsilon_{it}^2) = \sigma_v^2 + g_{it}^2 \cdot \sigma_\theta^2\,, \tag{7}$$

where $E(v_{it}^2)=\sigma_v^2$, and $Var(\theta_{it})=\sigma_\theta^2$. Equation (8) shows that the error in the regression indicated by (5) is heteroskedastic. Therefore an efficient GMM estimator is needed.

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22 See, in particular, Simar, Lovell and Vanden Eeckaut (1994), and the references in Kumbhakar and Lovell (2000).

23 In the empirical illustration below we include a dummy variable for binding capacity constraints that helps explaining the differential of prices over marginal costs. This variable is interpreted here as a determinant of marginal cost.

Suppose that we can find a vector of m instruments M_{it} that satisfy the following moment condition:

$$E[M_{it} \cdot \varepsilon_{it}] = E[M_{it} \cdot (P_t - mc(q_{it}, \alpha) - g_{it} \cdot \theta)] = E[m_{it}(\alpha, \theta)] = 0 \,. \tag{8}$$

The efficient two-step GMM estimator is then the parameter vector that solves:

$$(\hat{\alpha}, \hat{\theta}) = \arg\min [\Sigma_i \Sigma_t m_{it}(\alpha, \theta)]' W^{-1} [\Sigma_i \Sigma_t m_{it}(\alpha, \theta)], \tag{9}$$

where W is an optimal weighting matrix obtained from a consistent preliminary GMM estimator.[24]

3.2. Second Stage: Variance Decomposition

The pricing equation (5) estimated in the first stage is equivalent to standard specification of a structural market power econometric model, where an industry-average conduct is estimated (jointly with other demand and cost parameters in most applications). As we mentioned earlier in the introduction section, our paper aims to exploit the asymmetry of the composed error term (i.e., the skewness of the conduct random variable) to get firm-specific market power estimates in the second and third stages. These stages therefore are central to our analysis.

In the *second* stage of the estimation procedure, distributional assumptions are invoked to obtain consistent estimates of the parameter(s) describing the variance of θ_{it} and v_{it} (i.e., σ_θ and σ_v), conditional on the first-stage estimated parameters. This stage is critical as it allows us to distinguish variation in market conduct, measured by σ_θ, from variation in demand and costs, measured by σ_v. We can estimate σ_v and σ_θ using either MM or ML. [25] Given that we have assumed a particular distribution for the conduct term, the ML estimators are obtained by maximizing the likelihood function associated to the error term $\varepsilon_{it} = v_{it} + g_{it}\theta_{it}$ that can be obtained from an estimate of the first-stage pricing equation (5).

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[24] This optimal weighting matrix can take into account both heteroskedasticity and autocorrelation of the error term.

[25] Olson *et al*. (1980) showed that the choice of estimator (ML versus MM) depends on the relative values of the variance of both random terms and the sample size. When the sample size is large (as in our application) and the variance of the one-sided error component, compared to the variance of the noise term, is small, then ML outperforms MM in a mean-squared error sense.

The MM estimators are derived using the second and third moments of the error term ε_{it} in equation (5).[26] The third moment of ε_{it} can be written as:

$$E(\varepsilon_{it}^3) = g_{it}^3 \cdot E\left[(\theta_{it} - \theta)^3\right]. \tag{10}$$

Equation (10) shows that the third moment of ε_{it} is simply the third moment of the random conduct term, adjusted by g_{it}^3. That is, while the second moment (7) provides information about both σ_v and σ_θ, the third moment (10) only provides information about the asymmetric random conduct term. Now, if we assume a specific distribution for θ_{it}, we can infer σ_θ from (10), and then σ_v from (7). In practice, the MM approach has two potential problems. First, it is possible that, given our distribution assumptions, ε_{it} has the "wrong" skewness implying a negative σ_θ. The second problem arises when ε_{it} has the "right" skewness, but the implied σ_θ is sufficiently large to cause $\sigma_v<0$. Because earlier versions of the present study resulted in negative values using the MM approach in some time-periods and specifications, in Section 4 we only report the results using the ML approach.

Whatever the approach we choose in the present stage, we need to choose a distribution for θ_{it}. The selected distribution for the random conduct term reflects the researcher's beliefs about the underlying oligopolistic equilibrium that generates the data. Therefore, different distributions for the conduct random term can be estimated to test for different types of oligopolistic equilibrium. The pool of distribution functions is, however, limited as we need to choose a *simple* distribution for the asymmetric term to be able to estimate the empirical model, while satisfying the restrictions of the economic theory The need for tractability prevents us from using more sophisticated distributions that, for instance, would allow us to model industries formed by two groups of firms with two different types of behaviour, i.e., an industry with two modes of the conduct term.

The distribution for the asymmetric term adopted in this study is the *double-bounded* distribution that imposes both lower and upper theoretical bounds on the values of the random conduct term, i.e., $0 \leq \theta_{it} \leq 1/s_{it}$. In doing so, we follow Almanidis *et*

[26] Note that $\tilde{\varepsilon}_{it}$ is simply the error term in equation (5), plus $g_{it}\theta$, and hence both $\tilde{\varepsilon}_{it}$ and ε_{it} have the same third moments.

al. (2011) who propose a model where the distribution of the inefficiency (here, the conduct) term is a normal distribution N(μ,σ_u) that is truncated at zero on the left tail *and* at $1/s_{it}$ on the right tail.[27] The model is estimated by maximizing a well-defined likelihood function associated to the error term that can be obtained from an estimate of the first-stage pricing equation.[28]

As it is well known in the stochastic frontier literature, neglected heteroskedasticity in either or both of the two random terms causes estimates of inefficiency (here, the market power scores) to be biased.[29] To address this problem we propose estimating our model allowing for firm-specific and/or heteroskedastic random terms. In particular, we extend the classical homoscedastic model by assuming that variation in the error term is an exponential function of an intercept term, the day-ahead forecast of total demand and its square (i.e., FQ, FQ^2), that are included in the model in order to capture possible demand-size effects, and a vector of days-of-the-week dummies (DAY). These variables allow for time-varying heteroskedasticity in the error term. In addition, firm-specific dummy variables (FIRM) are included to test whether variation of the error term is correlated with (unobservable) characteristics of firms/observations. Therefore, the variation in the noise term can be written in logs as:[30]

$$\ln \sigma_{\upsilon,it} = \tau_0 + \tau_1 FQ_t + \tau_2 FQ_t^2 + \sum_{d=2}^{7} \pi_d \cdot DAY_d + \sum_{i=2}^{N} \delta_i \cdot FIRM_i \, . \qquad (11)$$

Regarding the conduct random term, we assume that its variation is also an exponential function of several covariates. Because the upper bounds are firm-specific, we should expect a higher variation in θ_{it} for those firms with lower market share, and vice versa. For this reason, we include s_{it} as a determinant of variation in market conduct and we expect a negative coefficient for this variable. Since Porter (1983), who

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[27] Table A.1 and Figure A.1 in the technical appendix illustrate the density function of this double-bounded distribution.

[28] An important caveat in estimating doubly truncated normal models is whether it is globally identifiable. Almanidis et al. (2011) show that when both the mean and the upper-bound of the pre-truncated normal distribution are estimated simultaneously, and the combination of these two parameters yield a (post-truncated) symmetric distribution identification problems may arise. Fortunately, these problems vanish in a structural model of market power because the upper-bound is fixed by the theory and it does not need to be estimated in practice.

[29] See Kumbhakar and Lovell (2000), for more details about this important issue in the stochastic frontier analysis framework.

[30] In empirical application we have scaled the day-ahead forecast of total demand dividing it by its sample mean in order to put all explanatory variables in a similar scale.

estimates a regime-switching model, there is a large tradition in the empirical industrial organization literature that extended Porter's model by adding a Markov structure to the state (i.e., discrete) random variable capturing periods of either price wars or collusion (see, for instance, Ellison, 1994, and Fabra and Toro, 2005). Under this structure, the regimes are not independent and they are correlated over time, so that a collusion state today can be likely to lead to another collusion state next day.

Although imposing an autoregressive structure on the conduct term θ_{it} might be a more realistic assumption, in this study we still assume that θ_{it} is independent over time. There are two reasons for doing so. First, in our model, random conduct parameter θ_{it} varies across both firms and over time, and is treated as a continuous random term that, in addition, it is truncated twice. This makes it difficult to allow for correlation over time in the random conduct term. In a finite-state framework, the model can be estimated by maximizing the joint likelihood function of v_{it} and θ_{it} if a Markov structure is not imposed. When this structure is added, the computation of the likelihood function of the model is much more complicated because it necessities to integrate out $\theta_{i1},\ldots,\theta_{i1T}$. Several filtering methods have been proposed (e.g., Hamilton, 1989) to make tractable the likelihood function, and to jointly estimate the hidden states and the parameters of the model. As pointed out by Emvalomatis *et al.* (2011), these filtering methods cannot be easily adapted to a continuous *and* non-negative random variable. For instance, the traditional Kalman filtering techniques cannot be used in our framework when the latent variable (here θ_{it}) is not normally distributed, and a one-to-one, non-linear transformation of θ_{it} should be used before putting θ_{it} in an autoregressive form. It is clearly out of scope of the present paper to extend the proposed approach to double truncated random variables. Second, Alvarez *et al.* (2006) pointed out that we can still get consistent parameter estimates if the correlation of unobserved conduct term over time is ignored. The justification is based on a quasi-maximum likelihood argument, where the density of a firm's efficiency score at time *t*, could still be correctly specified, marginally with respect to the efficiency score in previous periods.

Although we do not explicitly incorporate autoregressive specification of unobserved conduct term θ_{it}, we do attempt to control for observed past behaviour in some target variables.[31] In particular, and following Fabra and Toro's (2005) application to the Spanish electricity market, we include the lagged first-difference of market shares, i.e., $\Delta s_{it-1}=s_{it-1}-s_{it-2}$, as a target variable A negative value of Δs_{it-1} indicates that other strategic rivals have got yesterday a higher market share than the day before. If the increase in rivals' market share is taken as a signal of weakness of a potential tacit collusion arrangement among firms, it might encourage firm *i* to behave more aggressive next day. If this is the case, we should expect a positive sign of the coefficient associated to this variable.[32] Hence, our final specification of the conduct variation is:

$$\ln \sigma_{u,it} = \upsilon_0 + \upsilon_1 s_{it} + \upsilon_2 \Delta s_{it-1} + \sum_{i=2}^{N} \varsigma_i \cdot FIRM_i \tag{12}$$

3.3. Third Stage: Obtaining Firm-Specific Market Power Estimates

In the third stage we obtain the estimates of market power for each firm. From previous stages we have estimates of $\varepsilon_{it} = \upsilon_{it} + g_{it}\theta_{it} = \upsilon_{it} + \tilde{\theta}_{it}$, which obviously contain information on θ_{it}. The problem is to extract the information that ε_{it} contains on θ_{it}. Jondrow *et al.* (1982) face the same problem in the frontier production function literature and propose using the *conditional* distribution of the asymmetric random term (here $\tilde{\theta}_{it}$) given the composed error term (here ε_{it}). In the technical appendix, Table A.2 we provide distributional assumptions for the analytical form for $E(\tilde{\theta}_{it} \mid \varepsilon_{it})$, which is the best predictor of the conduct term (see Kumbhakar and Lovell, 2000, and Almanidis

[31] Since these variables in a regime-switching framework mainly affect the probability of starting a price war, they are label as "trigger" variables or "triggers". We prefer using the term "target" because in our model we do not have collusion and price-war regimes, and hence we do not have to estimate transition probabilities from one discrete regime to another.

[32] We have also included other variables in order to capture the influence of past behaviour on actual market conduct. In particular, we have also used week-differences and other lags of the first-differences of market shares. Following Ellison (1994) we have also created more sophisticated target variables, such as, deviations with respect it predicted value, using the average of the same variable for the previous seven days. The results were almost the same as those obtained using Δs_{it-1}.

et al., 2011).[33] Once we have a point estimator for $\tilde{\theta}_{it}$, the conduct parameter θ_{it} can be obtained using the identity $\theta_{it} \equiv \tilde{\theta}_{it} / g_{it}$.[34]

4. Empirical Application to California Electricity Market

In this section we illustrate the proposed approach with an application to the California electricity generating market. This market was opened to competition in 1998 allowing firms to compete to supply electricity to the network. The wholesale prices stayed at "normal" levels from 1998 to May 2000, and then skyrocketed during summer and fall 2000, resulting in the breakdown of the liberalized electricity market by the end of 2000. While the California electricity crisis was a complex situation affected by a number of factors, such as poor wholesale market design, absence of long-term contracting, unexpected increase in generation input costs, and hike in end-use electricity demand due to unusually hot weather, a number of studies pointed to the evidence of significant market power in this restructured market. Borenstein (2002) and Wolak (2005) are two excellent surveys of the California electricity market restructuring disaster.

Our empirical application analyzes the competitive behavior of five strategic large firms from Puller's (2007) study of monopoly power in California restructured electricity markets using the same sample period (from April 1998 to November 2000). Following Borenstein *et al.* (2002), Kim and Knittel (2006), and Puller (2007), we define five large firms that owned fossil-fueled generators (AES, DST, Duke, Reliant and Southern) as 'strategic' firms, i.e., pricing according to equation (1). The competitive fringe includes generation from nuclear, hydroelectric, and small independent producers, and imports from outside California. Puller (2007, p.77) argues that these suppliers were either relatively small or did not face strong incentives to

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[33] Both the mean and the mode of the conditional distribution can be used as a point estimator for the conduct term $\tilde{\theta}_{it}$. However, the mean is, by far, the most employed in the frontier literature.

[34] Although $\hat{\theta}_{it}$ is the minimum mean squared error estimate of θ_{it}, and it is unbiased in the unconditional sense [$E(\hat{\theta}_{it} - \theta_{it}) = 0$], it is a shrinkage of θ_{it} toward its mean (Wang and Schmidt, 2009). An implication of shrinkage is that on average we will overestimate θ_{it} when it is small and underestimate θ_{it} when it is large. This result, however, simply reflects the familiar principle that an optimal (conditional expectation) forecast is less variable than the term being forecasted.

influence the price.[35] Other studies (Bushnell and Wolak 1999, Borenstein et al 2008), however, find that competitive fringe occasionally did have incentives to act strategically and bid elastic supply and demand schedules to counter exercise of market power by the strategic firms. Because electricity storage is prohibitively costly,[36] both strategic and non-strategic firms had to produce a quantity equal to demand at all times.[37] The five large firms and a competitive fringe interacted daily in a market where rivals' costs were nearly common knowledge, which created strong incentives for tacit collusion (Puller, 2007). And the residual demand for electricity was highly inelastic, which, given institutional weaknesses of California Power Exchange, allowed individual firms to raise prices unilaterally (Wolak, 2003).

We first carry out a standard econometric exercise and estimate consistently by GMM the parameters of the pricing equation (1). In particular, and in order to be sure that our first stage is sound, we try to reproduce Puller's (2007) results, using the same dataset, and the same specification for the pricing equation (1), and the same set of dependent and explanatory variables.[38] Unlike Puller (2007) we use a different estimate of the elasticity of residual hourly demand function of the five strategic firms. This is because Puller (2007) does not observe actual residual demand schedules. Instead, he

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[35] Specifically, Puller (2007) argued that independent and nuclear units were paid under regulatory side agreements, so their revenues were independent of the price in the energy market. The owners of hydroelectric assets were the same utilities that were also buyers of power and had very dulled incentives to influence the price. Finally, firms importing power into California were likely to behave competitively because most were utilities with the primary responsibility of serving their native demand and then simply exporting any excess generation.

[36] One of the ways of storing electricity for load balancing is through pumped-storage hydroelectricity. The method stores energy in the form of water, pumped from a lower elevation reservoir to a higher elevation. Low-cost off-peak electric power is used to run the pumps. During periods of high electrical demand, the stored water is released through turbines to produce electric power. In California, there is a significant amount of hydropower including some pumped storage. Notwithstanding relative abundance pumped storage in California, it's potential for load balancing is limited as hydropower schedules are relatively fixed in part due to environmental (low flow maintenance, etc.) rules.

[37] Modelling of market power in wholesale electricity markets becomes more complex if firms forward-contract some of their output. As Puller (2007, p.85) notes, in the presence of unobserved contract positions the estimate of conduct parameters would be biased. This was generally not an issue in California wholesale electricity market during sample period. As Borenstein (2002, p. 199) points out, "Although the investor owned utilities had by 2000 received permission to buy a limited amount of power under long-term contracts, they were […] still procuring about 90 percent of their "net short" position […] in the Power Exchange's day-ahead or the system operator's real-time market. Puller (2007, p. 85) argues that "there is a widespread belief that in 2000 Duke forward-contracted some of its production." If data on contract positions were available, one could correct this bias by adjusting infra-marginal sales by the amount that was forward-contracted. Unfortunately, as in earlier studies on market power in California wholesale electricity market the contract positions are not observable in our dataset.

[38] Careful description of the dataset can be found in the technical appendix of Puller (2007, pp.86-87).

estimates the supply function of competitive fringe, and calculates the slope of the fringe supply, “which has the same magnitude but opposite sign of the slope of the residual demand faced by the five strategic firms” (Puller 2007, p. 78). This is problematic because Puller’s (2007) estimates are correct if and only if the fringe firms act non-strategically (i.e., bid perfectly inelastic supply and demand schedules). As we noted above, this assumption is questioned by a number of studies. Instead we use the estimates of residual demand elasticities based on actual bids from California Power Exchange (PX) as suggested by Wolak (2003). For comparison purposes we also report the results based on Puller’s (2007) elasticity estimates using the same definition of strategic/non-strategic firms.

After estimating the parameters of the pricing equation, we carry out the second and third stages assuming particular distributions for the conduct random term, all of them imposing the conduct term to be positive *and* less than the number of strategic firms.

4.1. Pricing Equation and Data

Following Puller (2007, eq. 3) the pricing equation to be estimated in the first stage of our procedure is:

$$(P - mc)_{it} = \alpha \cdot CAPBIND_{it} + \theta \cdot \frac{P_t \, q_{it} / Q^S_{strat,t}}{\eta^D_{strat,t}} + \varepsilon_{it}\,, \qquad (13)$$

where α and $\theta = E(\theta_{it})$ are parameters to be estimated, P_t is market price, mc_{it} is firm’s marginal costs, q_{it} is firm’s output, $CAPBIND_{it}$ is a dummy variable that is equal to 1 if capacity constraints are binding and equal to 0 otherwise, and $Q^S_{strat,t}$ is total electricity supply by the strategic firms and $\eta^D_{strat,t}$ is the elasticity of residual hourly demand function of the five strategic firms.

We use hourly firm-level data on output and marginal cost. As in Puller (2007), we focus on an hour of sustained peak demand from 5 to 6 p.m. (hour 18) each day, when inter-temporal adjustment constraints on the rate at which power plants can increase or decrease output are unlikely to bind. Following Borenstein *et al*. (2002), we calculate the hourly marginal cost of fossil-fuel electricity plants as the sum of marginal fuel, emission permit, and variable operating and maintenance costs.[39] We assume the marginal cost function to be constant up to the capacity of the generator. A firm's marginal cost of producing one more megawatt hour of electricity is defined as the marginal cost of the most expensive unit that it is operating and that has excess capacity.

Our measure of output is the total production by each firm's generating units as reported in the Continuous Emissions Monitoring System (CEMS), that contains data on the hourly operation status and power output of fossil-fuelled generation units in California. We use the California Power Exchange (PX) day-ahead electricity price, because 80%–90% of all transactions occurred in the PX. Prices vary by location when transmission constraints between the north and south bind.[40] Most firms own power plants in a single transmission zone, so we use a PX zonal price. Table A.4 in the technical appendix reports the summary statistics for all these variables.

We compute the value of the residual demand elasticity facing the five large suppliers evaluated at the hourly market clearing price, P_h, as described in Wolak (2003). We first compute the aggregate demand for electricity in the PX day-ahead energy market and subtract from that the total amount supplied at different prices in the neighborhood of the P_h by all market participants besides five strategic firms. As the resulting residual demand curve is a step function, computing the slope of the residual demand curve at the P_h involves some approximation. Wolak (2003) argues the approximation of the step function is reasonably accurate as there are large numbers of steps in the residual demand curve, particularly in the neighborhood of the market-clearing price. To compute the slope of the residual demand curve at the hourly market-clearing price, we find the closest price above P_h, such that the residual demand is less than the value at P_h. Following the notation in Wolak (2003), let $P_h(\text{low})$ be this price, and $DR_{strat,h}(P_h(\text{low}))$ be the associated value of the residual demand facing five strategic firms at $P_h(\text{low})$. Next, we find the closest price below P_h such that residual

[39] We do not observe the spot prices for natural gas for California hubs in 1998 and 1999, and use prices from Henry Hub instead. The difference between natural gas prices between these hubs before 2000 (for which we have the data available) was relatively small (see Woo et al., 2006, p. 2062, Fig. 2).

[40] An important implication of transmission congestions is that they cause the slope of residual demand to differ for firms in the north and south of California. Puller (2007) estimated his model based on a subsample of uncongested hours and found smaller conduct parameter estimates relative to full sample (though his qualitative conclusions did not change). Our choice of residual demand elasticities based on PX data (see below) captures the effect of transmission constraints.

demand is greater than the value at P_h. Let P_h(high) be this price, and $DR_{strat,h}(P_h(\text{high}))$ be the associated value of the residual demand facing five strategic firms at P_h(high). The elasticity of the residual demand curve facing five strategic firms *jointly* during hour h at price P_h is equal to the arc elasticity, computed as

$$\eta^{D}_{strat,h} = \frac{DR_{strat,h}\left(P_h(high)\right) - DR_{strat,h}\left(P_h(low)\right)}{P_h(high) - P_h(low)} \times \frac{P_h(high) + P_h(low)}{DR_{strat,h}\left(P_h(high)\right) + DR_{strat,h}\left(P_h(low)\right)}, \tag{14}$$

Following Wolak (2003) we set P_h(low) and P_h(high) equal to \$1 below and above P_h.[41] For comparison purposes we also replicate Puller's (2007) residual demand elasticity estimates to compute the expected value of the random conduct term. Puller (2007) computes residual demand elasticity as

$$\eta^{D}{}_{strat,t} = \hat{\beta}\, Q^{S}_{fringe,t} \big/ Q^{S}_{strat,t}\ , \tag{15}$$

where $Q^{S}{}_{fringe,t}$ is electric power supply by the competitive fringe, and $\hat{\beta} = \dfrac{P_t}{P_t^{'} Q^{S}_{fringe,t}}$ is the price elasticity of the fringe supply. We obtain the estimates of $\hat{\beta}$ from Puller (2007, Table 3, p. 83).

Figure A.2 in the technical appendix shows calculated price-cost margins. This figure is almost identical to Figure 1 in Puller (2007), and shows that margins vary considerably over sample period. They are also higher during the third and fourth quarters of each year, when total demand for electricity is high. Figure A.3 in the technical appendix shows variation across time of the residual demand elasticities based on California PX bidding data and from Puller (2007). While both series exhibit similar trend, the elasticities based on PX data are considerably higher (in absolute terms) and more volatile. We next analyze the extent to which higher margins resulted from less competitive pricing behavior rather than from less elastic demand.

4.2. Pricing Equation Estimates

[41] Wolak (2003) notes that this procedure does not guarantee that the difference between $DR_{strat,h}(P_h(high))$ and $DR_{strat,h}(P_h(low))$ is positive and therefore can produce zero values of $\eta^{D}{}_{strat,t}$. We used \$0.50, \$1, and \$5 to determine $P_h(low)$ and $P_h(high)$, and, similar to Wolak (2003), did not find noticeably different distributions of nonzero values of $\eta^{D}{}_{strat,t}$.

This section describes estimation results of pricing equation (5), which result in the first-stage parameter estimates. We consider different specifications, estimation methods, and time-periods. First, we estimate equation (5) using elasticities of residual demand, calculated based on PX data and based on Puller's (2007) estimates.

Second, we allow for output to be an endogenous variable as the error term ε_{it} in (5) could include marginal cost shocks that are observed by the utility.[42] To account for endogeneity of output we estimate equation (5) by the ordinary least squares (OLS), treating $P_t \cdot q_{it}/Q^S_{strat,t}$ (hereafter x_{it}) as exogenous variable, and by GMM using instruments for x_{it}. We use four instruments for x_{it}: the inverse of the day-ahead forecast of total electricity output, $1/FQ_t$, the dummy variable for binding capacity constraints, $CAPBIND_{it}$, the ratio of one week lagged output to current output, Q_{t-7}/Q_t , and firm´s generation capacity, k_{it}. The first two instruments are from Puller (2007).[43] We assume that the ratio of one week lagged output to current output is exogenous based on the standard argument in economic literature that unpredictable random variables do not affect realizations of firms' past planning decisions (Hall, 1988). We assume that firm´s generation capacity is orthogonal to the error term because it can be viewed as a quasi-fixed variable, independent of current levels of operation. We then perform Hansen's (1982) *J* test, *F*-test for weak instruments (Staiger and Stock, 1997) and Hausman's (1978) specification test to test for overidentifying restrictions, instruments' strength, and consistency of the OLS estimates.

Finally, we estimate equation (6) over two periods described in Puller (2007). The first period from July 1998 to April 1999 covers four strategic firms (AES, DST/Dynegy, Duke, and Reliant). The second period from May 1999 to November 2000 covers five strategic firms following Southern entry.[44]

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[42] Puller (2007) makes similar point.

[43] Puller (2007) adopts the day-ahead forecast of total electricity output, rather than it's inverse. We do not use the day-ahead forecast of total electricity output here as an instrument because it failed Hansen's (1982) *J* test. Notwithstanding this difference, the economic interpretation of using this instrument is the same as in Puller (2007).

[44] Puller (2007) also reports estimates for the period from June 2000 to November 2000, which covers the price run-up preceding collapse of California liberalized electricity market. We chose not report these estimates because though the incentives of some market participants changed during this period (Borenstein *et al*. 2008), the market structure itself was not fundamentally different.

Table 1a. Pricing equation estimates (July 1, 1998 - April 15, 1999)

Dependent variable: $(P\text{-}mc)_{it}$; No. of strategic firms: 4; Method: OLS and Two-step GMM [(a)]

		Elasticities based on Puller (2007)		Elasticities based on PX bids	
Explanatory variables	Coef.	OLS	GMM[(b)]	OLS	GMM[(b)]
$CAPBIND_{it}$	A	-4.98 (3.70)	10.74*** (4.21)	36.67*** (6.08)	8.11 (10.63)
$x_{it} = P_t\, q_{it} / \eta^{D}_{strat,t} Q^{S}_{strat,t}$	θ	1.42*** (0.07)	0.95*** (0.06)	0.125*** (0.04)	0.74*** (0.11)
Observations		864	864	864	864
Mean of the dependent variable		8.56	8.56	8.56	8.56
Standard error of residuals		13.14	14.18	20.28	28.34
Hausman test [(c)]			61.4***		41.64***
Hansen test [(c)]			4.48**		1.78
Test for weak instruments [(c)]			226.5***		32.6***

Notes:

[(a)] Standard errors robust to heteroskedasticity in parenthesis. *(**)(***) stands for statistically significance at 10%(5%)(1%).

[(b)] Instruments: $CAPBIND_{it}$, k_{it}, $1/FQ_t$, where FQ is day-ahead forecast of total (perfectly inelastic) demand and k_{it} is capacity.

[(c)] Both Hausman and Hansen tests follow a χ^2 distribution with 1 degree of freedom. The Hausman test is sometimes based in only one parameter in order to provide a positive value. The test for weak instruments follows F distribution with 2 and (obs-3) degrees of freedom.

Table 1b. Pricing equation estimates (April 16, 1999 – November 30, 2000)

Dependent variable: $(P\text{-}mc)_{it}$; No. of strategic firms: 5; Method: OLS and Two-step GMM [(a)]

		Elasticities based on Puller (2007)		Elasticities based on PX bids	
Explanatory variables	Coef.	OLS	GMM[(b)]	OLS	GMM[(b)]
$CAPBIND_{it}$	A	-5.16	30.01^{***}	76.591^{***}	50.39^{***}
		(4.19)	(6.69)	(10.78)	(13.19)
$x_{it} = P_t\, q_{it} / \eta_{Puller} Q^S_{strat,t}$	θ	1.363^{***}	0.80^{***}	0.065^{***}	1.05^{***}
		(0.059)	(0.034)	(0.021)	(0.123)
Observations		2300	2300	2300	2300
Mean of the dependent variable		18.43	18.43	18.43	18.43
Standard error of residuals		27.83	34.80	57.69	80.76
Hausman test [(c)]			20.51^{***}		66.28^{***}
Hansen test [(c)]			0.65		1.41
Test for weak instruments [(c)]			412.5^{***}		71.6^{***}

Notes:

[(a)] Standard errors robust to heteroskedasticity in parenthesis. *(**)(***) stands for statistically significance at 10%(5%)(1%).

[(b)] Instruments: $CAPBIND_{it}$, k_{it}, $Q(-7)/Q$, where Q(-7) is total demand lagged one week, and k_{it} is capacity.

[(c)] Both Hausman and Hansen tests follow a χ^2 distribution with 1 degree of freedom. The Hausman test is sometimes based in only one parameter in order to provide a positive value. Test for weak instruments follows F distribution with 2 and (obs-3) degrees of freedom.

Tables 1a and 1b summarize the specification, estimation and fit of the pricing equation (5) using different set of instruments and calculated elasticities of residual demand, over the periods analyzed in Puller (2007). All estimated values of the conduct parameter are statistically significant from zero. The results of Hansen's *J* test and *F*-test for weak instruments indicate that the chosen instruments are generally valid[45], whereas Hausman's (1978) specification test indicates that the OLS results are biased and inconsistent. The size of this OLS bias, (measured by the difference between OLS and GMM estimates) is large indicating a significant correlation between the term x_{it} and unobserved error term.

The columns 4 and 5 of Tables 1a and 1b shows the estimated coefficients for the pricing equation (5) using residual demand elasticities calculated based on PX data. The GMM estimates of the conduct parameter are quite similar to those obtained by Puller (2007). Compared to Puller's (2007) estimates (see columns 2 and 3 of Tables 1a and 1b), the estimated value of the conduct parameter is smaller over the period from July 1998 to April 1999 (0.74 vs. 0.95) and larger over the period May 1999 to November 2000 (1.05 vs. 0.80). However, in both cases it is not statistically different from Puller's (2007) estimate of 0.97.

4.3. Variance Decomposition

Once all parameters of the pricing equation (5) are estimated, we can get estimates of the parameters describing the structure of the two error components included in the composed random term ε_{it} (second-stage). Conditional on these parameter estimates, market power scores can be then estimated for *each* firm by decomposing the estimated residual into a noise component and a market-power component (third-stage).

Following the discussion in the section 3.2, to obtain the estimates of the parameters describing the structure of error components we first need to specify the distribution of the unobserved random conduct term. We must also impose both lower and upper theoretical bounds on the values of the random conduct term, i.e., $0 \leq \theta_{it} \leq 1/s_{it}$.

[45] Chosen Instruments fail Hansen's J test at 5% level of significance over the period from July 1998 - April 1999 using residual demand elasticities calculated based on Puller's (2007) estimates.

Table 2. Second-stage Parameter Estimates.[(a)]

	Elasticities based on Puller (2007)				Elasticities based on PX bids			
Component / Parameter	July, 1998 –April, 1999		April, 1998 –November, 2000		July, 1998 –April, 1999		April, 1998 -November, 2000	
Symmetric component, σ_v								
Intercept	1.14***	(0.07)	1.88***	(0.04)	2.27***	(0.03)	3.62***	(0.02)
FQ_t	-1.82***	(0.45)	-1.26***	(0.20)	3.78***	(0.16)	5.04***	(0.04)
$0.5 \cdot FQ_t^2$	11.7***	(2.81)	3.35***	(1.27)	3.28***	(0.87)	2.51***	(0.58)
D_{DST}	0.03	(0.07)	0.29***	(0.06)	0.01	(0.04)	0.05***	(0.02)
D_{Duke}	-0.18**	(0.07)	0.47***	(0.05)	-0.07*	(0.04)	-0.01	(0.02)
$D_{Reliant}$	0.10	(0.08)	0.05	(0.05)	0.01	(0.04)	0.02	(0.02)
$D_{Southern}$			-0.37***	(0.07)			-0.14***	(0.02)
$D_{tuesday}$	0.23	(0.15)	0.25**	(0.11)	-0.19	(0.16)	-0.96***	(0.08)
$D_{wednesday}$	0.74***	(0.10)	0.17	(0.20)	0.44***	(0.12)	-0.47***	(0.06)
$D_{thuersday}$	0.58***	(0.13)	0.22**	(0.11)	0.41***	(0.10)	-0.26***	(0.05)
D_{friday}	-0.23	(0.24)	-0.09	(0.12)	-0.40**	(0.20)	0.01	(0.04)
$D_{Saturday}$	0.32	(0.31)	0.07	(0.13)	-0.17	(0.20)	-0.51***	(0.05)
D_{Sunday}	0.19	(0.30)	0.16	(0.14)	-0.60***	(0.18)	-0.11**	(0.05)
Asymmetric component, σ_θ								
Intercept	0.78***	(0.13)	1.22***	(0.09)	0.86***	(0.31)	1.12***	(0.25)
s_{it}	-2.59***	(0.39)	-6.45***	(0.37)	-3.33***	(0.78)	-6.23***	(1.06)
D_{DST}	1.69***	(0.15)	-0.15**	(0.07)	1.06***	(0.33)	-0.49	(0.30)
D_{Duke}	0.43***	(0.15)	-0.08	(0.08)	0.61***	(0.30)		
$D_{Reliant}$	0.16	(0.10)	-0.04	(0.07)	0.12	(0.27)	-0.13	(0.24)
$D_{Southern}$			0.08	(0.07)			0.58***	(0.16)
s_{it-1}-s_{it-2}	0.17	(0.49)	-0.19	(0.45)	1.22	(1.29)	0.85	(1.12)
Mean log-likelihood	-3.24		-3.93		-3.77		-5.03	
Observations	864		2300		864		2300	

Note: [(a)] Standard errors in parenthesis. *(**)(***) stands for statistically significance at 10%(5%)(1%).

To achieve this objective, we consider the doubly truncated normal model introduced by Almanidis *et al.* (2011) that allows us to impose both theoretical restrictions.[46] For robustness grounds, several specifications of the doubly truncated normal model were estimated, corresponding to different levels of μ, i.e., the mean of the pre-truncated random term that, after truncation, yields θ_{it}. For all models, we examine the values of μ equal to 0, 1, and 2 because the value of the conduct parameter estimated in the first stage of our procedure is around one. We then estimate the model using maximum likelihood and choose the preferred level of truncation based on the lowest value of the Akaike information criterion (AIC) from estimated specifications. In the technical appendix, Table A.4, we show the results of the test to select the value of the mean of the pre-truncated normal distribution, μ. Table A.4 in the technical appendix shows that the preferred level of truncation is 0 across all specifications. This implies that the conduct random term can be modeled using the truncated half normal distribution that assumes zero modal value of θ_{it}.

Table 2 describes the parameter estimates of the doubly truncated normal model describing the structure of θ_{it} and v_{it} (i.e., σ_θ and σ_v) across different specifications, conditional on the first-stage estimated parameters. In all cases, the variance of asymmetric component (the conduct term) is lower than the variance of the symmetric component (traditional error term). This outcome indicates that both demand and cost random shocks, which are captured by the traditional error term, explains most of the overall variance of the composed error term, σ_ε.

In all models we reject the hypothesis of homoscedastic variation in both the noise term and the conduct term (see Table A.5 in the technical appendix). Many of the day-of-the-week dummy variables are statistically significant in most periods. As expected, variation in conduct decreases with firms' market shares, s_{it}. The coefficient of the target variable Δs_{it-1} is not significant at all in all periods and using elasticities based either on Puller or PX bids. This result is robust to the inclusion of other

[46] To measure the convenience of using double-bounded distributions in practice, in previous versions of the present paper we also estimated the traditional half-normal distribution, which only imposes the conduct term be positive. The market power scores for the half-normal distributions were, on average, much higher than the upper-bound indicated by the theory, indicating that the one-sided specifications, traditional in the stochastic frontier literature, should not be used in the present application, and theory-consistent double-bounded distributions need to be estimated.

alternative variables to capture the influence of the past behaviour on the present market conduct, such as week-differences and other lags of the first-differences of market shares. The coefficient of dummy for DST in the conduct term part of the model has a large positive and significant coefficient in the first period. This result and the fact that the average market share of DST in the first period is much less than the average market share of its rivals explain our subsequent finding that DST market power scores are much higher than those obtained for the other strategic firms.

4.4. Firm-specific market power scores

Based on the previous estimates, the third stage allows us to obtain firm-specific market power scores. Table 3 provides the arithmetic average scores of each firm obtained using ML estimates of doubly truncated normal model. For comparison purposes we also report the firm-specific estimates of Puller (2007).

Table 3 illustrates several interesting points that are worth mentioning. First, like in Puller (2007), the estimated firm-level values of the conduct parameter are closer to Cournot (θ_{it} =1) than to static collusion ($\theta_{it} =1/s_{it}$) across all specifications. A notable exception is DST, whose average market power score is much larger than the other averages during this period. Puller (2007, p.84) finds similar result and argues that from these high conduct parameter estimates may result from incomplete quantity data for some of Dynegy's small peaker units. Unlike Puller (2007), we do not find an increase in market power if we compare the average values in the first period with those obtained in the second, regardless of which residual demand elasticity measure we use.

Second, we find notable differences among utilities in terms of market power. This suggests that assuming a common conduct parameter for all firms is not appropriate. For instance, firms with smaller market shares (e.g., DST) have consistently higher market power scores, whereas firms with larger market share (e.g., Duke) have consistently lower market power scores, compared to other firms. These results seem to indicate that the traditional 1st-stage parameter estimate tends to overweight the market power of larger firms and underweight the market power of smaller firms.[47]

Table 3. Firm-Specific Conduct Parameter Estimates

Firm	Market Share (s_{it})		Elasticities based on Puller (2007)		Elasticities based on PX bids		Puller (2007)
	Mean	St. Dev.	Mean	St. Dev.	Mean	St. Dev.	
July 1, 1998 - April 15, 1999							
AES	0.28	0.15	0.92	0.53	0.83	0.45	0.99
DST	0.07	0.08	6.89	4.58	4.29	1.67	5.15
Duke	0.48	0.20	0.83	0.56	0.78	0.53	1.02
Reliant	0.19	0.10	1.30	0.74	1.17	0.49	1.48
Industry average			*2.49*		*1.77*		*2.16*
Industry average (excl. DST)			*1.02*		*0.93*		*1.16*
1st stage mean			*0.95*		*0.74*		*0.97*
April 16, 1999 – November 30, 2000							
AES	0.17	0.09	1.02	0.70	0.94	0.48	0.82
DST	0.12	0.05	1.11	0.65	0.72	0.20	1.75
Duke	0.31	0.12	0.48	0.53	0.47	0.41	0.81
Reliant	0.20	0.07	0.76	0.47	0.66	0.27	1.01
Southern	0.20	0.08	0.93	0.54	1.38	0.66	1.21
Industry average			*0.86*		*0.83*		*1.12*
1st stage mean			*0.80*		*1.05*		*0.97*

Third, as illustrated in the technical appendix, Figure A.4, our approach based on the estimated distribution of the random conduct yields similar firm-specific market power scores to those of Puller (2007) using a fixed-effect approach. This result demonstrates that both approaches are, in practice, equivalent or interchangeable. Our procedure has the advantage over Puller's approach that it can be applied with cross-sectional data sets; when the time dimension of the data set is short; or when the available instruments are valid to estimate a common pricing equation to all

[47] Interesting enough, the average industry score for the first period (July 1, 1998 - April 15, 1999) are much larger than the 1st-stage common conduct parameter in all models. If we exclude DST in all models, the averages are again similar. This also happens in Puller (2007). This suggests that the common parameter is *not* the simple average of individual conduct parameters. For this reason, we have not imposed this condition when estimating the structure of the error term in the second stage of our procedure.

observations (see Hansen tests in Tables 1a and 1b), but they are not valid when a separable pricing equation is estimated for each firm.

In a panel data setting the most important advantage of our methodology is that we can analyze changes in market conduct over time. Because our approach does not impose the restrictions on the temporal path of these scores they are allowed to change from one day to another. In Figures 1a-1b, and 2a-2b we show the temporal evolution of the average market power scores of the four/five strategic firms during the periods analyzed in the present paper.[48] Our results indicate that the estimated firm-specific conduct parameters do vary significantly across time. Notwithstanding these differences, firm-specific conduct parameters generally tend to move in the same direction across time. This result indicates that firms tend to pursue similar market strategies across time, and is consistent with the implied equilibrium behaviour of repeated dynamic games in homogenous product market setting. The notable exception is Duke, whose market strategies are occasionally different from other firms. Puller (2007) notes that there is a widespread belief that Duke violated California electricity market rules and forward-contracted some of its production, which in part explains observed Duke's behaviour.

Figures 1a and 1b show the intertemporal variation in estimated conduct parameters over the period from July 1, 1998 to April 15, 1999. Both figures show that during this period firms electricity pricing were at (or slightly above) Cournot levels. The most notable exception is DST/Dynegy, whose conduct was well above Cournot level during summer 1998 and close to full collusion in winter 1998/1999. As explained above, high estimates of the conduct parameter for DST during these periods may reflect the bias from incomplete generation asset data for this firm. Another notable observation is rapid increase in the conduct term for Reliant and DST in winter 1998/1999.

[48] To smooth the variation across time, we report the monthly moving averages of the estimated conduct parameter.

Figure 1a. Firm-Specific Conduct Parameter Estimates (Monthly Averages over July 1, 1998 – April 15, 1999, Elasticities based on Puller 2007)

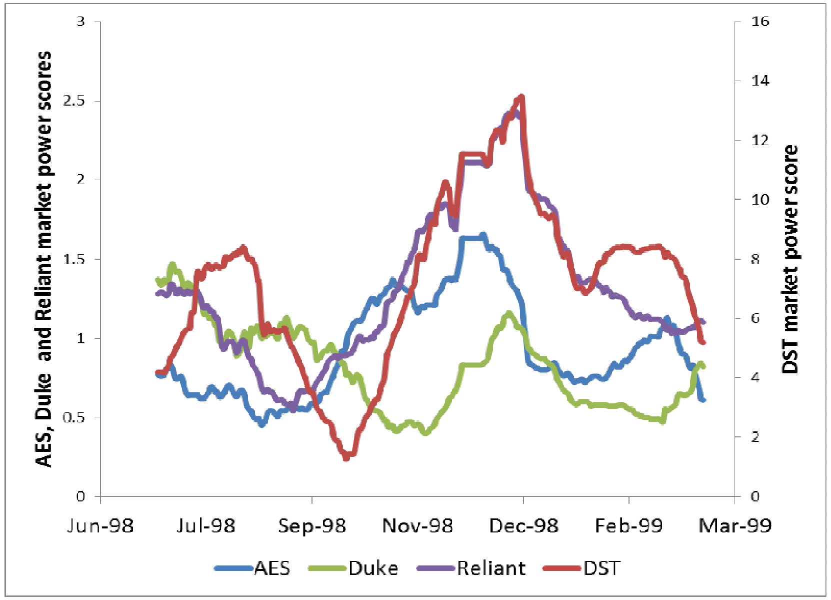


Figure 1b. Firm-Specific Conduct Parameter Estimates (Monthly Averages over July 1, 1998 – April 15, 1999, Elasticities based on PX Data)

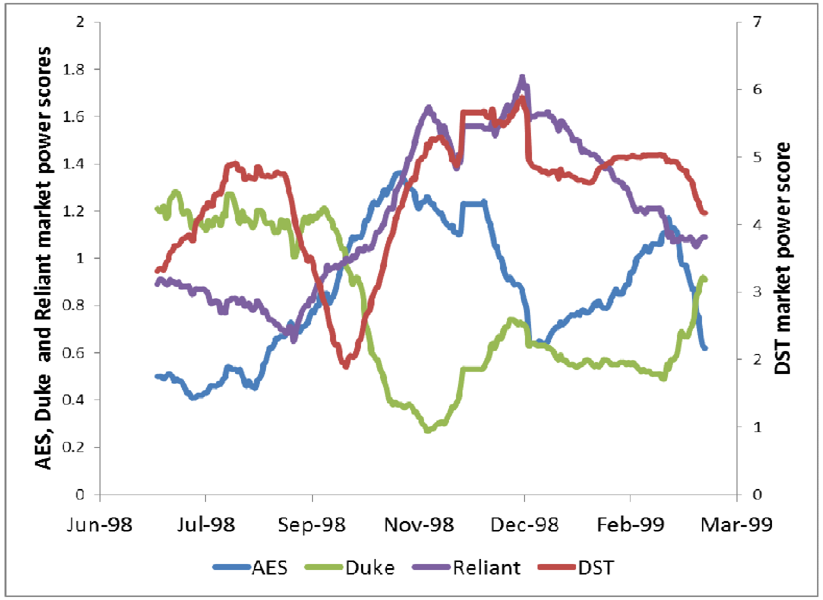


Figure 2a. Firm-Specific Conduct Parameter Estimates (Monthly Averages over April 16, 1999 – May 30, 2000, Elasticities based on Puller 2007)

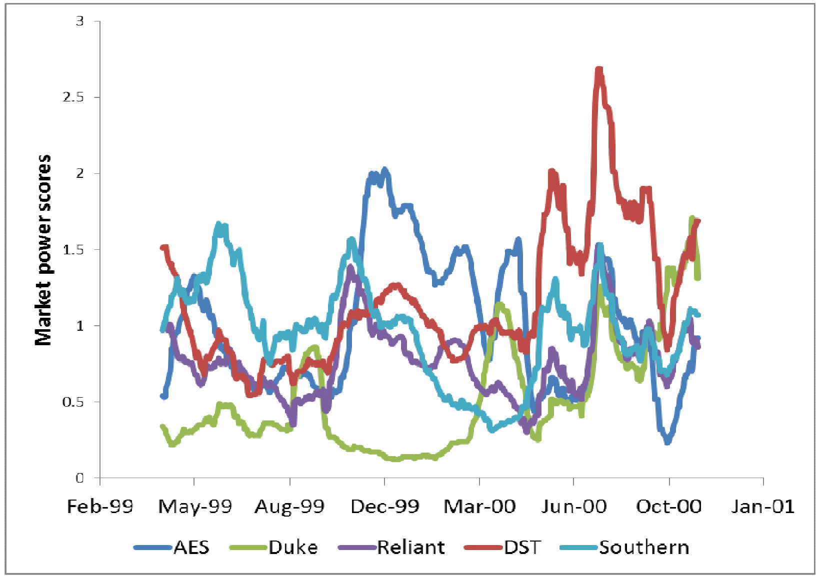
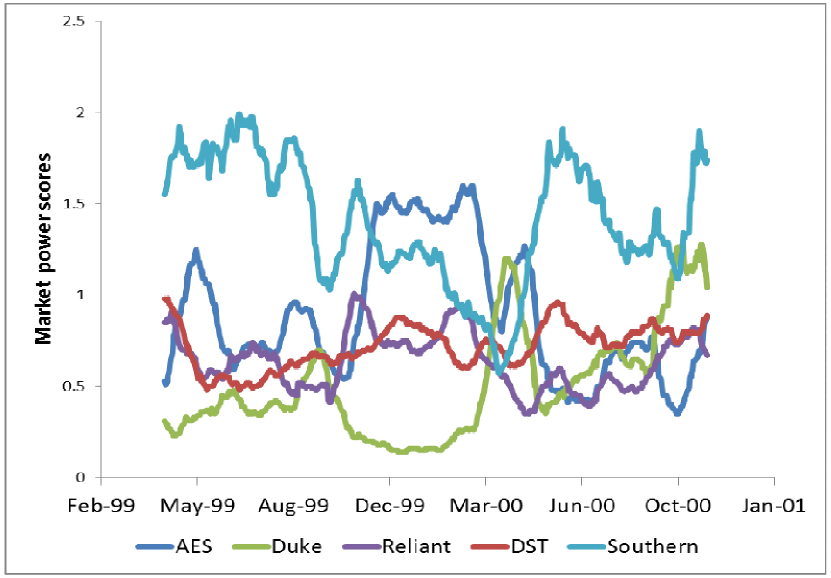


Figure 2b. Firm-Specific Conduct Parameter Estimates (Monthly Averages over April 16, 1999 – May 30, 2000, Elasticities based on PX Data)



Figures 2a and 2b show the intertemporal variation in estimated conduct parameters over the period from April 16, 1999 to May 30, 2000 following the entry of Southern. Both figures demonstrate that firms' pricing strategies are still close to Cournot levels for most of this period. On average, over this period, the new entrant Southern tends to have a higher value of the estimated conduct parameter, whereas Duke tends to have a lower value of the estimated conduct parameter.

Firms' pricing strategies exhibit a larger variation during this period. For example, the market conduct of Southern increases above Cournot levels in summer 1999, and the market conduct of Southern, Reliant, and AES increases above Cournot levels in summer 1999. There is also a difference in the inferred firms' conduct for the results using the residual demand elasticities based on Puller (2007) and the residual demand elasticities based on PX bid data. The results using the residual demand elasticities based on Puller (2007) show that the conduct parameter of all firms (and most notably, DST) increases above Cournot levels during the notorious price run-up period of summer 2000. On the contrary, the results using the residual demand elasticities based on PX bid data show that pricing strategies of all firms, except for Southern, are at Cournot levels. As regards Southern, though pricing strategy is above Cournot levels, it is not different from its strategy in summer 1999. These results indicate that correctly specified residual demand elasticities are critical to understanding market conduct.

4.5. Unilateral vs. Coordinated Market Power

Wolak (2003) used the actual bids submitted to the California Independent System Operator's real-time energy market, and demonstrated that residual demand curves facing five largest electric power suppliers were steep enough so that it was "unilaterally expected-profit-maximizing for each firm to bid to raise prices significantly in excess of the marginal cost of their highest-cost unit operating."[49] Based on that finding, Wolak (2003) argued that the potential for exercising market power unilaterally "made collusive behavior on the part of suppliers to the California market unnecessary to explain the enormous increase in market power exercised starting in

[49] Wolak (2003, p.430)

June 2000,"[50] although these considerations cannot rule out the possibility that collusive behavior took place.

We use the results of the analysis carried out in this paper to clarify the extent to which firms' potential for exercising market power unilaterally affects their market conduct. In doing so, we follow Wolak (2003) and apply equation (15) to compute the residual demand elasticities facing each firm *individually* on the California PX market, and use their reciprocals (Lerner indices) as a measure of the firms' potential to exercise unilateral market power.[51] We then compare estimated firms' conduct parameters to calculated Lerner indices[52] to deduct whether firms' conduct is correlated with higher potential for exercising of unilateral market power.

Figures 3a and 3b show the variation of calculated Lerner indices across time over the periods from July 1, 1998 to April 15, 1999 (preceding entry of Southern), and from April 16, 1999 to November 30, 2000. For most of the sample period their values fluctuate between 0.05 and 0.15, and are close to the averages reported in Wolak (2003, Table 1). However, for some periods, such as summers of 1998, 1999, and 2000, and the winters of 1998 and 1999 the values of calculated Lerner indices exceed 0.2, indicating substantial potential for the unilateral exercise of market power.

We then examine the relationship between firms' abilities to exercise unilateral market power, measured by Lerner index, and engage in collusive practices, measured by the conduct parameter. Figures 4a and 4b show the variation of both unilateral and coordinated market power across time over the periods from July 1, 1998 to April 15, 1999, and from April 16, 1999 to November 30, 2000. The shaded areas in these figures

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[50] Ibid.

[51] It is important to point out that because suppliers had the opportunity to sell their capacity in the CAISO ancillary services markets and the real-time energy market, the calculated Lerner indices are not the actual measure of the unilateral market power, unlike in Wolak (2003). Rather, we use this measure as a (maximum) potential for the unilateral exercise of the market power. However, given that PX market accounted for 85% of all electricity delivered in the CAISO control area, whereas CAISO's real time market accounted for just 5% (Borenstein *et al.* 2002), the ancillary services market was very small, and there was no substantial divergence between PX and ISO market clearing prices for the most of the time covered in this study (Borenstein et al. 2008) we believe our measure provides a reasonable approximation for the exercise of the unilateral market power.

[52] Wolak (2003, p.426) points out that regardless of the residual-demand realization, the following equation holds for each hour of the day, h, and each supplier, $j{:}(P_h-MC_{jh})/P_h=-1/\varepsilon_{hj}$ where where P_h is the market price in hour h, MC_{jh} is the marginal cost of the highest cost produced by firm j in hour h, and ε_{hj} is elasticity of the residual demand curve facing firm j during hour h evaluated at P_h. Following Wolak (2003) we define the Lerner index for firm j in hour h as. $\mathrm{L}_{hj}=-1/\varepsilon_{hj}$.

Figure 3a. Firm-Specific Lerner Indices
(Monthly Averages over July 1, 1998 – April 15, 1999,
Elasticities based on PX data)

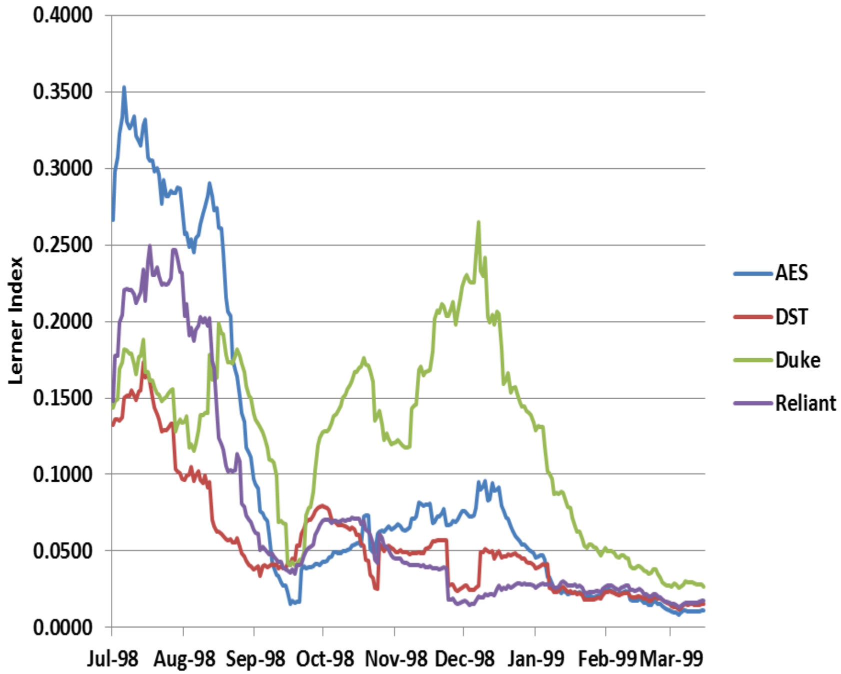


Figure 3b. Firm-Specific Lerner Indices
(Monthly Averages over April 16, 1999 – November 30, 2000,
Elasticities based on PX data)

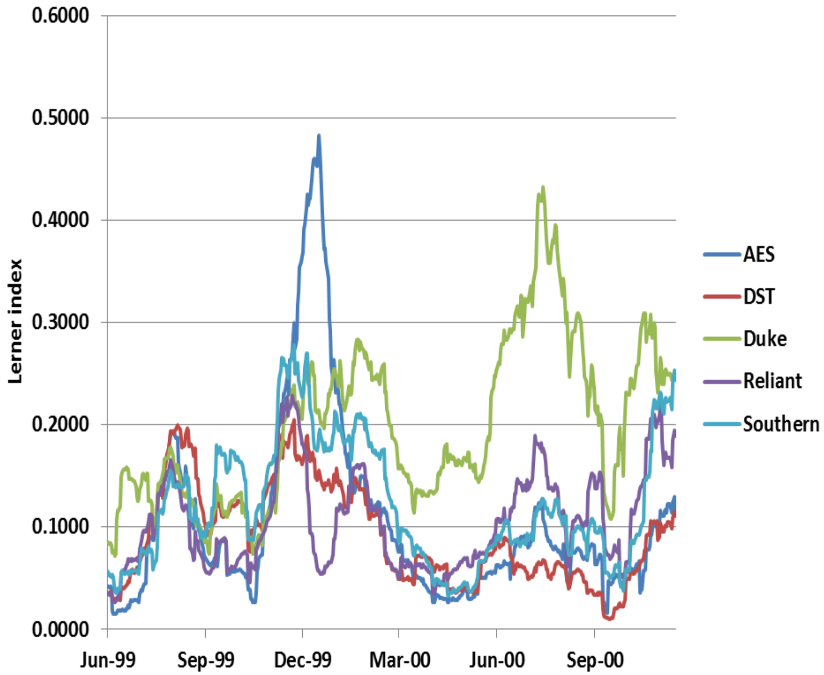
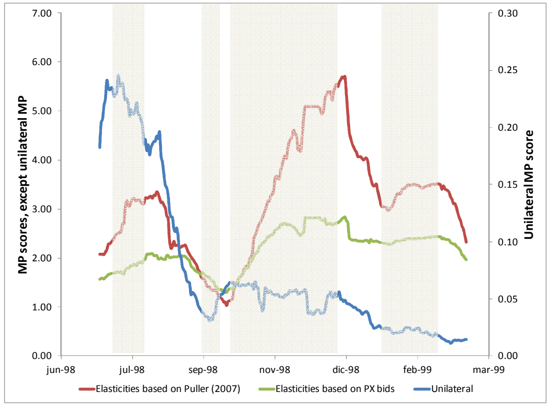


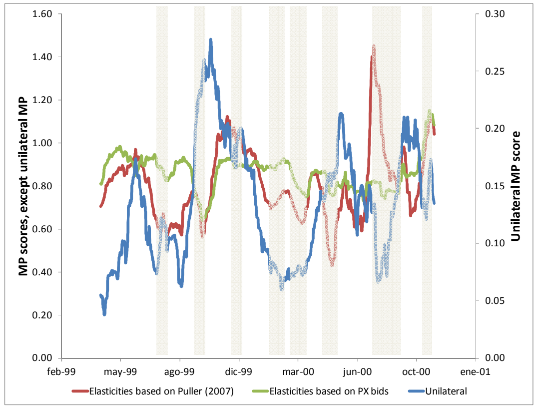
Figure 4a. Unilateral vs. coordinated conduct scores
(Monthly Averages over July 1, 1998 – April 15, 1999)

Figure 4b. Unilateral vs. coordinated conduct scores
(Monthly Averages over April 16, 1999 – November 30, 2000)

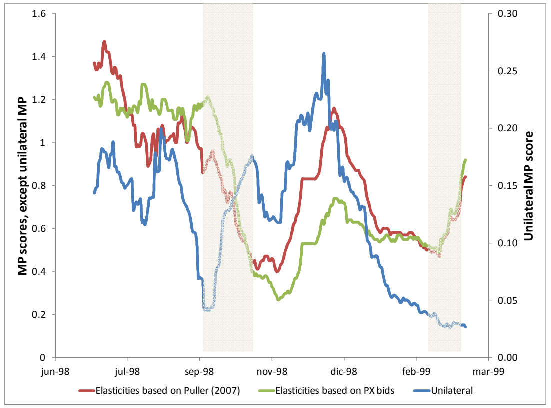
Industry Average (exc. Duke)



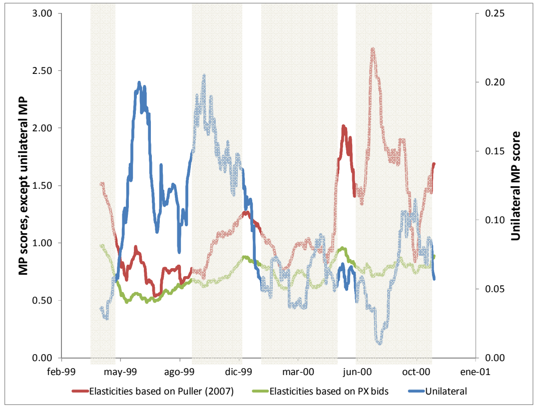
Industry Average (exc. DST)



Duke



DST



indicate that both sources of market power roughly move in opposite directions, and hence the non-shaded areas indicate co-movements of unilateral and coordinated market power scores. Figures A.5 and A.6 in the technical appendix show firm-level correlations between calculated Lerner indices and estimated conduct parameters over two periods covered in this study. Figure 4a demonstrates that, with the exception of Duke, unilateral and coordinated market power scores move in opposite directions most of the period between July 1, 1998 and April 15, 1999. This is confirmed by Figure A.5 in the appendix where a strong negative correlation has found between Lerner indices and conduct parameters for all firms but Duke over the period between July 1, 1998 and April 15, 1999. This finding implies that firms were more likely to engage in collusive practices when their potential for unilateral market power was limited.

Figure 4b shows a slight change in firms' conduct after the entry of Southern. With the exception of DST where both unilateral and coordinated market power scores clearly move in opposite directions during most of the period between April 16, 1999 and November 30, 2000, there are not a clear relationship between both sources of market power. This is confirmed by Figure A.6 that shows a strong negative correlation between Lerner indices and conduct parameters for only two firms out five – DST and Reliant (R^2 is 0.24 and 0.08 respectively) over the period between April 16, 1999 and November 30, 2000. For other three firms, such correlation is weak or does not exist. This result indicates that firms' market conduct is not necessarily affected by its potential to exercise unilateral market power.

5. Conclusions

This study contributes to the literature on estimating market power in homogenous product markets. Our econometric approach allows for the value of estimated conduct parameter to vary across *both* firms and time. We estimate a composed error model, where the stochastic part of the firm's pricing equation is formed by two random variables: the traditional error term, capturing random shocks, and a random conduct term, which measures the degree of market power. Treating firms' behaviour as a random parameter helps solving the over-parameterization problem in the continuous time. Other advantages of our approach are its applicability to cross-sectional or short data sets, and to cases in which individual pricing equations cannot be consistently estimated with the available instruments. In addition, by imposing upper bound on the value of estimated conduct parameter we ensure that estimated market power scores are always consistent with the economic theory.

The model can be estimated in three stages using either cross-sectional or panel data sets. While the first stage of our model is the same as in the previous literature, the second and the third stages allow us to distinguish variation in market power from volatility in demand and cost, and get firm-specific market power scores, conditional on the first-stage parameter estimates. Model identification is based on the assumption that the conduct term is asymmetrically distributed, which, to our best knowledge, has not been previously used in the empirical industrial organization literature.

We illustrate the proposed approach with an application to the California wholesale electricity market using a well-known dataset from Puller (2007). We supplement the dataset with a different, and more accurate measure of the elasticity of residual hourly demand function of the five strategic firms, calculated based on California Power Exchange bidding data. After estimating the parameters of the pricing equation, we implement the second and third stages based on the truncated normal distributions, which imposes both lower and upper theoretical bounds on the values of the random conduct term.

Our first-stage results based on the estimated distribution of the random conduct are generally similar to previous findings of Puller (2007) using a fixed-effect approach. This result demonstrates that both approaches are, in practice, equivalent or interchangeable for estimating firms' pricing equation. However, our approach yields more reasonable market power scores than a fixed-effect treatment as estimated market power scores are always consistent with the economic theory.

Similar to Puller (2007) our average conduct parameter estimates are closer to Cournot than to static collusion. We find an increase in collusive behavior of all firms above Cournot levels during the period of price run-up in June – November 2000, using the residual demand elasticities based on Puller (2007) but not using the residual demand elasticities based on PX data. The analysis of firm-specific conduct parameters suggests that realization of market power varies significantly over *both* time and firms.

We find strong negative correlation between Lerner indices and estimated conduct parameters for 3 out of 4 firms during the first period of our sample (before entry of Southern) and for 2 out of 5 firms during the second period of our sample. This result indicates that, for some firms the potential for realization of the market power unilaterally is associated with lower values of the conduct parameter.

References

Abreu, D. Pearce, D and Stacchetti, E. (1986), “Optimal Cartel Equilibria with Imperfect Monitoring”, *Journal of Economic Theory*, 39, 251-269.

Álvarez, A., Amsler, C., Orea, L., and Schmidt, P. (2006), "Interpreting and Testing the Scaling Property in Models where Inefficiency Depends on Firm Characteristics", *Journal of Productivity Analysis*, 25, 201-212. Bounded Stochastic Frontiers with an Application to the US Banking Industry: 1984-2009

Almanidis, P, J. Qian, and R. Sickles (2011), “Bounded Stochastic Frontiers with an Application to the US Banking Industry: 1984-2009”, Working Paper, Rice University.

Appelbaum, E., (1982), “The Estimation of the Degree of Oligopoly Power,” *Journal of Econometrics*, 19, 287-299.

Battese, G.E. and T.J. Coelli (1995), “A Model for Technical Efficiency for Panel Data”, *Empirical Economics*, 20, 325-332.

Borenstein, S. (2002), “The Trouble with Electricity Markets: Understanding California’s Restructuring Disaster”, *Journal of Economic Perspectives*, 16(1), 191–211.

Borenstein, S., J.B. Bushnell, and F.A. Wolak, (2002), “Measuring Market Inefficiencies in California’s Restructured Wholesale Electricity Market”, *American Economic Review*, 92, 1376-1405.

Borenstein, S., J. B. Bushnell, C. R. Knittel, and C. Wolfram, (2008), "Inefficiencies and Market Power in Financial Arbitrage: A Study of California's Electricity Markets", *Journal of Industrial Economics*, 56(2), 347-378.

Borenstein, S., and N.L. Rose (1994), "Competition and Price Dispersion in the US Airline Industry", *Journal of Political Economy*, 102,653-683.

Borenstein, S. and A. Shepard (1996), "Dynamic Pricing in Retail Gasoline Markets", *The RAND Journal of Economics*, 27, 429-451.

Brander, A. J. and A. Zhang, (1993), "Dynamic Oligopoly Behavior in the Airline Industry", *International Journal of Industrial Organization*, 11, 407-435.

Bresnahan, T. (1989), "Empirical Studies of Industries with Market Power", in Schmalensee, R. and Willig, R. (eds), *Handbook of Industrial Organization*, Vol. 2, chapter 17, 1011-1057.

Bushnell, J. B., and F. A.Wolak, (1999), "Regulation and the Leverage of Local Market Power: Reliability Must-Run Contracts in the California Electricity Market", POWER working paper no. PWP-070, University of California Energy Institute.

California Public Utilities Commission, (2002), *Executive Summary - Wholesale Generator Investigative Report*. September 2002. Accessed online at http://www.hks.harvard.edu/hepg/Papers/CPUC_Wholesale.Gnerator.Investigation.Report_9-02.pdf

Chamberlain, G.C. (1980), "Analysis of Covariance with Qualitative Data", *Review of Economics Studies*, 47, 225-238.

Clay, K., and W. Troesken (2003), "Further Tests of Static Oligopoly Models: Whiskey, 1882–1898", *Journal of Industrial Economics*, 51(2), 151–166.

Corts, K. (1999), "Conduct Parameters and the Measurement of Market Power," *Journal of Econometrics*, 88, 227-250.

Ellison, G. (1994) "Theories of Cartel Stability and the Joint Executive Committee", *Rand Journal of Economics*, 25(1), 37-57.

Emvalomatis, G., S.E. Stefanou and A.O. Lansink (2011), "A Reduced-Form Model for Dynamic Efficiency Measurement: Application to Dairy Farms in Germany and the Netherlands," *American Journal of Agricultural Economics* 93 (1), 161-174.

Fabra, N., and J. Toro, (2005), "Price Wars and Collusion in the Spanish Electricity Market," *International Journal of Industrial Organization*, 23 (3-4), 155-181.

Figuieres, C., A. Jean-Marie, N. Querou, and M. Tidball, (2004), *Theory of Conjectural Variations*, World Scientific Publishing.

Fried, H., C. A. Knox Lovell, and Shelton S. Schmidt (2008), *The Measurement of Productive Efficiency and Productivity Growth*, Oxford University Press.

Gallet, A.G. and John R. Schroeter, (1995), "The Effects of the Business Cycle on Oligopoly Coordination: Evidence from the U.S. Rayon Industry", *Review of Industrial Organization*, 181-196.

Gollop, D., and Roberts, M., (1979), "Firm Interdependence in Oligopolistic Markets," *Journal of Econometrics*, 10, 313-331.

Genesove, D. and W. Mullin, (1994), "Testing Static Oligopoly Models: Conduct and Cost in the Sugar Industry, 1890–1914", *Rand Journal of Economics*, 29(2), 355–377.

Green, E.J., Porter, R.H. (1984), "Noncooperative Collusion under Imperfect Price Information", *Econometrica*, 52, 87-100.

Hall, R.E. (1988), "Intertemporal Substitution in Consumption," *The Journal of Political Economy*, 96(2), 339–57.

Hamilton, J.D. (1989), "Analysis of Time Series Subject to Changes in Regime," *Journal of Econometrics*, 45 (1–2), 39–70.

Han, C., L. Orea, and P. Schmidt (2005),"Estimation of a Panel Data Model with Parametric Temporal Variation in Individual Effects", *Journal of Econometrics*, 126, 241-267.

Hansen, L.P. (1982), "Large Sample Properties of Generalized Method of Moments Estimators", *Econometrica*, 50, 1029-1054.

Hausman, J. A. (1978), ''Specification Tests in Econometrics'', *Econometrica* 46, 1251–1271.

Huang, C.J., and J.T. Liu (1994),"Estimation of Non-neutral Stochastic Frontier production Function", *Journal of Productivity Analysis*, 5(2), 171-180.

Itaya, J.-I., and M. Okamura (2003), "Conjectural Variations and Voluntary Public Good Provision in a Repeated Game Setting. *Journal of Public Economic Theory*, 5(1), 51-66.

Itaya J.-I., and K. Shimomura (2001) "A Dynamic Conjectural Variations Model in the Private Provision of Public Goods: a Differential Game Approach." *Journal of Public Economics*, 81, 153-172.

Iwata, G. (1974), "Measurement of Conjectural Variations in Oligopoly," *Econometrica* 42, 949-966.

Jaumandreu, J., and J. Lorences (2002), "Modelling Price Competition across Many Markets (An Application to the Spanish Loans Market)," *European Economic Review*, 46, 93-115.

Jondrow, J., C.A.K. Lovell, S. Materov, and P. Schmidt (1982), "On the Estimation of Technical Efficiency in the Stochastic Frontier Production Function Model", *Journal of Econometrics*, 19(2/3), 233-238.

Joskow, P.L., and E.Kahn (2002), "A Quantitative Analysis of Pricing Behavior In California's Wholesale Electricity Market During Summer 2000", *Energy Journal*, 23, 1-35.

Kim, D. (2006), "Measuring Market Power in a Dynamic Oligopoly Model: The Dallas-Forth Worth Milk Market Case", *Economic Development & Policy Series* EDP06-4, GSIR Working Papers.

Kim, D.W., and C.R. Knittel (2006), "Biased in Static Oligopoly Models? Evidence from the California Electricity Market", *Journal of Industrial Economics*, Volume 54, No. 4, p. 451-470.

Kole, S., and K. Lehn (1999), "Deregulation and the Adaptation of Governance Structure: the Case of the U.S. Airline Industry", *Journal of Financial Economics*, 52, 79-117.

Kumbhakar, S.C., and Lovell, C.A.K. (2000), *Stochastic Frontier Analysis*. Cambridge University Press.

Nevo, A. (2001): “Measuring Market Power in the Ready-to-Eat Cereal Industry", *Econometrica*, 69(2), 307-342.

Olson, J.A., P. Schmidt, and D.M. Waldman (1980), “A Monte Carlo Study of Estimators of Stochastic Frontier Production Functions”, *Journal of Econometrics*, 13(1), 67-82.

Perloff, J.M., L. Karp, and A. Golan (2007), *Estimating Market Power and Strategies*, Cambridge University Press.

Porter, R.H. (1983a). “A Study of Cartel Stability: The Joint Executive Committee, 1880–1886”, *Bell Journal of Economics* 14(2), 301–314.

Porter, R.H. (1983b), "Optimal Cartel Trigger Price Strategies." *Journal of Economic Theory*, 29, 313-338.

Puller, S. (2009), “Estimation of Competitive Conduct when Firms are Efficiently Colluding: Addressing the Corts Critique” *Applied Economics Letters*, 16 (15), 1497-1500.

Puller, S. (2007), “Pricing and Firm Conduct in California’s Deregulated Electricity Market”, *Review of Economics and Statistics*, 89 (1),75-87.

Reiss, P.C. and F.A. Wolak (2007), “Structural Econometric Modeling: Rationales and Examples from Industrial Organization”, *Handbook of Econometrics*, Volume 6, Elsevier B.V., p. 4280-4370.

Rigobon, R. (2003) “Identification through Heteroskedasticity”, *Review of Economics and Statistics*, 85(4), 777—792.

Rotemberg, J.J., Saloner, G. A (1986), “Supergame-Theoretic Model of Price Wars During Booms”, *American Economic Review*, 76, 390-407.

Simar, L., CAK Lovell, and P. Vanden-Eeckaut (1994), “Stochastic Frontiers Incorporating Exogenous Influences on Efficiency”, Discussion Paper Nº 9403, Institut de Statistique, Université Catholique de Louvain, Louvain-la-Neuve, Belgium.

Staiger, D., and J. H. Stock (1997), ‘‘Instrumental Variables Regression with Weak Instruments’’, *Econometrica*, 65, 557–586.

Stigler, G.J. (1964), “A Theory of Oligopoly”, *Journal of Political Economy*, 72, 44-61.

Verbeek, M. (2000), *A Guide to Modern Econometrics*, John Wiley and Sons, First edition.

Wang, H.J. and P. Schmidt (2002), “One-Step and Two-Step Estimation of the Effects of Exogenous Variables on Technical Efficiency Levels,” *Journal of Productivity Analysis*, 18, 129-144.

Wang, W.S. and P. Schmidt (2009), “On the Distribution of Estimated Technical Efficiency in Stochastic Frontier Models”, *Journal of Econometrics*, 148, 36-45.

Wolak, F.A. (2003), “Measuring Unilateral Market Power in Wholesale Electricity Markets: The California Market, 1998–2000”, *American Economic Review* 93, 425–430.

Wolak, F.A. (2005), “Lessons from the California Electricity Crisis”, in J.M. Griffin and S.L. Puller (eds.) *Electricity Deregulation Choices and Challenges*, University of Chicago Press.

Woo, C.K., A. Olson, I. Horowitzc, and S. Lu (2006), “Bi-directional Causality in California’s Electricity and Natural-gas Markets”, Energy Policy 34, 2060–207.

Technical Appendix

Table A.1. Double-bounded density functions (0≤u≤B)

Model	Density function of $f(\varepsilon = \upsilon + u)$
Doubly truncated normal	$\left[\Phi\left(\frac{B-\mu}{\sigma_v}\right)-\Phi\left(\frac{-\mu}{\sigma_v}\right)\right]^{-1}\cdot\frac{1}{\sigma}\phi\left(\frac{-\varepsilon+\mu}{\sigma}\right)\cdot$ $\left[\Phi\left(\frac{(B-\varepsilon)\lambda}{\sigma}+\frac{(B-\mu)}{\sigma\lambda}\right)-\Phi\left(-\frac{\varepsilon\lambda}{\sigma}-\frac{\mu}{\sigma\lambda}\right)\right]$ $\sigma=\sqrt{\sigma_v^2+\sigma_u^2} \quad \lambda=\sigma_v/\sigma_u$

Source: Almanidis *et al.* (2011)

Table A.2. Conditional means for selected distributions

Model	Functional form of $E(u \mid \upsilon + u)$
Doubly truncated normal	$\mu_*+\sigma_*\left[\varphi\left(\frac{-\mu_*}{\sigma_*}\right)-\varphi\left(\frac{B-\mu_*}{\sigma_*}\right)\right]\left[\Phi\left(\frac{B-\mu_*}{\sigma_*}\right)-\Phi\left(\frac{-\mu_*}{\sigma_*}\right)\right]^{-1}$ $\mu_*=\frac{\mu\sigma_v^2+\varepsilon\sigma_u^2}{\sigma^2} \quad , \quad \sigma_*=\frac{\sigma_u\sigma_v}{\sigma}$

Source: Almanidis *et al.* (2011)

Table A. 3. Summary statistics (hour 18)

	Mean	St.dev.	Min	Max	Obs
July 1, 1998 - April 15, 1999					
Price (P_t)	35.2	21.0	4.9	180.4	864
Marginal cost (mc_{it})	26.6	3.1	19.5	33.7	864
Margin (P_t -mc_{it})	8.6	21.0	-25.0	158.6	864
$CAPBIND_{it}$	0.05	0.22	0.00	1.00	864
Capacity (k_{it})	2463	1054	670	3879	864
Output (q_{it})	813	844	0	3720	864
Market demand (Q_t)	30395	4146	20057	43847	864
Elasticities based on PX bids	6.91	6.36	0.05	24.65	864
Elasticities based on Puller (2007)	2.12	1.33	0.56	10.77	864
April 16, 1999 – November 30, 2000					
Price (P_t)	61.2	68.4	9.5	750.0	2300
Marginal cost (mc_{it})	42.7	22.9	22.3	214.5	2300
Margin (P_t -mc_{it})	18.4	57.3	-33.4	697.1	2300
$CAPBIND_{it}$	0.05	0.21	0.00	1.00	2300
Capacity (k_{it})	2955	769	1020	3879	2300
Output (q_{it})	1223	793	0	3317	2300
Market demand (Q_t)	30604	3658	22076	42404	2300
Elasticities based on PX bids	4.02	4.35	0.01	24.89	2300
Elasticities based on Puller (2007)	1.02	0.68	0.35	5.26	2300

Table A.4. Selection of Pre-truncated Mean

	Elasticities based on Puller (2007)		Elasticities based on PX bids	
Null Hypothesis	Average log-likelihood	AIC	Average log-likelihood	AIC
July 1, 1998 - April 15, 1999				
μ=0	**-3.24**	**5601.4**	**-3.77**	**6517.4**
μ=1	-3.30	5702.5	-3.80	6565.4
μ=2	-3.37	5829.0	-3.83	6610.1
Obs.	864		864	
April 16, 1999 – November 30, 2000				
μ=0	**-3.93**	**18092.3**	**-5.03**	**23135.8**
μ=1	-4.09	18833.8	-5.06	23284.6
μ=2	-4.42	20319.6	-5.08	23396.4
Obs.	2300		2300	

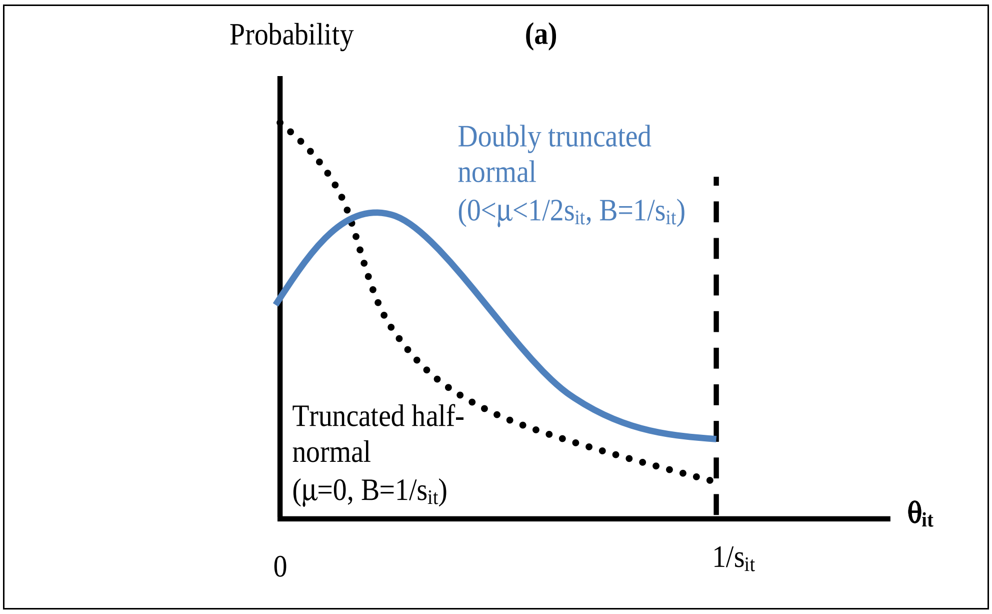
Note: AIC: Akaike Information Criterion; Obs.: number of observations. The values, which correspond to the minimal value of AIC are shown in **bold.**

Table A.5. Likelihood Ratio Tests for Heteroscedasticity in Composed Error Term

	Elasticities based on Puller (2007)		**Elasticities based on PX bids**	
Null Hypothesis	Average log-likelihood	LR Test, χ^2	Average log-likelihood	LR test, χ^2
July 1, 1998 - April 15, 1999				
$\upsilon_1=\upsilon_2=0$, $\zeta_2=\zeta_3=\zeta_4=0$	-3.42	306.9^{***} (5)	-3.79	88.4^{***} (5)
$\tau_1=\tau_2=0$, $\delta_2=\delta_3=\delta_4=0$ $\pi_2=\pi_3=\pi_4=\pi_5=\pi_6=\pi_7=0$	-3.49	117.5^{***} (11)	-4.16	1710.3^{***} (11)
Unrestricted model	-3.24		-3.77	
April 16, 1999 – November 30, 2000				
$\upsilon_1=\upsilon_2=0$, $\zeta_2=\zeta_3=\zeta_4=\zeta_5=0$	-4.04	197.1^{***} (6)	-5.04	59.11^{***} (5)
$\tau_1=\tau_2=0$; $\delta_2=\delta_3=\delta_4=\delta_5=0$ $\pi_2=\pi_3=\pi_4=\pi_5=\pi_6=\pi_7=0$	-4.09	78.3^{***} (12)	-5.47	1948.1^{***} (12)
Unrestricted model	-3.93		-5.03	

Notes: Tests are based on equations (11) and (12). (***) indicate that the null hypothesis is rejected at 1% level; degrees of freedom in parentheses.

Figure A.1. Double-bounded distributions



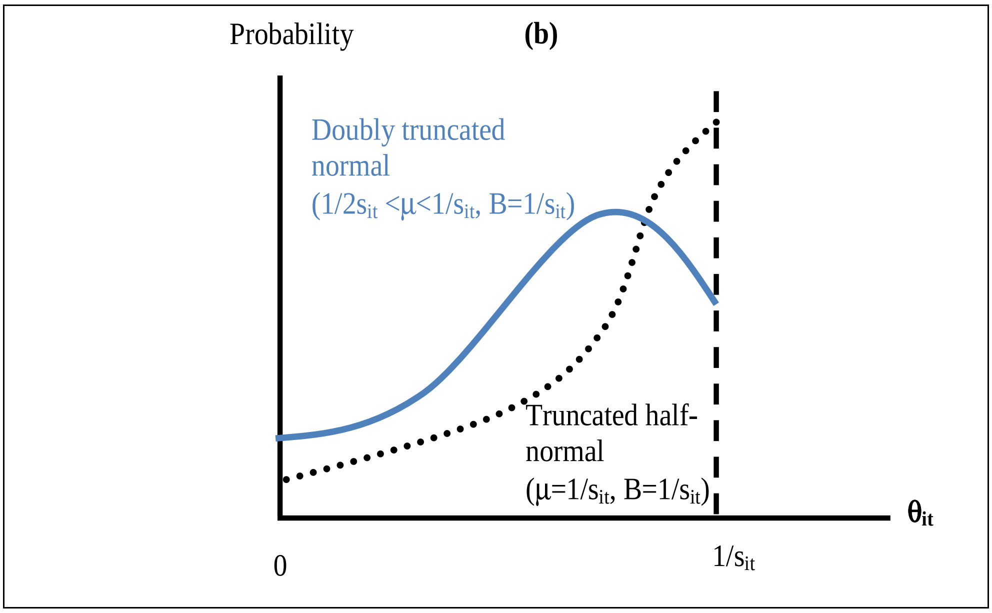


Figure A.2. Price-cost margins in hour 18 (July 3, 1998 – November 30, 2000)

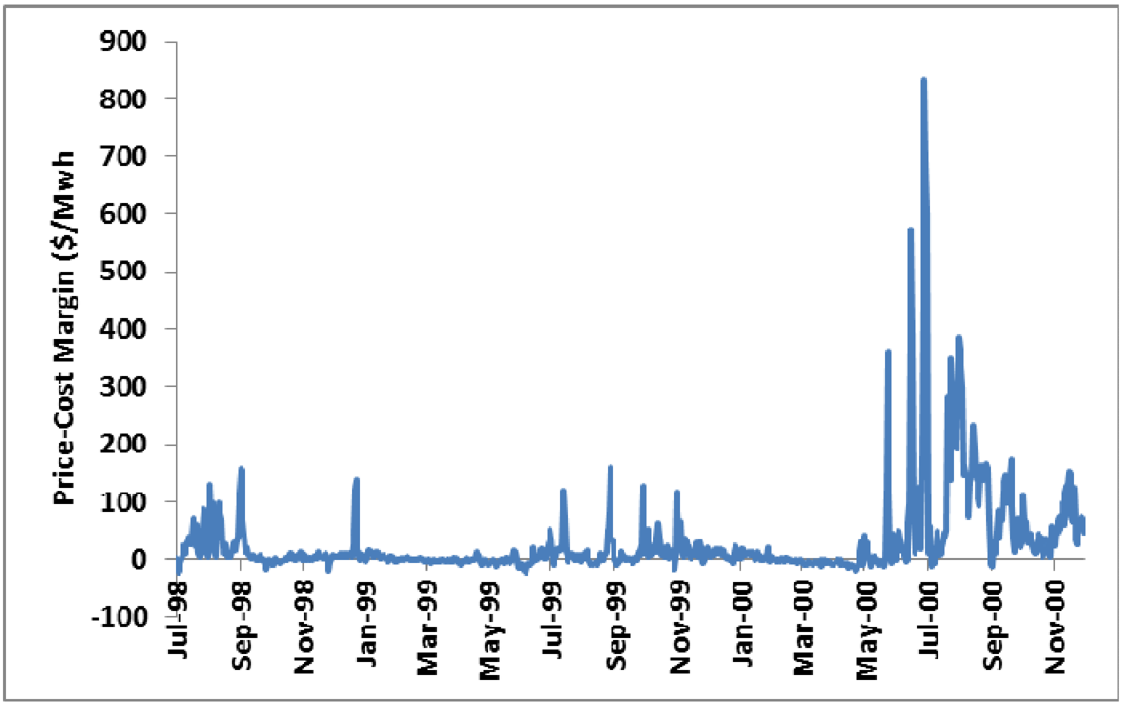


Figure A.3. Residual Demand Elasticities Facing Strategic Firms in hour 18 (Median Monthly Absolute Values, July, 1998 – November, 2000)

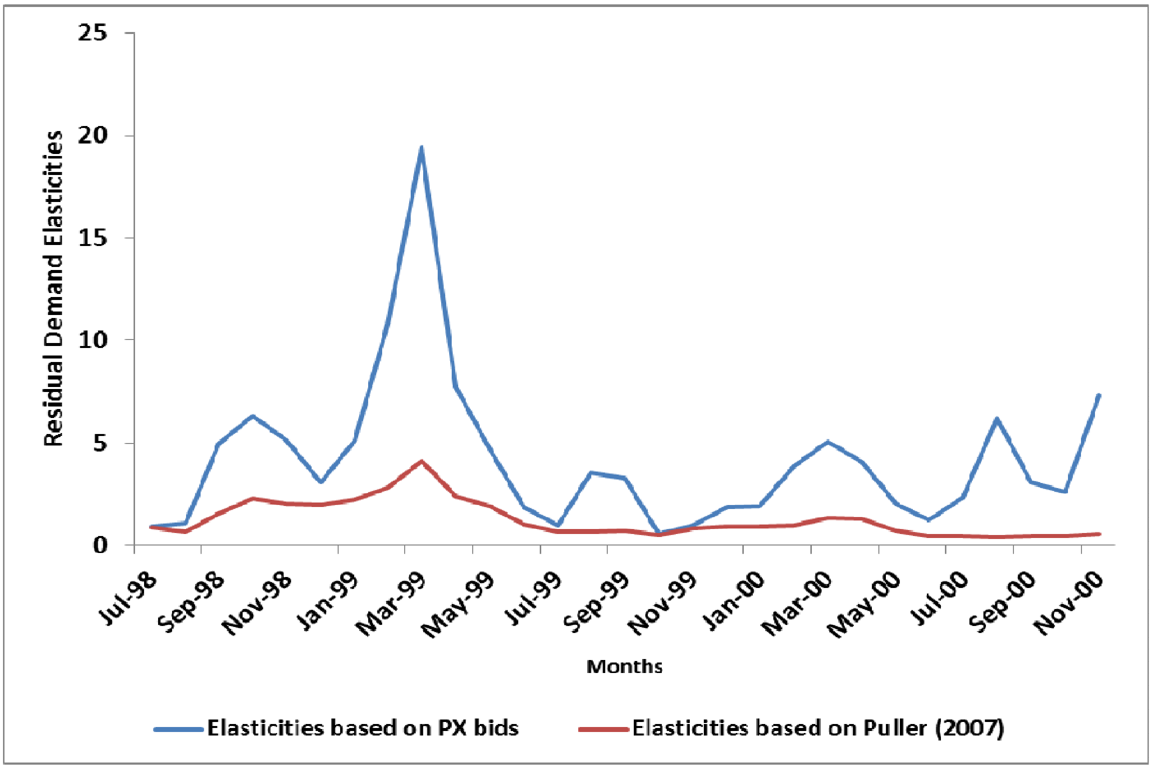


Figure A.4. Comparison of market power scores using elasticities based on Puller (2007).

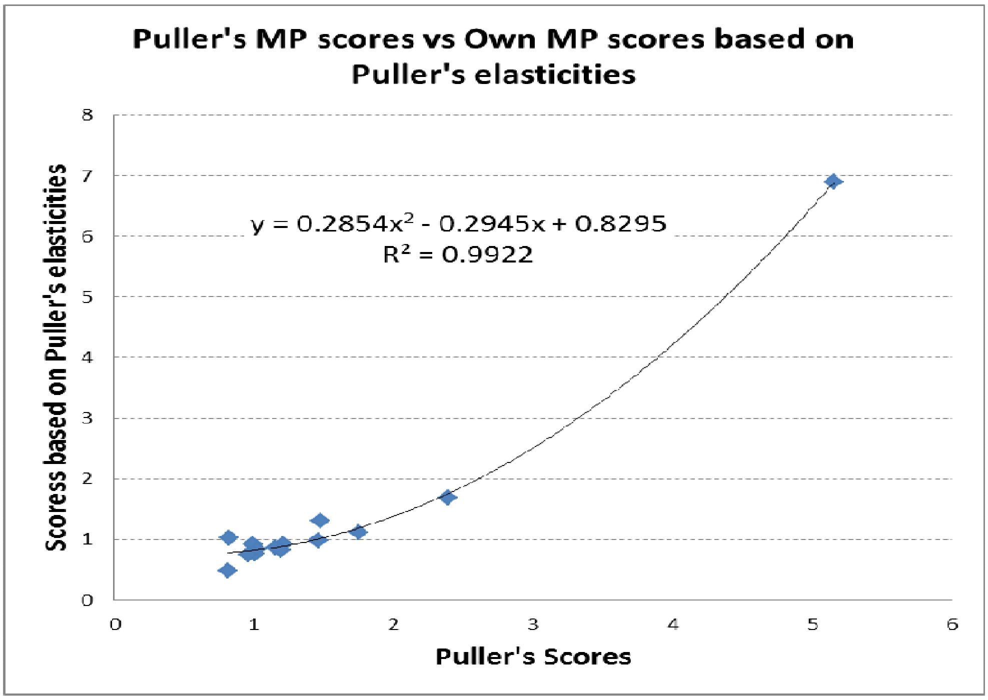


Figure A.5. Firm-Specific Conduct Parameter Estimates vs. Firm-Specific Lerner Indices (over July 1, 1998 – April 15, 1999, elasticities based on PX data)

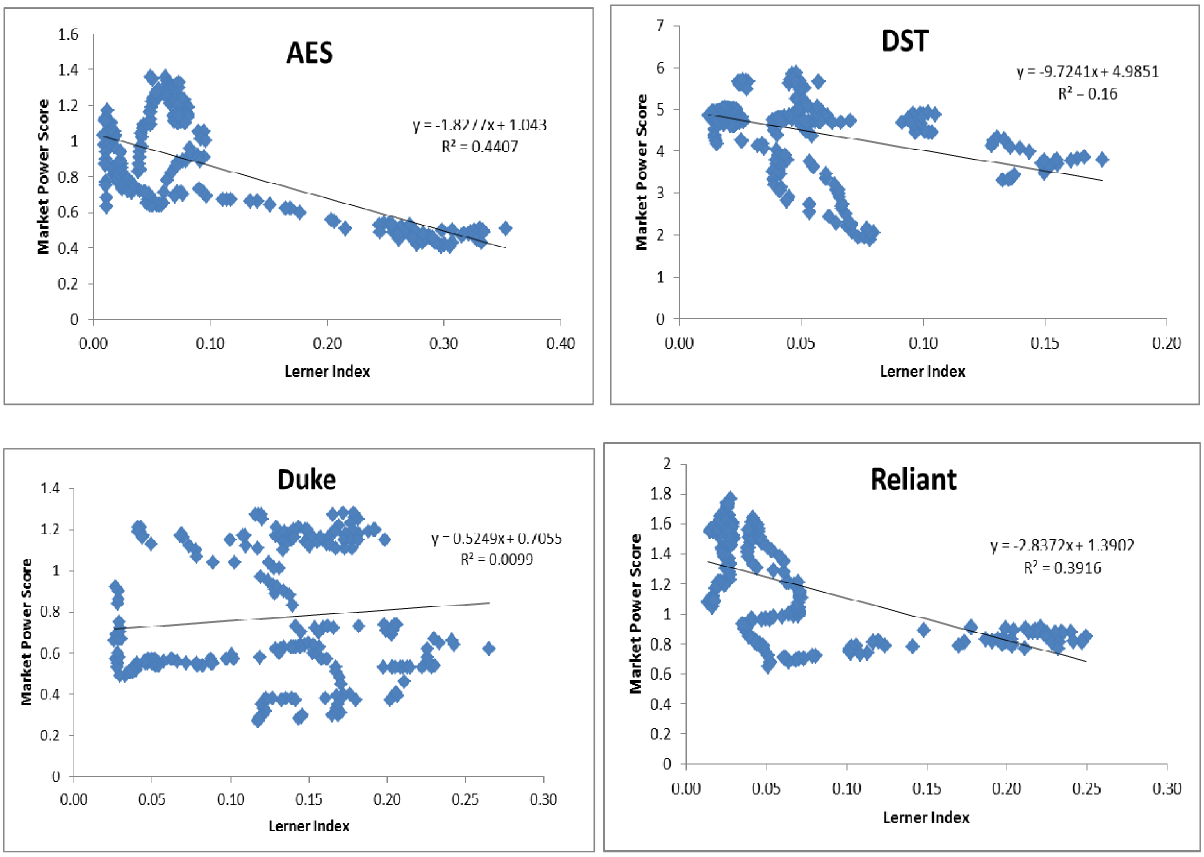


Figure A.6. Firm-Specific Conduct Parameter Estimates vs. Firm-Specific Lerner Indices (over April 16, 1999 – November 30, 2000, elasticities based on PX data)