ESTIMATING MARKET POWER IN HOMOGENOUS PRODUCT MARKETS USING A COMPOSED ERROR MODEL: APPLICATION TO THE CALIFORNIA ELECTRICITY MARKET

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PRELIMINARY DRAFT
(PLEASE DO NOT QUOTE)

First version: 19 June 2010

Abstract

A large and growing economic literature in empirical industrial organization relies on structural models to infer what types of firm behaviour ("conduct") are associated with prices that exceed marginal costs. Most of existing studies impose some *restrictions* on the value of the conduct parameter across observations or time. We instead treat firms' behaviour as a random parameter. 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 measures market power. We propose multistage estimator that allows us to obtain time-varying firm-specific market power scores. This additional information, usually ignored in previous structural econometric studies estimating conduct parameters provides a better understanding of firm-level pricing strategies. We illustrate the proposed approach with an application to the California Electricity generating market using the same data as Puller (2007).

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

JEL codes: C51, D21, L13

1. Introduction

Starting from seminal research works of Iwata (1974), Gallop 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 empirical industrial organization 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, $\theta_{it}=0$ and price equals marginal cost. When $\theta_{it}=N$ we face a perfect cartel, and when $0<\theta_{it}<N$ various oligopoly regimes apply. 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.[2]

The conduct parameter may vary across time as market conditions change, and firms change their own pricing strategies.[3] 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).[4] Obviously, allowing the conduct parameter to vary both by firms and time-series results in an overparameterized model. To avoid this problem the 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

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

[2] 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. Bresnahan (1989) and 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. We therefore interpret this parameter as a simple descriptive measure of firm's degree of market power.

[3] 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.

[4] 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.

price wars or similar breakdowns in cooperation (Porter 1983a), allowing for different conduct parameters between two or more groups of firms (Gallop and Roberts 1979) , or assuming firm-specific, but time-invariant, conduct parameters in a panel data framework (Puller 2007).

Most of the structural econometric models treat the firm's conduct as a common parameter to be estimated jointly with other cost and demand parameters. We instead propose treating firms' behaviour θ_{it} as a random variable. Our approach relies on estimating 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 measures market power. 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 papers relies on making simple assumption about a specific component in the error term, which is unobservable. 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. What distinguishes our paper is the attempt to estimate a double-bounded distribution that imposes both lower and upper theoretical bounds (i.e. $0\leq\theta_{it}\leq N$) to a continuous random conduct term. Moreover, 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.[5] The continuous nature of our conduct random term thus allows us to capture *gradual* changes in firm behaviour.[6]

The model can be estimated in three stages.[7] Once all parameters describing the structure of the pricing equation (1) are estimated using appropriate econometric techniques (first-stage), distributional assumptions on random conduct term are invoked to obtain consistent estimates of the parameters describing the structure of the two error components (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). These firm-specific market power scores can be used to complement time-invariant or common conduct estimates obtained in the first stage.

Because the firm-specific market power estimates in our model relies on distributional assumptions on the two error components, they can be obtained just using

[5] 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.
[6] Kole and Lehn (1999) argue that for many firms the decision-making apparatus is slow 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).
[7] 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).

cross-sectional data sets, unlike in previous papers that used a fixed effect treatment to estimate firm average conduct in a panel data framework (see, for instance, Puller, 2007).Therefore, our approach is especially useful when: *i*) no panel data sets are available;[8] *ii*) the time dimension of the data set is sort; [9] *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.

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. Indeed, 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 likely positively or negatively skewed. As we aware, skewness of conduct parameter in oligopolistic industry settings is not examined explicitly in most (if any) of the previous studies. Skewness and truncation allow us to isolate the random conduct term from other random shocks. In addition to the mean value estimated in the first-stage of our procedure, this permits estimating the variance and mode of the random conduct term. This new knowledge may provide relevant information about the oligopolistic equilibrium behind the data generating process. Indeed, price or conduct rigidity is often attributed to reluctance among firms to disturb an existing cooperative consensus.[10] Hence, variation in conduct can be used as a measure of the degree of collusive *discipline* across firms and/or over time. For instance, a large conduct variation might suggest large differences in firms' conduct or, if a cartel exists, that it is not all-inclusive. A large conduct variation might also indicate the existence of collusion break downs from time to time, gradual changes in firm behaviour or simply that cartel stability is not successful. This instability in turn might suggest the existence of monitoring problems among collusive firms. The mode, on the other hand, might provide information about the probability of observing higher (lower) market power scores than the estimated average conduct value.

Because variation in conduct can be interpreted as a measure of collusive discipline or instability, we advocate using the coefficient of conduct variation (computed from the market power scores estimated in the third stage) as a screening procedure to detect potential collusive firms or market power concentration.[11] The proposed screen can be viewed as a more sophisticated version of the collusive screen introduced by Abrantes-Metz *et al.* (2006) based on price variation. In particular, our

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[8] 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.

[9] 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 $N\rightarrow\infty$).

[10] Carlson and McAfee (1983) and Carlton (1986) analyzed price dispersion for homogeneous goods in an oligopolistic industry structure and found that price dispersion is related to the slope of the marginal cost curves and the degree of competition measured either by the number of firms or the industry concentration. Note that, from equation (1), price rigidity greater than cost fluctuations in oligopolistic settings can be attributed, among other sources, to low conduct dispersion. For subsequent research on price rigidity and competition see Connor (2005).

[11] A screen is a statistical procedure designed to detect conspiracies aimed at illegally manipulating a market. Because screens do not prove collusion as they might exhibit both false positives and false negatives, they just isolate outcomes that are improbable or anomalous in competitive settings. For a comprehensive survey of this literature, see Abrantes-Metz and Bajari (2009).

screen would identify a potential cartel as group of firms exhibiting low conduct variation and high conduct values relative to other firms.[12] On the other hand, from a dynamic perspective, the market power scores can be used to detect the creation/decline of collusion episodes, or to identify abrupt changes in mark-ups which cannot be explained by "normal" demand and cost random shocks.

While economic theory imposes both lower and upper theoretical bounds to the random conduct term, the skewness of its distribution is an empirical issue. [13] 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, to the dominant firm theory assumes that one (few) firm(s) has enough market power to fix prices over marginal cost. This market power is, however, attenuated by a fringe of (small) firms that do not behave strategically.[14] 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. θ_{it} =N. Less values of θ_{it} are possible due, for instance, to cheating behaviour. [15] This means that the modal value of the conduct random term in this equilibrium is one, with less values of θ_{it} increasingly less likely. That is, firm-conduct is negative 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 for each firm. We can therefore avoid complications from estimating cost parameters and focus our research on market power, avoiding biases due inaccurate estimates of marginal cost.[16] Hence, this data set provides a proper

[12] A notable caveat to our screen is that conduct variance can be higher under the collusive theory of Green and Porter (1984). Though collusion doesn't result in a higher conduct variance within either a collusive regime or a punishment regime, the conduct variance is higher when data spans the two regimes. Hence, like any other collusive marker, the proposed marker must be used with caution.

[13] The economic theory suggests that the conduct parameter always takes positive values, so it might follow one-sided or double-truncated distributions, such us a truncated normal, half-normal or exponential, widely used in the stochastic frontier literature. For a comprehensive survey of this literature, see Kumbhakar and Lovell (2000), and Fried *et al*. (2008).

[14] 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.

[15] It is well known that secret price cuts (or secrete 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).

[16] 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.

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 calculate the level of market power in California markets. In particular, Borenstein et al. (2002) and Joskow and Kahn (2001) estimate hourly marginal cost for the California market and compare these estimates to wholesale prices. They found that, in certain time periods, prices substantially exceeded marginal cost. Puller (2007) analysed the pricing behaviour of California electricity generating firms and found that price-cost margins varied substantially over time.

The rest of the paper is structured as follows. In Section 2 we explain the empirical model, and its dynamic extensions, and discuss how to incorporate conduct determinants and panel data specifications. 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. Theoretical background and alternative empirical specifications

The traditional structural econometric model of market power is formed by a demand function and a pricing equation. Because we are primarily interested in the estimation of industry or firm-specific market power scores, we only discuss here the estimation of the pricing equation (1), given a previous estimates of the demand parameters.[17] Otherwise, demand parameters should be is estimated jointly with cost and market power parameters.

In accordance with our empirical application to the wholesale electricity industry, in this section we develop a simple model where firms sell homogenous products (i.e. Kwh) and choose individual quantities each period so as to maximize their profits. Firm *i*'s profit function in period *t* can be written as:

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

where $\hat{\beta}$ is a vector of demand parameters already estimated, 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.

<u>Static specification</u>

We first assume a static model, where firms maximize their profits each period without explicit consideration of the competitive environment in other periods. We then extend the model to dynamic setting. In a static model 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 static FOC's are captured by equation (1), that is:

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

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

where $mc(q_{it},\alpha)$ stands for marginal cost, and $g_{it} = -P'(Q_t,\hat{\beta})q_{it} \geq 0$. The stochastic specification of the above FOC´s can be obtained by adding the traditional error term, capturing measurement and optimization errors:

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

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 noise term is *i.i.d.* and symmetric with zero mean, we also assume that θ_{it} follows a one-sided distribution once we incorporate the theoretical restriction that $0 \leq \theta_{it}$. 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 a *one-sided* random conduct term, $g_{it} \cdot \theta_{it}$, that reflects the market power. The one-sided restriction makes the composed error term asymmetric and allows getting separate estimates of θ_{it} and v_{it} from an estimate of the composed error term.

Dynamic specification

Corts (1999) argued that traditional approaches to estimating the conduct parameter from static pricing equations, such us (4), can yield inconsistent estimates of the conduct parameter if firms are engaged in an effective tacit collusion. The first order condition for a set of tacitly colluding firms is the solution to maximizing their total profit subject to an incentive compatibility constraint (ICC), so that no firm has an incentive to deviate. Following Puller (2009), the general model to be estimated within a dynamic framework can be written as:

$$P_t = mc(q_{it},\alpha) + g_{it}(\hat{\beta}) \cdot \theta_{it} + \left[\frac{\psi_t}{1+\psi_t / N} \cdot \frac{\partial \pi^b}{\partial Q_t} \right] + v_{it} \quad , \tag{5}$$

where ψ_t is the Lagrange multiplier on the incentive compatibility constraint, and π^b is the profit of a firm that unilaterally deviates from the collusive regime.

In equation (5) θ_{it} is still the same conduct parameter as in static model (4). Its estimation is more complex because in (5) firm's conduct depends both on the value of conduct parameter θ_{it}, and on whether the incentive compatibility condition binds, i.e. $\psi_t>0$. This equation captures, as special cases, some static (i.e. $\psi_t=0$) and dynamic solutions (i.e. $\psi_t>0$). If $\theta_{it}=0$ firm's conduct is consistent with Nash-Bertrand behaviour. If, in addition, $\psi_t=0$, this outcome is consistent with the static one-shot Nash-Bertrand competition. If $\theta_{it}=1$ and $\psi_t=0$, it is perfect collusion. Two imperfect collusions arise. If $\psi_t=0$, when $0<\theta_{it}<N$. When $\psi_t>0$ and $\theta_{it}=N$, conduct is consistent with the dynamic and efficient tacit collusion. Under efficient tacit collusion, firms jointly adjust prices so that no firm has an incentive to deviate from joint profit maximization. Corts (1999) showed that when the incentive compatibility condition is not modelled, the conduct parameter θ_{it} is biased and the bias depends on expected future demand and costs.[18] Puller (2009) pointed out that if the static model is correctly specified, the error term in (5) is a pure stochastic term and therefore should not affect a firm's pricing behaviour. However, if

[18] In particular, Corts (1999) argued that the robustness of the conduct parameter approach depends on the discount factor and the persistency of the demand. The conduct parameter approach cannot detect any market power if the discount factor is low and the demand is i.i.d. Puller (2007, p.84) argued that "California market [can be] viewed as an infinitely repeated game with a discount factor between days very close to 1". Our application to California electricity market as a static model is therefore sufficient for estimating market power consistently.

the ICC is binding (i.e. ψ_t>0) and the best-response profits are non-linear, the static conduct parameters are biased and inconsistent. To address this issue, he noticed that the dynamic term in (5) is common to all firms and, hence, Corts' critique can be avoided by estimating the pricing equation (6), and replacing the term in brackets in (5) by a set of time-dummy variables.

As firm's dynamic behaviour is affected by current demand, expected future demand, and expected future costs (Borenstein and Shephard, 1996), and these factors affect the ICC, consistent estimates can be also obtained by replacing the dynamic term in (5) by a function of expected demand and cost shocks, and estimating the following extended pricing equation:

$$P_t = mc(q_{it}, \alpha) + f(x_t, w_t, \pi) + g_{it}(\beta) \cdot \theta_{it} + v_{it}, \tag{6}$$

where x_t and w_t represent respectively industry expected demand and cost shocks, measured relative to current demand and costs. In practice, future market output and costs can be used to proxy expected values.

Kim (2006) proposed a similar solution to address Corts' critique. He suggested modelling the conduct parameter as a *core* time-invariant conduct parameter, θ_i^C, and a linear function of dynamic behaviour´s determinants, i.e. demand and cost shocks. That is:

$$\theta_{it} = \theta_i^C + (\pi_1 x_t + \pi_2 w_t) \tag{7}$$

In equation (7), the first term, the core conduct parameter, measures the firm-specific average level of collusion over time while the second linear term captures the deviation from the average level. Kim (2006) mentioned two advantages of the above specification. First, by specifying a time-varying conduct parameter we can test the relationship between the firm's conduct and both demand shocks and cost shocks.[19] Second, we can shed light on the source of bias that distinguishes the core conduct parameter θ_i* and the static conduct parameter θ when the ICC is not binding.

<u>Conduct determinants</u>

We now discuss how the model can be extended to include determinants of the (one-sided) conduct random term. This allows us to analyze, for instance, the cyclical behaviour of firm conduct, evaluate bias in static market-power measures (see above), identify clusters of firms with different strategic behaviour, or capture differences between peak and off-peak hours or between week and weekend days (see Kim and Knittel, 2006).

A general specification including a vector of conduct determinants, z_{it}, can be written as:

$$\theta_{it} = \theta_{it}(z_{it}) \tag{8}$$

where z_{it} might include, in addition to other determinants of firms' behaviour, expected future demand and expected future costs as suggested by theory. In this general

[19] For instance, if x_t has a negative sign, this implies countercyclical firm conduct and mark-up as in Rotemberg and Saloner (1986). If x_t is positively associated with θ, this implies procyclical firm conduct and mark-ups as in Green and Porter (1984).

specification the conduct determinants affect both the shape (i.e. the distribution characteristics) and magnitude of the one-sided random term, and their coefficients must be estimated using maximum likelihood (ML) techniques. In an important special case, if θ_{it} satisfies the so-called *scaling property* the model can be also estimated using a method-of-moments (MM) estimator.[20] In this case θ_{it} can be written as a scaling function $h(z_{it},\varphi)$ times a random variable u_{it} that does not depend on z_{it}, that is [21]

$$\theta_{it} \rightarrow h(z_{it},\varphi)\cdot u_{it} \tag{9}$$

This property implies that changes in z_{it} affect the scale but not the shape of u_{it}. This specification has a similar economic interpretation as in Kim (2006). If firm's behaviour is influenced by expected future demand and expected future costs, this is captured by the scaling function $h(z_{it},\varphi)$.[22] If we assume an exponential scaling function, i.e. $h(z_{it},\varphi)=exp(z_{it}'\varphi)$, the pricing equation (6) can be written as:

$$P_t = F_{it}(\alpha,\pi) + \tilde{g}_{it}(\varphi,\hat{\beta})\cdot u_{it} + v_{it} \tag{10}$$

where $F_{it}(\alpha,\pi) = mc(q_{it},\alpha) + f(x_t,w_t,\pi)$, and $\tilde{g}_{it}(\varphi,\hat{\beta}) = g_{it}(\hat{\beta})\cdot\exp(z_{it}'\varphi)$. Except for the new vector of parameters, φ, the model to be estimated is the same as (6), and a MM estimator can be used.[23]

<u>Panel data specification</u>

So far we have assumed that the θ_{it} are independent (conditional on the z_{it}) over time.[24] Although independence is likely an unrealistic assumption, it is generally not clear how to relax it, i.e. how to allow for correlation over time in a one-sided random conduct term. However, if scaling property is satisfied we may consider the following alternative model:

$$\theta_{it} = h(z_{it},\varphi)\cdot u_i \tag{11}$$

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[20] See Wang and Schmidt (2002) and Álvarez *et al*. (2006).

[21] The scaling property in (9) corresponds to a multiplicative decomposition of θ_{it}. 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 $\tau_{it} \leq h(z_{it},\varphi)$.

[22] Although it is an empirical question whether or not the scaling property should hold, it has some features that we find attractive. For instance, the interpretation of φ does not depend on the distribution of u_{it}, and simple scaling functions yield simple expressions for the effect of the z_{it} on the dynamic conduct parameter θ_{it}. For example, if we use an exponential scaling function, so that $\theta_{it}=exp(z_{it}'\varphi)\cdot u_{it}$, then the coefficients φ are just the derivatives of $\ln(\theta_{it})$ with respect to the z_{it}, and have standard interpretations as marginal effects.

[23] It is worth mentioning that previous papers allowing for conduct determinants (see, e.g., Gallet and Schroeter, 1995) have estimated the pricing equation (10) using a MM estimator, but assuming that $\theta_{it}(z_{it},\varphi)$ is an additive function of time-varying and firm-specific conduct determinants. Therefore, these papers assumed implicitly that θ_{it} satisfied the abovementioned scaling property. To relax this assumption, a ML estimator should have been used.

[24] Estimates from (9) will be consistent even if the conduct term θ_{it} is not independent over time, so long as the model is otherwise correctly specified. However, the estimated variances (or standard errors) of the estimated parameters, calculated under the assumption of independence, will not be correct if independence does not hold. It is possible to calculate asymptotically valid "corrected" estimated variances that allow for non-independence of unspecified form. These points are known in the econometric literature. For example, see Hayashi (2000) and Álvarez, Amsler, Orea and Schmidt (2006).

where u_i is a time-invariant individual effect. Several caveats should be made here. First, this specification is a restricted version of (9), with the restriction of $u_{it}=u_i$. This implies that θ_{it} only changes throughout the time-varying function $h(z_{it},\varphi)$. If we use (11) into (6), the model to be estimated is the same as (10), and, in addition to MM and ML, a "fixed-effect" estimator can be used to estimate u_i.[25] Second, the specification in (11) can be viewed as a multiplicative version of the additive conduct decomposition of θ_{it} suggested by Kim (2006). In fact, the term u_i can be viewed as the so-called (time-invariant) core conduct parameter θ_i^C and $h(z_{it},\varphi)$ as the dynamic term in (7) that is modelled as a function of demand and cost shocks respectively. Third, a distinctive feature of (11) is the interaction between the time-varying function $h(z_{it},\varphi)$ and the individual effect u_i. Models of this form have been proposed in the literature of production frontier functions, but all of this literature considered a "random-effects" treatment and proposed specific (truncated normal) distributions for the u_i, with estimation by maximum likelihood.[26] Because some regressors are endogenous and might be correlated with random effects (i.e. u_i), a "fixed-effects" treatment or a generalized method of moments (GMM) method should be employed.

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. 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). This stage is thus 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 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 New Empirical Industrial Organization (NEIO) literature, the second and third stages take advantage of the fact that the conduct

[25] Han, Orea and Schmidt (2005) shown, however, that a "fixed-effects" estimation of this type of models is not trivial due to the incidental parameters problem.
[26] Orea and Kumbhakar (2005) have estimated a model with a specification of one-sided random term (the efficiency of production) equivalent to (11). Their model is in turn a slight generalization of those introduced by Kumbhakar (1990) and Battese and Coelli (1992) where z_{it}=t.

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.[27]

First stage

Let us rewrite the pricing equation (6) as:

$$P_t = F_{it}(\alpha,\pi) + g_{it}(\hat{\beta})\cdot\theta + \varepsilon_{it} \tag{12}$$

where α is the vector of cost parameters,[28] π are parameters of the dynamic term to be estimated, $\hat{\beta}$ are demand parameters already estimated, $\theta = E(\theta_{it})$, and

$$\varepsilon_{it} = v_{it} + g_{it}(\hat{\beta})\cdot\{\theta_{it} - \theta\} \tag{13}$$

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:

$$E(\varepsilon_{it}^2) = \sigma_v^2 + g_{it}^2(\hat{\beta})\cdot\sigma_\theta^2 \tag{14}$$

where $E(v_{it}^2)=\sigma_v^2$, and $V(\theta_{it})=\sigma_\theta^2$. Equation (14) shows that the error in the regression indicated by (12) is heteroskedastic. Therefore an efficient GMM estimator is needed. Suppose that we can find a vector of m instruments M_{it} that satisfy the following moment condition:

$$E[M_{it}\cdot\varepsilon_{it}] = E[M_{it}\cdot(y_{it} - F_{it}(\alpha,\pi) - g_{it}(\hat{\beta})\cdot\theta)] = E[m_{it}(\alpha,\pi,\theta)] = 0 \tag{15}$$

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

$$(\hat{\alpha},\hat{\pi},\hat{\theta}) = arg\,min[\Sigma_i\Sigma_t m_{it}(\alpha,\pi,\theta)]'W^{-1}[\Sigma_i\Sigma_t m_{it}(\alpha,\pi,\theta)] \tag{16}$$

where W is an optimal weighting matrix obtained from a consistent preliminary GMM estimator.[29]

Clearly, we can estimate the above model for each firm when a panel data set is available, as it is the case in our empirical application. Similar to Puller (2007), this would allow us to estimate the average conduct for each firm in this stage, and temporal deviations from these individual averages in following stages (not carried out in Puller's paper).[30] However, we simply estimate a common pricing equation for all firms and compare it to that estimated by Puller (2007) assuming as well a common conduct term

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

[28] 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.

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

[30] This implies in turn that other moments of the conduct random term are also firm-specific.

for all firms. We then compute day-to-day deviations from this industry average to show the advantages of our procedure.

Second stage

The pricing equation (12) estimated in the first stage is equivalent to standard specification of a structural market power econometric model, where an industry-average market power level 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 the core of this paper.

In the *second* stage of the estimation procedure, distributional assumptions are invoked to obtain consistent estimates of the parameter(s) describing the structure of θ_{it} and v_{it} (i.e. σ_v and σ_θ), conditional on the first-stage estimated parameters.[31] This stage is critical as it allows us to distinguish collusion discipline/instability, measured by σ_θ, from demand and cost volatility, measured by σ_v. This stage of the procedure can be implemented using either the MM or ML estimator. The MM estimates of the two parameters describing the structure of θ_{it} and v_{it} are derived using the second and third moments of the error term. The third moment of ε_{it} can be written as:

$$E(\varepsilon_{it}^3) = g_{it}^3(\hat{\beta}) \cdot E\left[(\theta_{it} - \theta)^3\right] \tag{17}$$

Equation (17) shows that the third moment of ε_{it} is simply the third moment of the random conduct term, adjusted by $g_{it}^3(\hat{\beta})$. The variance of the traditional error term does not appear in (17) because it is symmetrically distributed. That is, while the second moment (14) provides information about both σ_v and σ_θ, the third moment (17) 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 the third moment of ε_{it}, and then σ_v from its second moment.

We can also estimate σ_v and σ_θ by maximum likelihood. 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 $\tilde{\varepsilon}_{it} = v_{it} + \tilde{\theta}_{it} = v_{it} + g_{it}(\hat{\beta})\theta_{it}$ that can be obtained from an estimate of the first-stage pricing equation (12).

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 σ_v<0.[32] Overall, these "unexpected" outcomes

[31] Our approach can also be extended in order to allow for a heteroskedastic error term.

[32] Olson *et al*. (1980) showed that resorting to a ML procedure instead of a MM procedure does not resolve the first problem as the ML estimate of σ_θ tends to be equal to zero when ε_{it} has the "wrong" skewness. Based on the results of a Monte Carlo experiment, they concluded 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 small and the variance of the one-sided error component, compared to the variance of the noise term, is not large the MM outperforms ML in a mean-squared error sense.

suggest that either the distributions chosen to model the underlying oligopolistic equilibrium, or the deterministic part of the pricing equation (12) are misspecified, and, hence, they need to be revised.

To carry out the second (and third) stage we need to choose a distribution for the asymmetric term. The selected distribution for the one-sided conduct term reflects the researcher's beliefs about the underlying oligopolistic equilibrium that generates the data. Hence, different distribution 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. The tractability principle 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 functions for the conduct random term can be classified into three classes: 1) the *lower-bound* distributions that impose the theoretical restriction that $0 \leq \theta_{it}$, but do not impose any upper bound; 2) the *upper-bound* distributions that impose the theoretical restriction that $\theta_{it} \leq N$, but do not impose any lower bound; and 3) the *double-bounded* distributions that impose both theoretical lower and upper bounds, i.e. $0 \leq \theta_{it} \leq N$.

Examples of the so-called *lower-bound* (or one-sided) distributions are the exponential distribution, gamma-distribution, the half-normal distribution, and the truncated normal distribution, which are well-known in the production frontier literature.[33] The half-normal distribution is obtained from the truncation below zero of a random variable which follows a normal distribution with zero mean and variance σ_u^2. In this case, the density function of $\theta_{it} \geq 0$ is given by

$$f(\theta_{it}) = \frac{2}{\sqrt{2\pi} \cdot \sigma_u} \cdot exp\left\{ -\frac{\theta_{it}^{\ 2}}{2\sigma_u^2} \right\} \tag{18}$$

If $\theta_{it} \geq 0$ follows an exponential distribution, the density function is:

$$f(\theta_{it}) = \frac{1}{\sigma_u} \cdot exp\left\{ \frac{-\theta_{it}}{\sigma_u} \right\} \tag{19}$$

Both half-normal and exponential are single-parameter distributions. The truncated normal distribution is a generalization of the one-parameter half-normal distribution.[34] If we assume that θ_{it} follows a truncated normal distribution, i.e. $\theta_{it} \sim N^+(\mu,\sigma_u^2)$, the density function is:

$$f(\theta_{it}) = \frac{1}{\sqrt{2\pi} \cdot \sigma_u} \cdot \Phi^{-1}(\mu/\sigma_u) \cdot exp\left\{ -\frac{(\theta_{it} - \mu)^2}{2\sigma_u^2} \right\} \tag{20}$$

where $\Phi(\cdot)$ is the standard normal cumulative distribution function. In Table 1 we list the first three population (central) moments of θ_{it} for the truncated normal distribution

[33] For a comprehensive discussion of these one-sided distributions, see Kumbhakar and Lovell (2000).
[34] It is one of the most employed distributions in the production frontier literature.

which are essential for the MM estimation (see Jawitz, 2004). The moments for the half normal distribution can be obtained by setting μ=0. [35]

As mentioned earlier, in the second stage of the estimation procedure we invoke distributional assumptions to obtain consistent estimates of the parameter(s) describing the structure of the two error components, *conditional* on the first-stage estimated parameters, which includes the estimate of the average value of conduct parameter θ. The first moment in Table 1 can thus be viewed as a nonlinear constraint between μ and σ_u. Using the first-stage residuals, the two equations formed by the nonlinear constraint and the (sample counterpart of the) third moment of the composed error term

$$\hat{\theta} = \mu + \eta_0 \sigma_u \tag{21}$$

$$\frac{1}{NT}\sum_{i=1}^{N}\sum_{t=1}^{T}\left[\frac{\hat{v}_{it}}{g_{it}(\hat{\beta})}\right]^3 = -\eta_0\sigma_u^3 + \eta_0^2\sigma_u^2\hat{\theta} + \eta_0\sigma_u\hat{\theta}^2 \tag{22}$$

provide estimates of μ and σ_u, which yield an estimate of $\eta_0 = \phi(\mu/\sigma_u)\cdot\Phi^{-1}(\mu/\sigma_u)$, and using the second moment of the composed error term, these estimates together yield an estimate of σ_v.

As regards the maximum likelihood estimation, the density function for a normal (v_{it}) plus a truncated-normal error term (u_{it}) can be written as:

$$f(\tilde{\varepsilon}) = \frac{1}{\sigma}\Phi^{-1}\left(\frac{\mu}{\sigma_u}\right)\cdot\phi\left(\frac{-\varepsilon+\mu}{\sigma}\right)\cdot\Phi\left(\frac{\mu}{\sigma\lambda}+\frac{\tilde{\varepsilon}\lambda}{\sigma}\right) \tag{23}$$

where $\tilde{\varepsilon} = v + u$, $\sigma \equiv \left(\sigma_u^2 + \sigma_v^2\right)^{1/2}$, $\lambda \equiv \sigma_u/\sigma_v$, and we have dropped the subscripts for convenience. The ML estimates in our model can be obtained by replacing μ and σ_u in (23) with $\mu\cdot g_{it}(\hat{\beta})$ and $\sigma_u\cdot g_{it}(\hat{\beta})$.

As illustrated in Figure 1, each of these distributions assumes the existence of one mode, with high values of the conduct parameter becoming increasingly less likely. However, from a theory perspective, the most important characteristic of these distributions is that all of them have a positive skewness. This suggests that the one-sided distribution has low probabilities for large (collusive) conduct values and high probabilities for small (competitive) conduct values. Finally, the values not supported by the theory can still be obtained here because these distributions do not impose the theoretical restriction that $\theta_{it} \leq N$. These values might appear when the model is not well specified or when the estimated error terms are occasionally high (e.g. due to large measurement errors).

The *upper-bound* distributions of θ_{it} are negative skewed. From the theory perspective, this suggests that collusive conduct values are more probable than competitive values, i.e. that only a small fraction of the firms is behaving competitively, while a large fraction is colluding. Similar to the lower-bound distributions, values not

[35] We do not present the moments for the exponential distribution because there is some evidence in the frontier literature that neither rankings of firms by their efficiency (here conduct) scores or the composition of the top and bottom scores deciles are particular sensitive to the single distribution (half-normal vs. exponential) assigned to the one-sided error term (see Kumbhakar and Lovell, 2000, p. 90).

supported by the theory can still be obtained because these distributions do not impose the theoretical restriction that $\theta_{it} \geq 0$.[36]

The third class is formed by *double-bounded* distributions that impose both lower and upper theoretical bounds, i.e. $0 \leq \theta_{it} \leq N$. Imposing both theoretical restrictions simultaneously *and* allowing for *simple* asymmetric distributions is a complex problem. No applicable double-bounded distribution for the one-sided term has been published yet.

A first (and promising) attempt to develop double-bounded distributions is Almanidis *et al.* (2010). In particular, these authors propose a model where the distribution of the one-sided (inefficiency) term is doubly truncated normal, that is, a normal distribution truncated at a point (say B) on the right tail as well as at zero. They also introduce the so-called truncated half normal model, which is a particular case of the doubly truncated normal, and the truncated exponential model. In Table 2, we reproduce the density functions of these double-bounded distributions, which are essential for the ML estimation.

Once we impose that the upper bound is equal to the number of firms (i.e. B=N) these models can be used to estimate the distribution of the conduct term. The doubly truncated normal model is very flexible as it nests other one-sided distributions such as truncated normal or half normal. One desirable feature of this model is that the doubly truncated normal distribution may be either positively or negatively skewed. In particular, as illustrated in Figure 2, it may exhibit (positive) negative skewness if the truncation on the right is closer (further than) to the mode than that on the left. And therefore it allows modelling oligopolistic equilibriums with a large fraction of firms behaving competitively, and vice versa.

While both the truncated model and the truncated exponential model are globally identified (i.e. can be estimated using traditional ML techniques), it is not clear that the doubly truncated normal is globally identifiable. Almanidis *et al.* (2010) show that these identification problems arise when both the mean of the pre-truncated normal distribution (μ) and the upper-bound (B) are estimated simultaneously, and the combination of these two parameters yield a (post-truncated) symmetric distribution. This problem might be quite important in the stochastic frontier framework where both parameters are permited to vary with freedom. However, the identification problems in the market power framework are less severe as the upper-bound is fixed by the theory and it does not need to be estimated in practice.

Although the doubly truncated normal is not globally identifiable, Almanidis *et al.* (2010) show that particular versions of this model are identified and can be estimated. A couple of them are of special interest in our framework: i) the truncated half normal with B=N which is positive skewed; and ii) the double-truncated normal with $B=\mu=N$, which is negative skewed. As these particular double truncated models allow us to "adjust" the traditional one-sided distributions mentioned above making them to satisfy both lower and upper theoretical bounds, they are our preferred models.

[36] These distributions have not been used in earlier literature because negative values do not make sense for estimating stochastic frontiers. However, the truncation over one can be converted into a (more traditional) truncation below zero if we just define $\theta_{it}=(N-\theta_{it}^*)$, where $\theta_{it}^* \geq 0$.

Third stage

The third stage is to obtain the estimates of market power for each firm. We have estimates of $\tilde{\varepsilon}_{it} = \varepsilon_{it} + g_{it}(\hat{\beta}) \cdot \theta_{it} = \varepsilon_{it} + \tilde{\theta}_{it}$, which obviously contains information on θ_{it}. The problem is to extract the information that $\tilde{\varepsilon}_{it}$ 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 one-sided random term (here $\tilde{\theta}_{it}$) given the composed error term (here $\tilde{\varepsilon}_{it}$). In Table 3 we provide under several distributional assumptions for the analytic form for $E(\tilde{\theta}_{it} \mid \tilde{\varepsilon}_{it})$, which is the best predictor of the conduct term (see Kumbhakar and Lovell, 2000, and Almanidis *et al.*, 2010).[37] Once we have a point estimator for $\tilde{\theta}_{it}$, a conduct score θ_{it} can be obtained using the identity $\theta_{it} \equiv \tilde{\theta}_{it} / g_{it}(\hat{\beta})$.[38] Two comments are in order. First, 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 thing being forecast. Second, in practice, this estimator uses the estimated σ_v as a measure of *historical* demand and cost random shocks, and adjusts the overall error term from "normal" random shocks in order to get an estimate of θ_{it}. Therefore, the estimated market power scores can be interpreted as mark-ups that cannot be explained by "normal" demand and cost random shocks.

4. Empirical illustration

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 skyrocketed during summer and fall 2000, resulting in breakdown of liberalized electricity market by the end of 2000. While California electricity crisis is a complex problem, driven by a number of factors, such as poor wholesale market design, absence of long-term contracting, unexpected increase in generation input costs, hike in end-use electricity

[37] 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.

[38] While we can get unbiased estimates of all parameters of the pricing equation (12) if v_{it} is heteroskedastic and it is ignored, an unwarranted assumption of homoskedasticity in v_{it} causes a wrong application of the conditional expectation that may bias the firm-specific conduct estimates. That is, estimating market power with a composed error model requires capturing not only the appropriate distribution for the conduct random term but also most of the variables which enters in the supply relationship because uncaptured differences among firms and over time might wrongly interpreted as differences or changes in conduct due to both phenomena shift the supply relationship. The procedure outlined above, however, can be generalized in order to accommodate for a heteroskedastic v_{it}. This can be achieved by modelling the variance of v_{it} as a function of firm-specific size-related variables or, when a panel data is available, by estimating a different σ_v^2 for each firm.

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 Puller (2007),[39] 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 assumed to supply at marginal cost includes generation from nuclear, hydroelectric, and small independent producers, and imports from outside California. These suppliers either are relatively small or do not face strong incentives to influence the price.[40] Because electricity storage is prohibitively costly, both strategic and non-strategic firms had to produce a quantity equal to demand at all times.[41] And the residual demand for electricity was relatively inelastic, which allowed individual firms to raise prices unilaterally.

As the main contribution of the proposed procedure is the estimation of firm-specific market power scores (i.e. our second and third stages), 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, , the same specification for the pricing equation (1), and the same set of dependent and explanatory variables. Our results are similar to those obtained by Puller, but they do not fully coincide because of small measurement error in construction of marginal costs[42], slightly different set of instruments,[43] and balancing the dataset.[44] As we mentioned

[39] See also Borenstein, Bushnell and Wolak (2002) and Kim and Knittel (2006).

[40] The 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.

[41] 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.

[42] This is because we did not observe the spot prices for natural gas for California hubs in 1998 and 1999, using 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).

[43] Though our instruments were somewhat different, the Hansen tests seem to indicate that we cannot reject them.

[44] Puller (2007) estimated the models by ignoring days when the price began to hit the price cap in summer 2000. We cannot drop those days from our sample because we do not know when the price hit

earlier, our analysis here is so far restricted to the estimation of the pricing equation (1), conditional on previous estimates of the demand parameters. The elasticity demand needed for the second and third stages of our procedure is taken from Puller's (2007) estimates as we use 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. In particular, we use both the traditional (one-sided) half-normal distribution that imposes the conduct term be positive, and the truncated half normal distribution, from Almanidis *et al.* (2010), that also imposes the conduct term be less than the number of strategic firms.[45]

Pricing equation and data

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

$$(P - mc)_{it} = \alpha \cdot CAPBIND_{it} + \gamma \cdot \frac{P_t q_{it}}{Q^S_{fringe,t}} + \varepsilon_{it} \quad , \tag{24}$$

where α and γ 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 $Q^S_{fringe,t}$ is supply by the competitive fringe, i.e. total demand minus total strategic demand. Note that in this equation γ is the expected value of the conduct random term θ_{it} divided by the elasticity of fringe demand already estimated, that is: $\gamma = \theta / \hat{\beta} = E(\theta_{it}) / \hat{\beta}$. Once the parameter γ is estimated consistently, we use Puller's (2007) demand elasticity estimates to compute the expected value of the conduct random term.

We use hourly firm-level data on output and marginal cost. Following 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. Similar to earlier studies on market power in California electricity markets mentioned above, we have calculated the hourly marginal cost of fossil-fuel electricity plants as the sum of marginal fuel, emission permit, and variable operating and maintenance costs.[46] 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.

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the cap. However, we do not expect significant changes in our results in the first-stage, where an average conduct value is estimated for the whole period, because this only affected 7.8% of his observations in 2000. It should be noted, on the other hand, that high conduct values can be obtained in the third-stage of our procedure in those days as the first-order condition underlying the supply relation does not hold with equality. This problem is less severe when double-bounded distributions are used as they restrict the conduct values to be smaller than the number of strategic firms.

[45] In next versions of the paper we will try to estimate other distribution functions as well as to carry out model selection tests to choose the specification that fits better the data. However, given the small conduct values obtained by Puller (2007), the distributions currently selected here seem to be quite probable.

[46] For more details, see technical appendix in Puller (2007). Also see footnote 38.

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. Most firms own power plants in a single transmission zone, so we use a PX zonal price. Table 4 reports the summary statistics for all these variables.

Price-cost margins are shown in Figure 3. This figure is almost the same as Figure 1 in Puller's (2007) paper, and shows that margins vary considerably over my sample period. They are also higher during the third and fourth quarters of each year, when total demand for electricity is high. We next analyze the extent to which higher margins resulted from less competitive pricing behavior rather than less elastic demand.

Pricing equation estimates

Let us comment in detail the econometric strategy for estimating (24) and obtaining the first-stage parameter estimates. Puller (2007) pointed out that actual output is likely an endogenous variable as the error term ε_{it} in (24) includes marginal cost shocks that are observed by the utility. Due to the correlation between actual output and the unobserved error, we need proper instruments for $P_t \cdot q_{it}/Q^S_{fringe,t}$ (hereafter x_{it}), which are correlated with actual output. Table 5 reports useful information on the specification, estimation and fit of the pricing equation using different set of instruments for the two periods analyzed in Puller (2007).

In regression 1 we treat x_{it} as an exogenous variable. The negative sign of $CAPBIND_{it}$ and the implicit large value for the average conduct (1.53) are likely caused by the endogeneity of x_{it} (Puller´s 2007 estimate is about one). In regression 2 we instrument the variable x_{it} with firm´s capacity, k_{it}, which we assume orthogonal to the error term because it can be viewed as a quasi-fixed variable, independent of current levels of operation. Using k_{it} as an instrument we get a dramatic improvement in both parameter estimates, especially the coefficient of $CAPBIND_{it}$ that now is positive and closer to Puller's estimate. In regression 3 we add capacity square as an additional instrument. This allows us to carry out a Hansen's (1982) J test. The Hansen's J test statistic value suggests that some endogeneity is still present or that just adding k_{it} and k^2_{it} is not sufficient to control for the endogeneity of x_{it} given the poor temporal information contained in firm´s capacity.

Puller (2007) instrumented utility output with the day-ahead forecast of total demand, FQ_t. Unlike k_{it}, this instrument does not vary among utilities, but changes over time. In Regression 4 we replace k^2_{it} by FQ_t. The increase in the value of the Hansen test indicates that adding day-ahead forecast of total demand as an additional instrument works even worse than using k^2_{it}. This is confirmed by regression 5 where just FQ_t is used as instrument of x_{it}, obtaining similar results as in Regression 1 with no instruments (in particular, a negative sign of $CAPBIND_{it}$).

It should be noted, however, that the day-ahead forecast error is also notably correlated with the supply of competitive fringe, which is in the denominator of x_{it}. For this reason, instead of using day-ahead forecast of total demand, in Regression 6 we use its reciprocal, $1/FQ_t$ as instrument of x_{it}, obtaining an improvement in the parameter estimate of $CAPBIND_{it}$. Finally, in Regression 7 we add k_{it} as an additional instrument for x_{it} to the previous model, obtaining a further improvement in the equation fit. Using the Hansen's (1982) J test we cannot reject the null hypothesis that the model is well specified and that the set of instruments are valid. This is our preferred estimate.

Regarding the second period from April 1999 to November 2000, the sequence of results is quite similar to that obtained for the first period. Again, the Regression 7 is our preferred model as the Hansen test suggests that the model is well specified and the instruments are valid. As in Puller (2007), the coefficient of x_{it} is similar in both periods, whereas the coefficient of $CAPBIND_{it}$ is much larger in the second period than in the first one, likely as a result of a higher demand in the second period. Using the estimates of demand elasticities from Puller (2007) the implicit average conduct values in both periods are 1.05 and 1.09 respectively, quite close to those obtained by Puller (2007).[47]

In general, we can conclude that our GMM parameters estimates of the pricing equation (24) are analogous to those obtained in Puller's paper, and we are therefore in a good situation to carry out the second and third stages of our procedure. In addition, at the bottom of both Tables 5a and 5b we also report non-normality test. In all specifications, we can reject that the composed error term is normally distributed. This seems to suggest that we can go ahead with the second and third stages as they take advantage of the skewness of the composed random term.

Firm-specific market power scores

Once all parameters of the pricing equation (24) 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 random error component and a market-power component (third-stage).

Given the small conduct values obtained in the first stage, we just provide an application using the truncated half normal distribution. As explained in section 2, this distribution satisfies both lower and upper theoretical bounds, i.e. $0\leq \theta_{it}\leq N$, and is positive skewed. In particular, this distribution implies that θ_{it} comes from pre-truncated normal distribution, $N(0,\sigma_u^2)$, that is truncated below zero *and* above the number of strategic firms, N . Table 6 compares the parameter estimates of the truncated half-normal of the two parameters describing the structure of θ_{it} and v_{it} (i.e. σ_v and σ_u), conditional on the first-stage estimated parameters. For comparison grounds, we also present the traditional half-normal distribution that only imposes the conduct term be positive, and hence it might yield market power scores higher than the number of strategic firms in the third stage. This allows us to measure the convenience of using double-bounded distributions in practice.[48] While the truncated half normal model is

[47] Puller (2007) obtained an identical conduct parameter θ=0.97 for both periods that is statistically indistinguishable from unity.

[48] We have tried to estimate doubly-truncated normal distributions with μ>0, but we have found convergence problems. This result is frequent in the production frontier literature. Indeed, Ritter and

estimated using ML techniques, the traditional half-normal model is estimated using both ML and MM approaches in order to evaluate the relative performance of both types of estimators.[49]

In general, the truncated half-normal and the one-sided half normal models yield similar values for both the random error term variance, σ_v, and the the pre-truncated conduct variance, σ_u. Moreover, both ML parameter estimates are even the same in the case of the second subperiod. In all cases, the conduct variance is much lower than the variance of the 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. Although both truncated and one-sided half-normal models yield similar variance estimates, market power scores higher than N are expected in the one-sided half normal model because the upper bound $\theta_{it} \leq N$ is not imposed. We also find that, whatever the model, the variation of the random conduct term is smaller in the second subperiod than in the first one.

Based on the previous estimates, the third stage allows us to get firm-specific market power scores. Table 7 provides the arithmetic average scores of each firm obtained using both ML truncated-half normal and half-normal distributions that does not impose the theoretical restriction $\theta_{it} \leq N$. This table displays an interesting finding: the market power scores for the half-normal distributions are, on average, much higher than the upper-bound indicated by the theory, *N*. This usually occurs when, like in the present application, the estimated first-stage errors terms are large. In this scenario, the traditional conditional expectation operator used in the third-stage tends to exagerate the one-sided error term. As this might be the case in many marker power applications, the above result suggests 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.

As regards the double-bounded distributions several interesting points are worth mentioning. First, like in Puller (2007), the estimated market power values are closer to Cournot (θ_{it} =1) than to static collusion (θ_{it} =N). Unlike Puller, we do not find an increase in market power if we compare the average values in the first period (1.21) with those obtained in the second (0.95). 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. Puller (2007) found also a similar outcome using a fixed-effect treatment for the conduct parameters. Here, this result is obtained without involving panel data estimators. Moreover, as shown in Figure 4, our market power estimates are quite similar to that estimated by Puller. This result is quite important because it means that we can get comparable results using two different modeling strategies, and hence both approaches can in principle be used to estimate firm-specific market power scores.

Simar (1997) shown that, the parameters describing a one-sided random term are hard to estimate, except for simple distributions such as exponential or half-normal. In addition, Almanidis *et al.* (2010) pointed out that identification problems may arise when estimating a $0<\mu<N$.

[49] It should be noted that ML estimates were obtained without imposing that the average conduct implied by the estimated two-stage model should be equal to the first-stage estimate of the average conduct. This restriction is imposed by construction when a MM estimator is used.

Our procedure has the advantage over Puller's approach that it can be applied when no panel data sets are available, when the time dimension of the data set is sort and, or when separable pricing equations cannot be estimated consistently because the available instruments are not valid.[50] Interesting enough, Puller (2007) pointed out that Dynegy's (i.e. DST) conduct parameter is biased upward. Our approach based on the estimated distribution of the random conduct term allow us to avoid this bias, as our point estimates for this firm are sound and satisfy the theoretical restrictions.

Figures 5 and 6 depict the histograms of the market power scores by firm for the two periods analyzed in the paper. The histograms in Figure 5 indicate that firms' pricing strategies are similar, i.e. all density curves are tightly peaked and concentrated about their modal value, indicating that those values are quite persistent over time. Regarding the second period, the histograms in Figure 6 suggest an important change in firms' pricing strategies though the average conduct value estimated for the whole industry in the first-stage of our procedure does not change from the first subperiod to the next. Now, all density curves, except that for DST, are flatter indicating the existence of both relative competitive and collusive strategies over time.

In the introduction section we propose using a screen based on the coefficient of variation of the firm-specific market power scores to identify collusive firms. In Table 8 we show the computed coefficients of variation for each firm using the estimated market power scores obtained using the double-bounded model. Our screen tries to identify potential collusive firms that exhibit low conduct variation and high conduct values relative to other firms. In general, we find low coefficients of variation in the first subperiod, suggesting that the estimated level of competition/collusion is quite stable. From Table 8, we also find that DST has the highest (average) conduct value in the first subperiod, but also the highest coefficient of variation. This result, hence, casts doubts about the superior market power of this firm. Reliant has more market power based on the coefficient of variation. [51] In general, we find a notable increase in all coefficients of variation from one period to the next, suggesting a reduction in collusion discipline or market stability. This higher instability might be caused by the entrance of Southern. The increase is especially remarkable in the case of Duke and Relaint with coefficients that are twice those in the first subperiod, indicating an important change in the pricing strategies of these firms.

Table 9 tries to analyze the coordination among firms over time. In general, we can conclude from this table that the temporal patterns of the market power scores often differ notably among firms, though some firms are steadily more (less) competitive. For instance, AES and DST seem to behave independently as their correlation in the first subperiod is quite low (0.28). The correlation between AES and DST in the second period is much higher, indicating an important change in the pricing strategies of these firms. All coefficients of correlation for Duke are quite low in the second period, and much lower than in the first period. This might suggest that, in the second period, Duke

[50] Indeed, following Puller (2007), we have estimated a pricing equation for each firm using the same set of instruments as in Table 4 and 5. The estimated conduct parameters (not shown) were quite similar to those obtained by Puller (2007). However, in all cases, except one, we rejected the null hypothesis that the model was well specified.
[51] Obviously, another explanation is possible if its large market power variance is caused by punishment episodes implemented by this firm to restore market power in the next future.

becomes a “maverick” firm with a pricing strategy that is notably different from the pricing strategies of other firms.

In a panel data setting the most important advantage of our methodology is that we can analyze changes in market conduct over time. Indeed, because our approach does not model the temporal path of these scores, they might change from one day to the next. This evidence can be used to complement time-invariant (firm-specific) conduct estimates obtained in the first stage. In Figures 7 and 8 we show the temporal evolution of the average market power scores of the four/five strategic firms during the two periods analyzed in the present paper.[52] In particular, our results suggest that market power scores do vary on average over time. For instance, we can see that, after a few months, market power was quite persistent over time in the first period, except at the begining of the period were higher market power scores were found. Another remarkable finding is that market scores are much more instable in the second period. This instability in turn rises a lot since June 2000, which coincide with the skyrocketing prices in 2000. Note also that, on average, market power scores increased in this period of instability.

Our market power estimates also allow us to analyze whether each firm reacts differently to changes in cost and demand conditions. In Figures 9 and 10 we show the market power score of each firm. These figures display interesting findings. First, the temporal patterns of the market power scores do not differ a lot among firms, especially in the first subperiod. Second, the ranking of market power scores is quite stable. Some firms are steadily more (less) competitive along the whole period. Compare, for instance, Duke and DST.

And, third, the estimated market power scores can also be used to identify patterns of behavior inconsistent with competitive settings. Harrington (2006) pointed out, for instance, that unless the market is characterized by some cyclical factors such as seasonal demand or supply movements, it would be unlikely for competition to result in significant price declines and then a steadily rising price over the span of a few periods. Interesting enough, this pattern is found at the begining of the first subperiod (see Figure 7) where after a conduct declining, market power scores steadily rose and stayed stable for several weeks.

5. Summary and future agenda

Measuring the degree of competition in oligopolistic markets is a key activity in empirical industrial organization. Earlier studies focused on estimating conduct parameters imposed some restrictions on the way the value of conduct parameter varies across firms and time. However, firms likely do no share the same conduct parameter and this parameter varies over time as market conditions change, and firms change their own pricing strategies, which is generally the case in recent restructured electricity markets. As allowing for the conduct parameter to vary freely both by firm and observation results in an overparameterized model, we suggest treating firms’ behaviour as a random parameter. In doing so, we estimate a “composed error” model where the

[52] Our market power scores vary along the week. To smooth the market and firm temporal series we have used 7-day moving averages of the observations.

stochastic part is formed by two random variables, i.e. the traditional error term, capturing random shocks, and a random conduct term, which measures market power.

The model can be estimated in three stages using either cross-sectional or panel data sets. While the first stage of our model is standard, the following stages allow us to first distinguish collusion discipline/instability from demand and cost volatility, and second to get firm-specific market power scores, conditional on the first-stage parameter estimates. These stages take advantage of the fact that the conduct term is likely positively or negatively skewed. As we aware, skewness of conduct parameter in oligopolistic industry settings are not examined explicitly in most (if any) of the previous empirical papers. The main contribution of the paper is that once all parameters describing the structure of the traditional pricing equation are estimated, additional information can be inferred from the next stages of our procedure. This information, usually ignored in previous papers estimating conduct parameters, provides a better understanding of pricing strategies at the firm level. In particular, the estimated conduct variation can be used as a measure of the degree of collusive discipline across firms and/or over time, and the market power scores can be used to detect the creation/decline of collusion episodes, or to identify abrupt changes in mark-ups which cannot be explained by "normal" demand and cost random shocks.

We illustrate the proposed approach with an application to the California wholesale electricity market using the same data (sample period, specification for the pricing equation, and set of dependent and independent variables) as Puller (2007). After estimating the parameters of the pricing equation, we have carried out the second and third stages using both the traditional half-normal distribution and the so-called truncated half normal distribution, recently developed by Almanidis *et al.* (2010) in the stochastic frontier literature but adapted here to measure market power.

Our first-stage results are quite similar to those obtained by Puller (2007). The estimated market power values are closer to Cournot (θ_{it} =1) than to static collusion (θ_{it}=N). However, we find notable differences among utilities in terms of market power. Our results suggest that market power varies over time. Although some firms are steadily more (less) competitive along the whole period, the temporal patterns of the market power scores also differ among firms. Moreover, our firm-specific market power scores are quite similar to that estimated by Puller (2007) using fixed-effect approach. This important result demostrate that both approaches can in principle be used to estimate firm-specific market power scores. Our procedure has the advantage over Puller's approach that it can be applied with cross-sectional or sort data sets; or when individual pricing equations cannot be consistenty estimated with the available instruments. In addition, our results suggest that our approach based on the estimated distribution of the random conduct term yield more reasonable market power scores than a fixed-effect approach.

A simple empirical application in the present paper illustrates how the proposed methodology works. In the future we will try to analyze the robustness of our results to different specifications for both the pricing equation (first-stage) and the following stages of our procedure. In particular, as suggested by the preliminary results, we will try to estimate other distribution functions as well as to carry out model selection tests to choose the specification that fits better the data. For the first-stage, we will estimate simultaneously both demand and pricing parameters, using more accurate sample selection and allowing for cyclical behaviour of firm conduct and differences in strategic behaviour among firms and between peak and off-peak hours or between week and weekend days. We also expect to extend the pricing equation into a dynamic framework as discussed in the first section.

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Table 1. Central moments of θ_{it} for the truncated normal distribution

Moment	Expression
$E(\theta_{it}) = \theta$	$\mu + \frac{\phi(\mu/\sigma_u)}{\Phi(\mu/\sigma_u)} \cdot \sigma_u$
$E\left[(\theta_{it} - \theta)^2\right] = \sigma_\theta^2$	$\sigma_u^2 - \frac{\phi(\mu/\sigma_u)}{\Phi(\mu/\sigma_u)} \cdot \sigma_u \cdot \theta$
$E\left[(\theta_{it} - \theta)^3\right]$	$-\frac{\phi(\mu/\sigma_u)}{\Phi(\mu/\sigma_u)}\sigma_u^3 + \left[\frac{\phi(\mu/\sigma_u)}{\Phi(\mu/\sigma_u)}\right]^2 \sigma_u^2 \cdot \theta + \frac{\phi(\mu/\sigma_u)}{\Phi(\mu/\sigma_u)} \cdot \sigma_u \cdot \theta^2$

Table 2. Double-bounded density functions (0≤u≤B)

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

Table 3. Conditional means for selected distributions

One-sided distributions	
Model	Functional form of $E(u\mid v+u)$
Truncated normal	$\mu_* + \sigma_* \phi\left(\frac{-\mu_*}{\sigma_*}\right)\left[\left[1-\Phi\left(\frac{-\mu_*}{\sigma_*}\right)\right]\right]^{-1}$ $\mu_* = \frac{\mu\sigma_v^2 + \varepsilon\sigma_u^2}{\sigma^2}$, $\sigma_* = \frac{\sigma_u\sigma_v}{\sigma}$
Half normal	$\mu_* + \sigma_* \phi\left(\frac{-\mu_*}{\sigma_*}\right)\left[\left[1-\Phi\left(\frac{-\mu_*}{\sigma_*}\right)\right]\right]^{-1}$ $\mu_* = \frac{\varepsilon\sigma_u^2}{\sigma^2}$, $\sigma_* = \frac{\sigma_u\sigma_v}{\sigma}$
Double-bounded distributions	
Doubly truncated normal	$\mu_* + \sigma_* \left[\phi\left(\frac{-\mu_*}{\sigma_*}\right) - \phi\left(\frac{B-\mu_*}{\sigma_*}\right)\right]\left[\Phi\left(\frac{B-\mu_*}{\sigma_*}\right) - \Phi\left(\frac{-\mu_*}{\sigma_*}\right)\right]^{-1}$ $\mu_* = \frac{\mu\sigma_v^2 + \varepsilon\sigma_u^2}{\sigma^2}$, $\sigma_* = \frac{\sigma_u\sigma_v}{\sigma}$
Truncated half normal	$\mu_* + \sigma_* \left[\phi\left(\frac{-\mu_*}{\sigma_*}\right) - \phi\left(\frac{B-\mu_*}{\sigma_*}\right)\right]\left[\Phi\left(\frac{B-\mu_*}{\sigma_*}\right) - \Phi\left(\frac{-\mu_*}{\sigma_*}\right)\right]^{-1}$ $\mu_* = \frac{\varepsilon\sigma_u^2}{\sigma^2}$, $\sigma_* = \frac{\sigma_u\sigma_v}{\sigma}$

Table 4. Summary statistics (hour 18)

July 1, 1998 - April 15, 1999	Mean	St.dev.	Min	Max	Obs
Price (P_t)	37.03038	26.24066	4.93	180.4462	1156
Marginal cost (mc_{it})	26.31697	3.14576	18.73386	33.7443	1156
Margin ($P_t - mc_{it}$)	10.71341	26.32763	-24.97757	158.61059	1156
$CAPBIND_{it}$	0.05623	0.23046	0	1	1156
Capacity (k_{it})	2466.25606	1060.90136	670	3879	1156
Output (q_{it})	809.48832	873.68	0	3720	1156
Market demand(Q_t)	30316.5536	4547.09194	20057	44009	1156

April 16, 1999 – November 30, 2000	Mean	St.dev.	Min	Max	Obs
Price (P_t)	83.06045	98.15182	9.5	1099.989	2975
Marginal cost (mc_{it})	45.87634	23.71389	22.30387	214.4733	2975
Margin ($P_t - mc_{it}$)	37.18411	88.66886	-33.35807	1053.29913	2975
$CAPBIND_{it}$	0.06689	0.24987	0	1	2975
Capacity (k_{it})	2960.23563	768.09479	1020	3879	2975
Output (q_{it})	1370.32782	833.23359	0	3317	2975
Market demand(Q_t)	31370.1698	4106.27907	22076	44160	2975

Table 5a. Pricing equation estimates (July 1, 1998 - April 15, 1999) [(d)]

Dependent variable: $(P\text{-}mc)_{it}$
No. of strategic firms: 4
Observations: 1156
Method: Two-step GMM [(a)]

Explanatory variables [(b)]	1	2	3	4	5	6	7
$CAPBIND_{it}$	-3.936	12.595	13.612	13.157	-0.809	9.302	13.130
	(-1.12)	(3.18)	(3.36)	(3.47)	(-0.20)	(2.21)	(3.26)
x_{it}	8.606	6.067	5.717	5.583	8.125	6.573	5.894
	(31.18)	(19.66)	(18.37)	(19.89)	(19.94)	(15.95)	(19.11)
Instruments: [(b)]	$CAPBIND_{it}$, x_{it}	$CAPBIND_{it}$, k_{it}	$CAPBIND_{it}$, k_{it}, k^2_{it}	$CAPBIND_{it}$, k_{it}, FQ_t	$CAPBIND_{it}$, FQ_t	$CAPBIND_{it}$, $1/FQ_t$	$CAPBIND_{it}$, k_{it}, $1/FQ_t$
Statistics:							
Hansen test (d.f.)			21.732 (1)	64.96 (1)			5.399 (1)
Skewness test (d.f.)		3168.9 (1)	3179.0 (1)	3204.1 (1)	2820.2 (1)	3187.1 (1)	3175.7 (1)
Jarque-Bera Test (d.f.)		26567.6 (2)	25360.4 (2)	24930.9 (2)	27699.7 (2)	28217.6 (2)	25993.6 (2)
Estimated average conduct value: [(c)]	1.53	1.08	1.02	0.99	1.44	1.17	1.05

Notes:
[(a)] T-ratios in parenthesis, computed from standard errors robust to heteroskedasticity.
[(b)] FQ_t is day-ahead forecast of total (perfectly inelastic) demand and $x_{it} = P_t q_{it} / Q^S_{fringe,t}$.
[(c)] $\hat{\theta} = \hat{\gamma} \cdot \hat{\beta}$, where $\hat{\beta} = 0.178$ comes from Puller's paper.
[(d)] Puller's estimates of these parameters are: $(P - mc)_{it} = \underset{(22.65)}{21.52} + \underset{(16.89)}{5.457}\ x_{it}$

Table 5b. Pricing equation estimates (April 16, 1999 – November 30, 2000) [(d)]

Dependent variable: $(P\text{-}mc)_{it}$
No. of strategic firms: 5
Observations: 2975
Method: Two-step GMM [(a)]

Explanatory variables [(b)]	1	2	3	4	5	6	7
$CAPBIND_{it}$	-9.512	28.022	27.558	26.384	19.441	27.225	27.221
	(-2.36)	(4.38)	(4.27)	(4.25)	(3.24)	(4.31)	(4.26)
x_{it}	8.204	5.685	5.553	5.276	6.261	5.738	5.679
	(41.71)	(41.17)	(40.43)	(41.46)	(40.21)	(39.03)	(40.95)
Instruments: [(b)]	$CAPBIND_{it}$, x_{it}	$CAPBIND_{it}$, k_{it}	$CAPBIND_{it}$, k_{it}, k^2_{it}	$CAPBIND_{it}$, k_{it}, FQ_t	$CAPBIND_{it}$, FQ_t	$CAPBIND_{it}$, $1/FQ_t$	$CAPBIND_{it}$, k_{it}, $1/FQ_t$
Statistics:							
Hansen test (d.f.)			30.886 (1)	98.322 (1)			1.24 (1)
Skewness test (d.f.)		15421.7 (1)	15621.5 (1)	15885.1 (1)	14795.6 (1)	15398.6 (1)	15487.0 (1)
Jarque-Bera Test (d.f.)		286585.5 (2)	283621.4 (2)	274742.2 (2)	308937.4 (2)	289252.7 (2)	287834.7 (2)
Estimated average conduct value: [(c)]	1.57	1.09	1.07	1.01	1.20	1.10	1.09

Notes:
[(a)] T-ratios in parenthesis, computed from standard errors robust to heteroskedasticity.
[(b)] FQ_t is day-ahead forecast of total (perfectly inelastic) demand and $x_{it} = P_t q_{it} / Q^S_{fringe,t}$.
[(c)] $\hat{\theta} = \hat{\gamma} \cdot \hat{\beta}$, where $\hat{\beta} = 0.192$ comes from Puller's paper.
[(d)] Puller's estimates of these parameters are: $\underset{}{(P - mc)_{it}} = \underset{(6.19)}{41.20} + \underset{(22.11)}{5.041}\ x_{it}$

Table 6. Second-stage parameter estimates

	First Period	Second Period
First-stage average conduct: $\hat{\theta} = E(\theta_{it})$	1.05	1.09
ML truncated-half normal		
σ_v	10.59	9.8976
	(40.92)	(51.16)
σ_u	1.563	1.1917
	(21.08)	(60.17)
Implicit average conduct:	1.21	0.95
Half-normal (ML approach)		
σ_v	6.730	9.8976
	(32.417)	(51.16)
σ_u	2.176	1.1917
	(28.58)	(60.17)
Implicit average conduct:	1.73	0.95
Half-normal (MM approach)		
σ_v	10.171	Negative
σ_u	1.314	1.044
Implicit average conduct:	1.05	0.83

Notes: T-ratios in parenthesis. Since the MM approach calculates rather than estimates the structure parameters of both random terms, the calculated values do not come with standard errors attached.

Table 7. Average market power scores per firm

Firm	July 1, 1998 - April 15, 1999			April 16, 1999 – November 30, 2000		
	Observations	Half-Normal	Truncated Half- Normal	Observations	Half-Normal	Truncated Half Normal
AES	289	11.60	1.10	595	40.94	0.91
DST	289	8.85	1.45	595	39.01	1.19
Duke	286	13.57	1.07	594	32.83	0.73
Reliant	273	12.22	1.20	593	41.61	0.87
Southern	-	-	-	595	36.21	0.98

Notes: For the first (second) period the market power should be less than 4 (5). The market power score cannot be estimated in a few observations due to they report zero output.

Table 8. Variation of market power scores per firm

Firm	July 1, 1998 - April 15, 1999			April 16, 1999 – November 30, 2000		
	Average	Standard deviation	Coefficient of variation	Average	Standard deviation	Coefficient of variation
AES	1.10	0.34	0.31	0.91	0.43	0.47
DST	1.45	0.64	0.44	1.19	0.80	0.67
Duke	1.07	0.34	0.31	0.73	0.53	0.73
Reliant	1.20	0.33	0.28	0.87	0.44	0.50
Southern	-	-	-	0.98	0.40	0.41

Table 9. Coefficient of correlations among firm-specific market power scores

	July 1, 1998 - April 15, 1999						*April 16, 1999 – November 30, 2000*				
	AES	DST	Duke	Reliant	Southern		AES	DST	Duke	Reliant	Southern
AES	1					AES	1				
DST	0.28	1				DST	0.71	1			
Duke	0.36	0.64	1			Duke	0.30	0.44	1		
Reliant	0.69	0.54	0.57	1		Reliant	0.78	0.76	0.38	1	
Southern	-	-	-	-	1	Southern	0.53	0.66	0.36	0.66	1

Figure 1. Traditional lower-bounded distributions

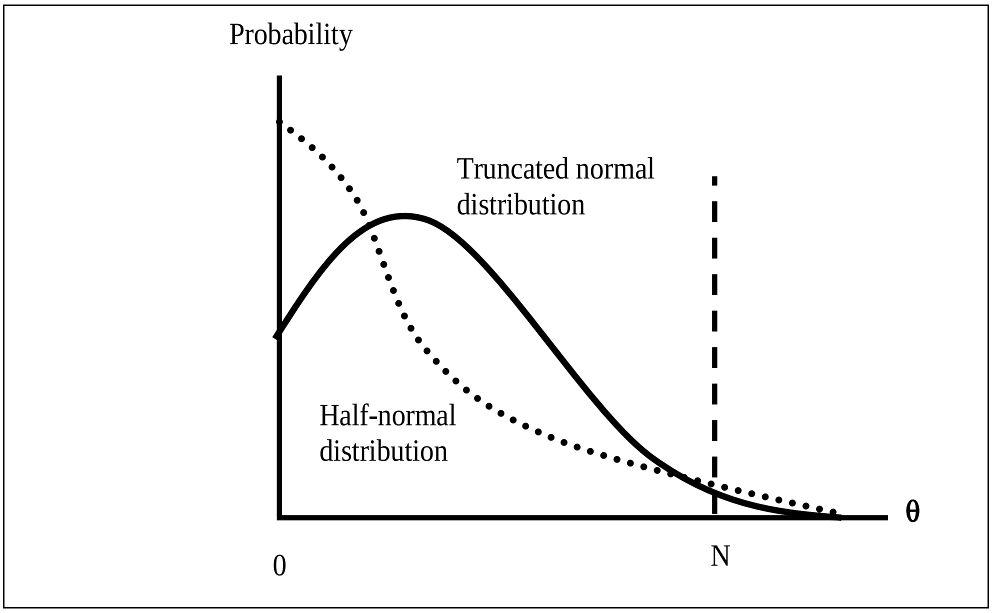
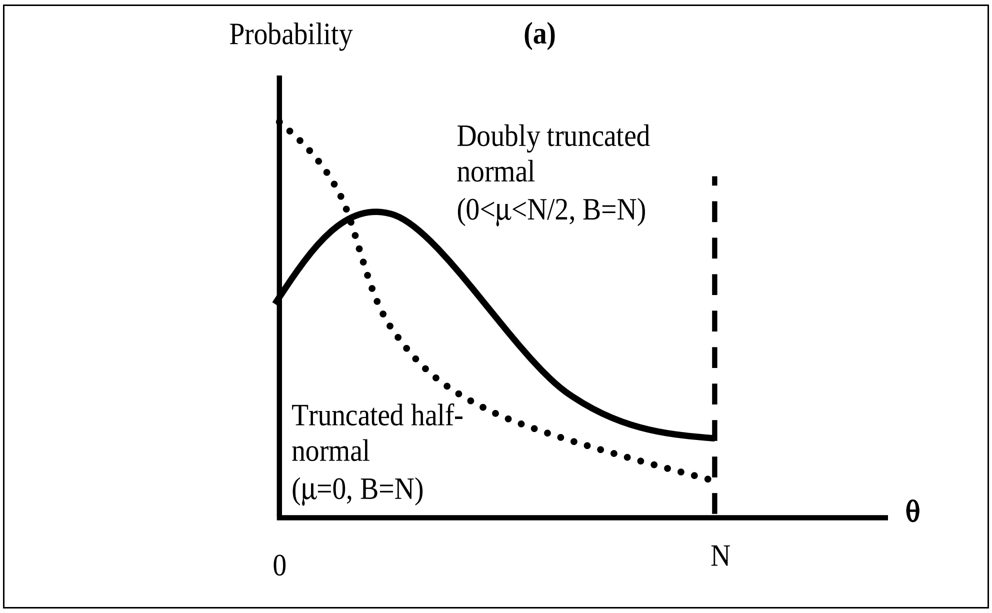


Figure 2. Double-bounded distributions



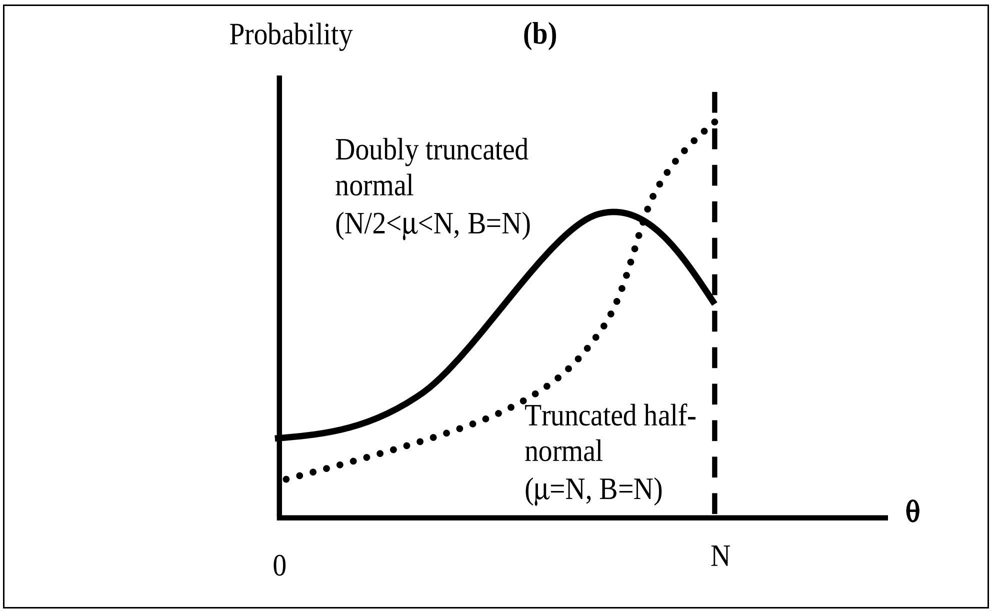


Figure 3. Price-cost margins in hour 18 (July 3, 1998 – November 30, 2000)

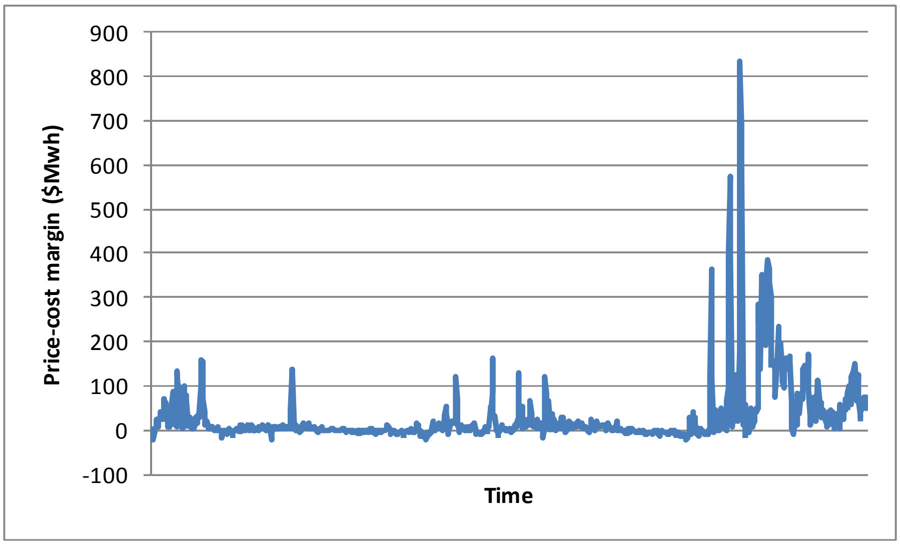
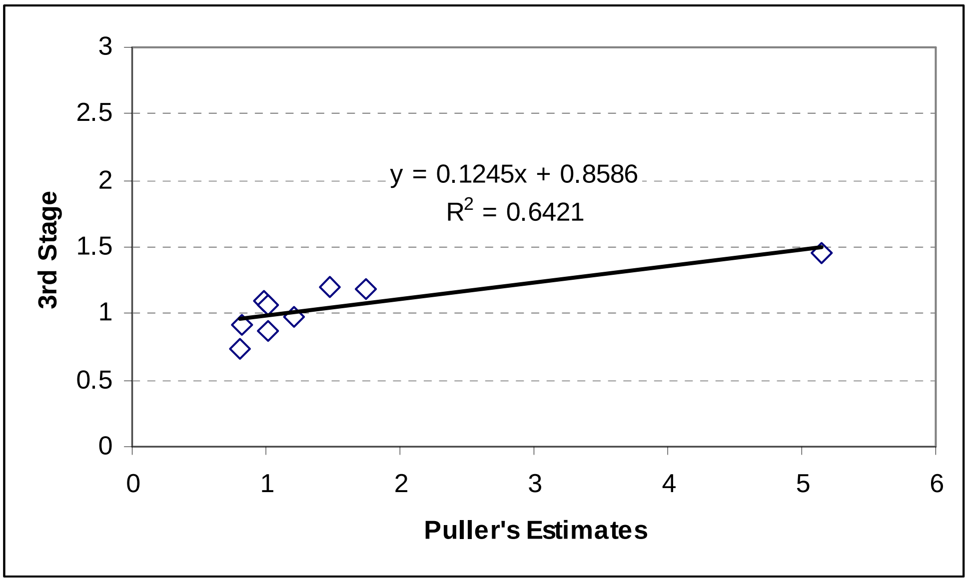


Figure 4. Comparison with Puller's (2007) firm-specific market power estimates



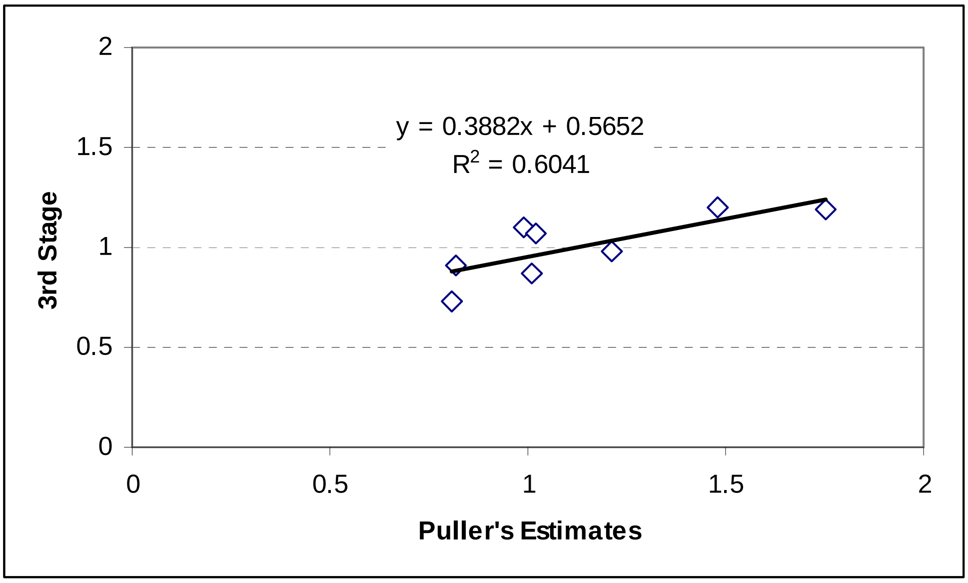


Figure 5. Firm-specific market power scores. Histograms.
(July 3, 1998 – April 15, 1999)

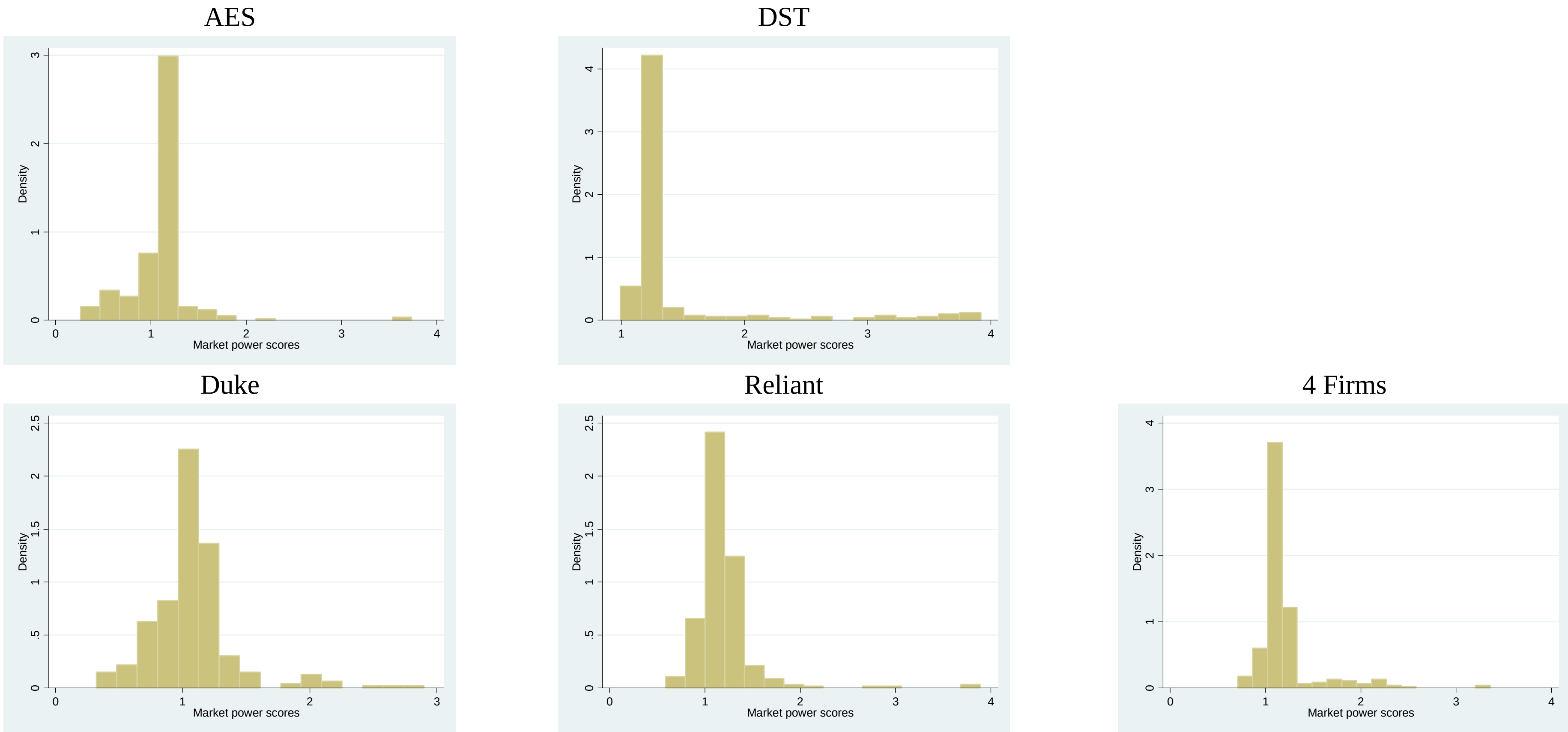


Figure 6. Firm-specific market power scores. Histograms.
(April 16, 1999 – November 30, 2000)

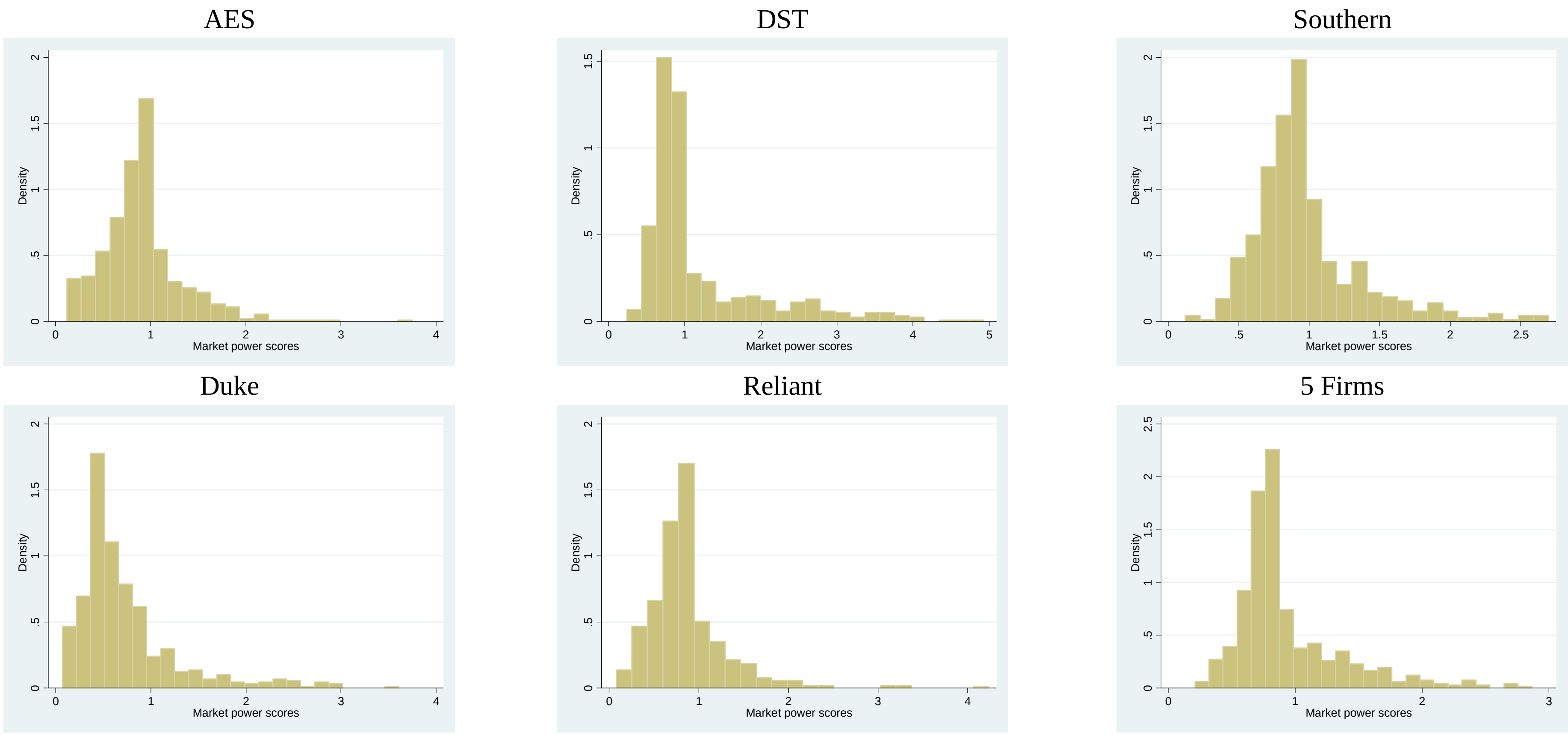


Figure 7. Industry average market power score
(July 3, 1998 – April 15, 1999)

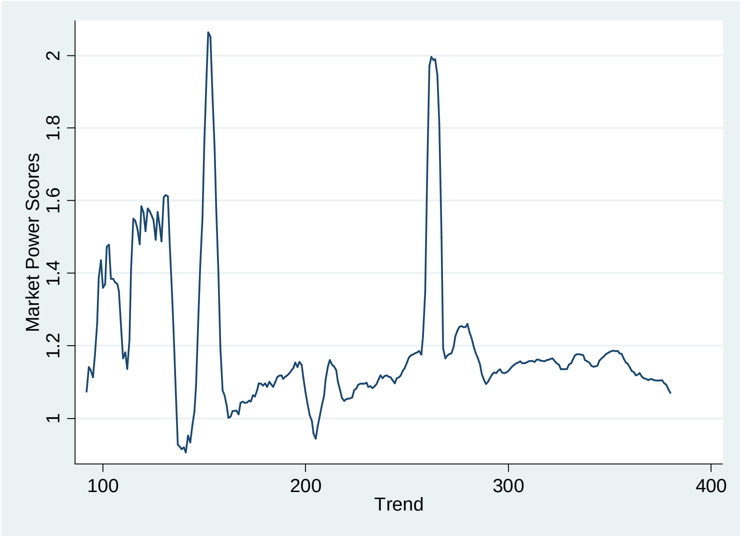


Figure 8. Industry average market power score
(April 16, 1999 – November 30, 2000)

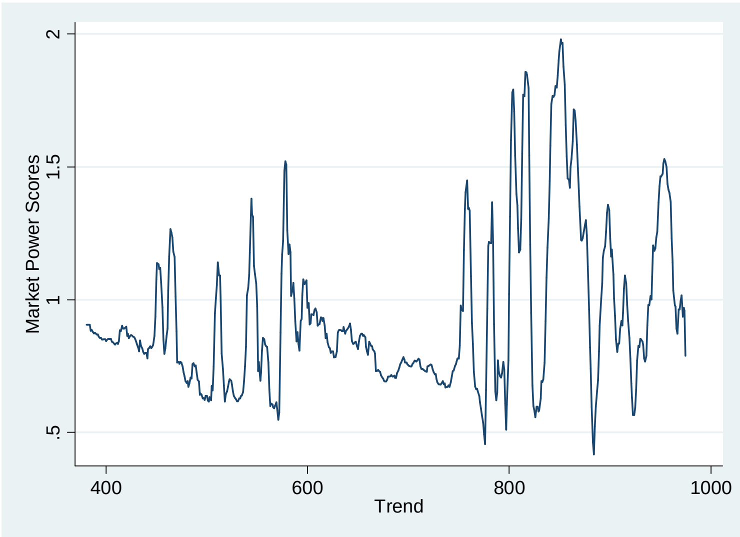


Figure 9. Firm-specific market power scores
(July 3, 1998 – April 15, 1999)

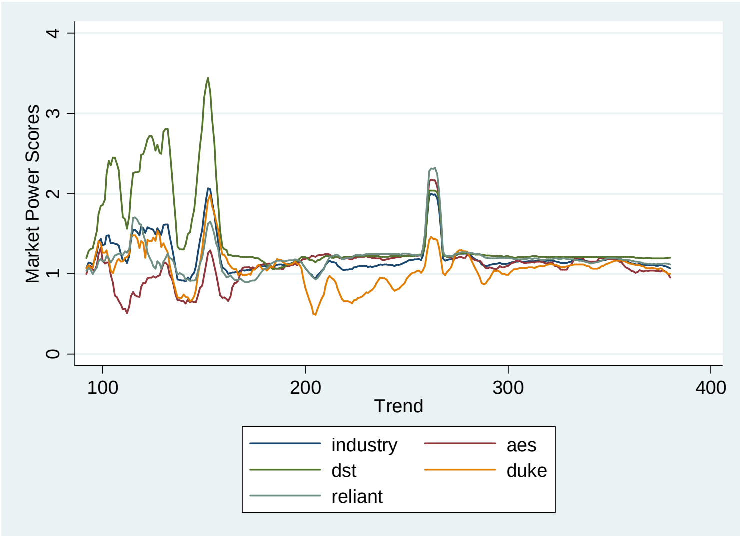
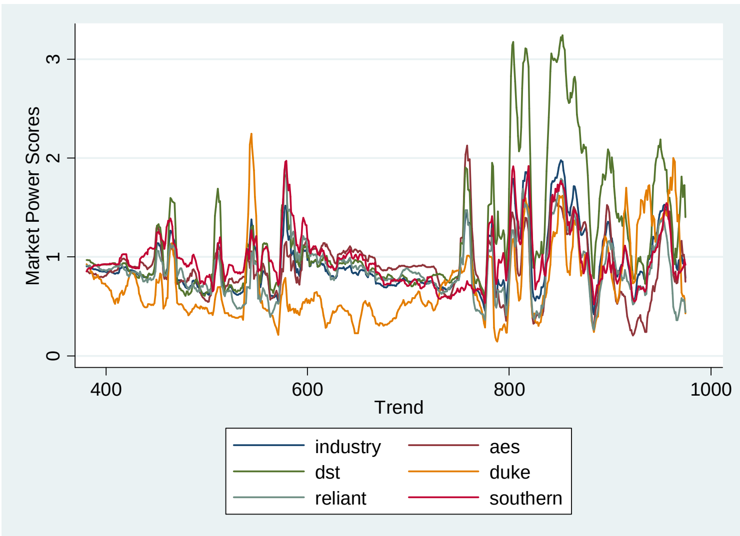


Figure 10. Firm-specific market power scores
(April 16, 1999 – November 30, 2000)



APPENDIX
(June 1, 2000 – November 30, 2000)

Figure A1. Firm-specific market power scores. Histograms.