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Surrey Energy Economics Centre

3rd International Workshop on Empirical Methods in Energy Economics (EMEE2010)

Surrey Energy Economics Centre (SEEC)

University of Surrey, UK

24th – 25th June 2010

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

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AN ONGOING PAPER, VERY PRELIMINARY RESULTS

COMMENTS ARE WELCOME !!!!

Outline

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3) Our proposal
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   - When is our proposal useful?
4) Empirical Application
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   - Second-stage parameter estimates
   - Firm-specific market power scores
5) Summary and conclusions

1. Objective

- **Objective**:
  - We propose another way to analyze market power over time and across firms, based on a three-stage estimator which can be viewed as an extension of the traditional conduct parameter approach to measure market power.
  - We illustrate the proposed approach with an application to the California Electricity generating market using the same data as Puller (2007).
- **Why the California electricity generating market**?
  - Homogenous product market
  - High concerns regarding market power since it was opened to competition in 1998.
  - Detailed price, cost, and output data is available.
  - Firms' MC must not be estimated → focus on market power.
  - In addition, this data set has been used in previous papers:
    - Puller (2007) → Traditional conduct parameter approach

2. Motivation

- Our approach relies on estimating a "conduct parameter" model that distinguish collusive behaviour from non-collusive behaviour.
  - Background: Iwata (1974), Appelbaum (1982), Brander and Zhang (1993), Gallet and Schroeter (1995), ..., and Puller (2007).
- The traditional "conduct parameter" approach:

$$P_t = mc_{it}(\cdot) + P'(Q_t)q_{it} \cdot \theta_{it} + v_{it}$$

Bertrand or Perfect competition → θ=0
Cournot → θ=1
Perfect cartel → θ=N

Continuation…

- **The conduct parameter varies across firms!**
  - “There is nothing in the logic of oligopoly theory to force all firms to have the same conduct” (Bresnahan, *Handbook of Industrial Organization*, 1989).
  - Full flexibility→ **overparameterized model.**

Traditional solutions

- Industry aggregation (Iwata, 1974) → θ_{it} is replaced by a common parameter measuring the average conduct in the industry:

$$P_t = mc_{it}(\cdot) + P'(Q_t)q_{it} \cdot \overline{\theta} + v_{it}$$

- Reducing the time variation into a period of cartel and a period of price wars (Porter, 1983) → θ_{it} is replaced by θ_t.
- Allowing different conduct parameters between two or more groups of firms (Coello, 1994).
- Using a fixed-effect treatment and a panel data set (Puller, 2007) → θ_{it} is replaced by θ_i.

3. Our proposal

- We propose treating firms' behavior (i.e. θ_{it}) as a random variable, instead of treating it as a parameter to be estimated.
- Our approach relies on the estimation of a composed error model:

$$P_t = mc_{it}(\cdot) + \varepsilon_{it} \quad , \quad \varepsilon_{it} = v_{it} + g_{it}(\cdot)\theta_{it}$$

- where ε_{it} is formed by two random variables, i.e. the traditional noise term capturing random shocks (v_{it}), and a random conduct term (θ_{it}), which measures market power.
- Here θ_{it} varies both across firms and over time, and is treated as a *continuous* random term.

Key features of the proposed model

- 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.
  - Our model roots on the stochastic frontier literature where (in)efficiency (here θ_{it}) always follows a one-sided distribution.
- Evidence on oligopolies often suggests skewed (asymmetric) distributions for θ_{it}.
- This asymmetry, in addition, allows us to get firm-specific market power estimates.
  - If symmetric → no firm-specific market power scores can be obtained.

Estimation strategy

- **First stage:**
  - GMM is used to estimate consistently the pricing equation (marginal cost parameters plus average market power).
  - This is NOT new !!
  - This stage is independent of distributional assumptions.
- **Second stage:**
  - Distributional assumptions are invoked in order to obtain consistent estimates of the variances of the two error components (i.e. σ_v and σ_θ).
  - This stage can be implemented using either the MM or ML estimator.
- **Third stage:**
  - Firm-specific market power scores (θ_{it}) are estimated by decomposing the estimated residual.

When is our approach useful?

- No panel data sets are available or the time dimension of the data set is sort
  - The fixed-effect treatment is only consistent when $T \to \infty$.
- If the panel data set is long when…
  - The assumption of time-invariant conduct is not reasonable.
  - Separable pricing equations cannot be estimated consistently because the available instruments are not valid.
- In cross-sectional 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.

More information about the oligopolistic equilibrium?

- The **second stage** allows us to distinguish variation in conduct (σ_θ) from demand and cost volatility (σ_v).
- Variation in conduct can be used as a measure of the degree of collusive *discipline* across firms and/or over time.
- A large conduct variation might suggest …
  - large differences in firms' conduct,
  - if a cartel exists, that it is not all-inclusive,
  - the existence of monitoring problems among collusive firms,
  - gradual changes in firm behaviour, …

Continuation…

- In the **<u>third stage</u>** we get market power scores for each observation.
- The procedure uses the estimated σ_v as a measure of *historical* demand and cost random shocks, and adjusts the estimated mark-ups from "<u>normal</u>" random shocks.
- The market power scores can be used to identify changes in mark-ups which cannot be explained by "normal" random shocks.
    - In this sense, they can be used to detect the creation/decline of collusion episodes.
- We advocate using the <u>coefficient of conduct variation</u> (market power scores) as a collusive screening procedure:
    - In particular, our screen would identify a potential cartel as group of firms exhibiting low conduct variation and high conduct values relative to other firms.

4. Empirical application

- **Market**: California electricity market.
- **Strategic firms**: five large firms that owned fossil-fueled generators (AES, DST, Duke, Reliant and Southern)
- **Periods**: the same as Puller (2007)
  - July 1, 1998 - April 15, 1999
  - April 16, 1999 – November 30, 2000
- **Frequency**: daily data on prices, costs, demand,…
- **First-stage (Pricing equation)**: the same as Puller (2007)
- Our first-stage results are **similar** to those obtained by Puller..
  - **… but** they do not fully coincide because small measurement errors in construction of marginal costs, different set of instruments, and balanced panel data set.

Pricing equation and data (first stage)

- Following Puller (2007, eq. 3) the pricing equation to be estimated is:

$$(P - mc)_{it} = \alpha \cdot CAPBIND_{it} + \underbrace{\left(\frac{\theta}{\hat{\beta}}\right)}_{\gamma} \cdot \underbrace{\frac{P_t q_{it}}{Q^S_{fringe,t}}}_{x_{it}} + \varepsilon_{it}$$

- $CAPBIND_{it}$ is a dummy variable that is equal to 1 if capacity constraints are binding and equal to 0 otherwise.
- x_{it} is endogenous → GMM estimator with proper instruments.
- We focus on an hour of sustained peak demand from 5 to 6 p.m. (hour 18) → no inter-temporal adjustment constraints.
- firm's marginal cost = marginal cost of the most expensive unit that it is operating.

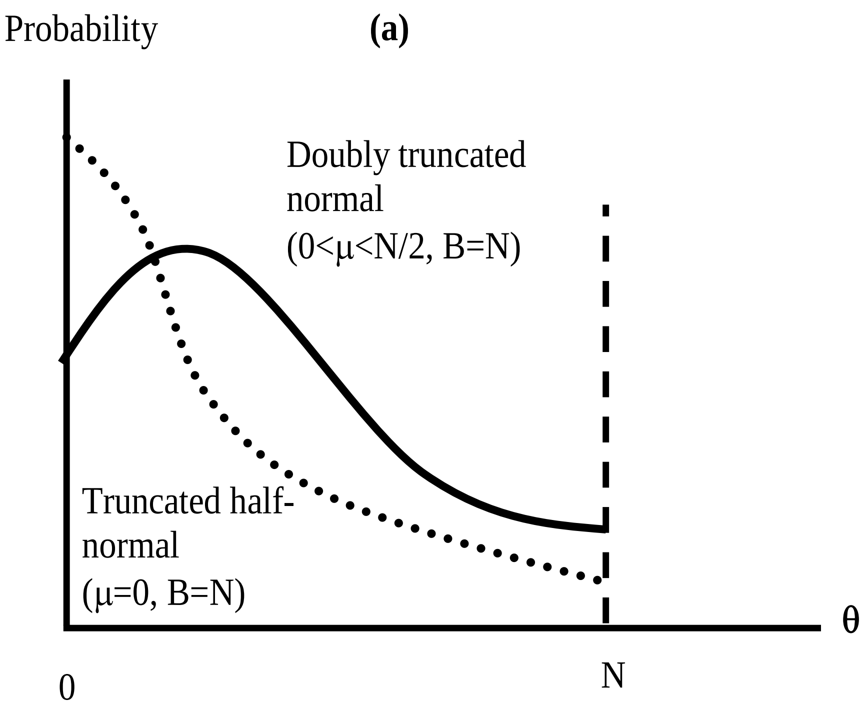
Pricing equation estimates
(July 1, 1998 - April 15, 1999)

Explanatory variables [b]	OLS Model	Preferred Model	Puller's Model
$CAPBIND_{it}$	-3.936 (-1.12)	13.130 (3.26)	21.52 (22.65)
x_{it}	8.606 (31.18)	5.894 (19.11)	5.457 (16.89)
Instruments: [b]	$CAPBIND_{it}$, x_{it}	$CAPBIND_{it}$, k_{it}, $1/FQ_t$	$CAPBIND_{it}$, FQ_t
Hansen test (d.f.)		5.399 (1)	
Estimated average conduct: [c]	1.53	1.05	0.97

Pricing equation estimates
(April 16, 1999 – November 30, 2000)

Explanatory variables [b]	OLS Model	Preferred Model	Puller's Model
$CAPBIND_{it}$	-9.512 (-2.36)	27.221 (4.26)	41.20 (6.19)
x_{it}	8.204 (41.71)	5.679 (40.95)	5.041 (22.11)
Instruments: [b]	$CAPBIND_{it}$, x_{it}	$CAPBIND_{it}$, k_{it}, $1/FQ_t$	$CAPBIND_{it}$, FQ_t
Hansen test (d.f.)		1.24 (1)	
Estimated average conduct: [c]	1.57	1.09	0.97

Doubly-truncated normal distributions (Almanidis, *et al*. 2010)



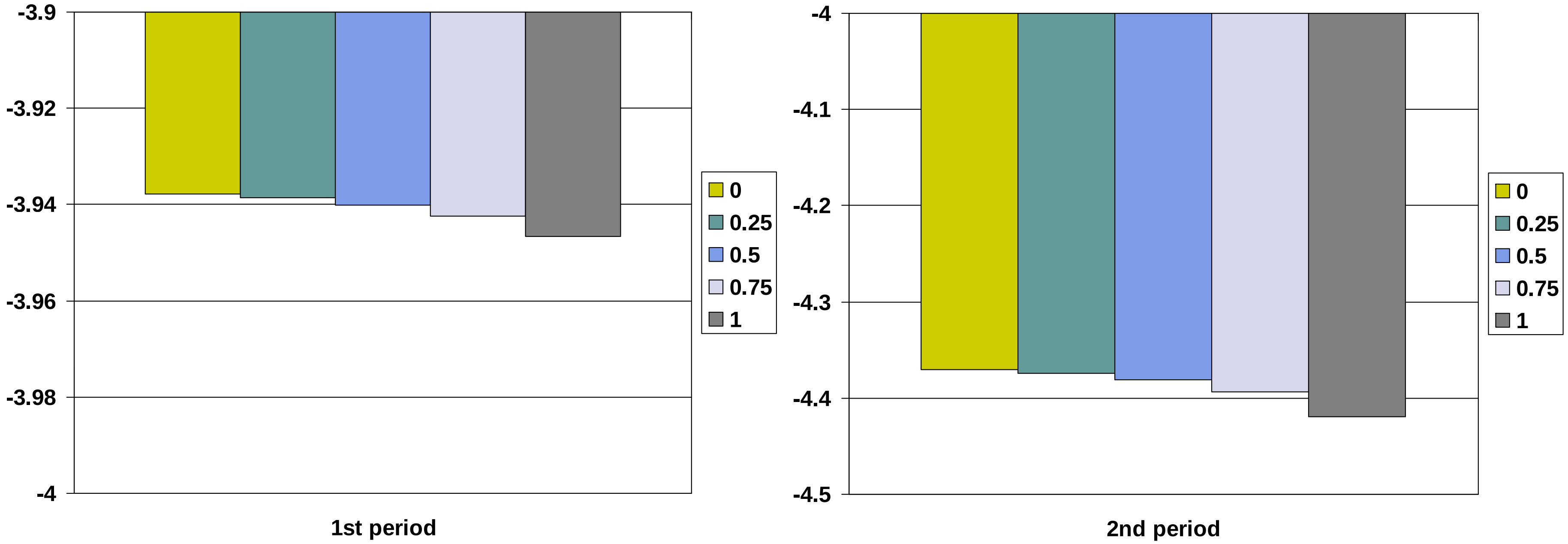
$$\theta_{it} \rightarrow N_0^B(\mu, \sigma_u)$$

Normal distribution truncated below 0 and over B

Doubly-truncated distributions (Almanidis, *et al*. 2010)

Model	Density function
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	$\frac{\exp\left(-\tilde{\varepsilon}/\sigma_u+\sigma_v^2/\sigma_u^2\right)}{\sigma_u(1-\exp(-\sigma_u/B))}\left[\Phi\left(\frac{(B-\tilde{\varepsilon})}{\sigma_v}+\frac{\sigma_u}{\sigma_v}\right)-\Phi\left(\frac{-\tilde{\varepsilon}}{\sigma_v}+\frac{\sigma_v}{\sigma_u}\right)\right]$

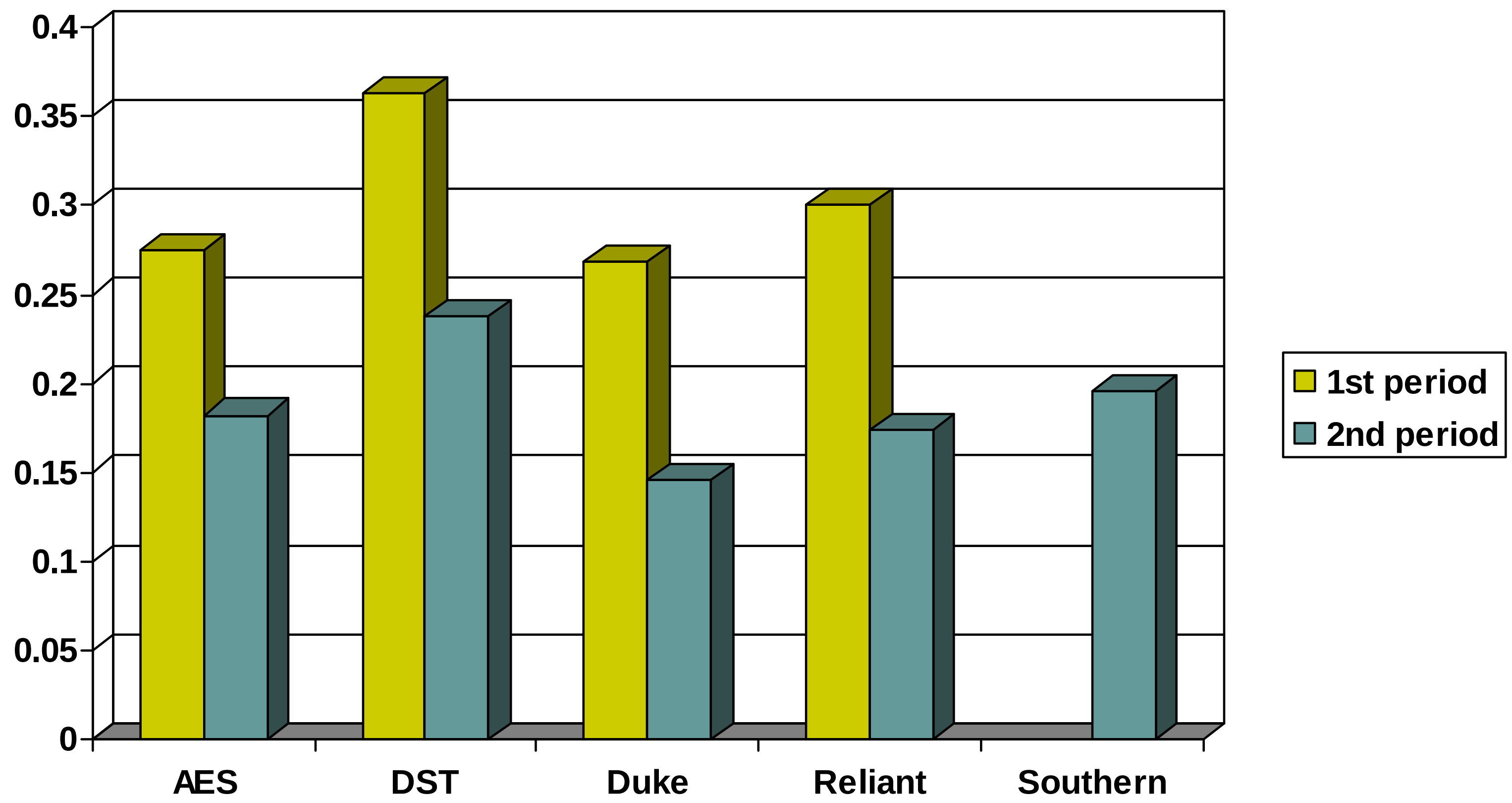
Value of the likelihood funcion for different mu's



Second-stage parameter estimates (ML truncated-half normal, mu=0)

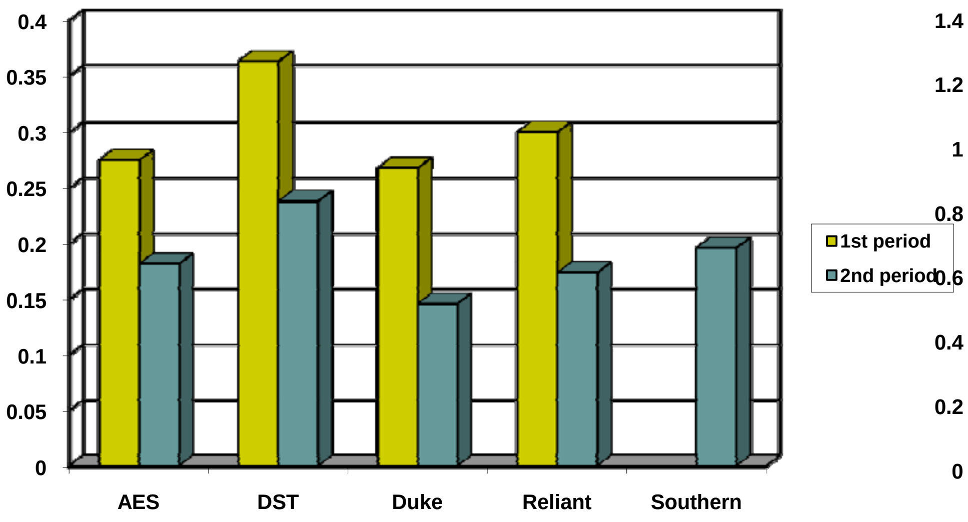
	First Period	**Second Period**
First-stage average conduct	1.05	1.09
Sigma_v	10.59 (40.92)	9.8976 (51.16)
Sigma_u	1.563 (21.08)	1.1917 (60.17)
Implicit average conduct:	1.21	0.95

Firm-specific market power scores (third stage)

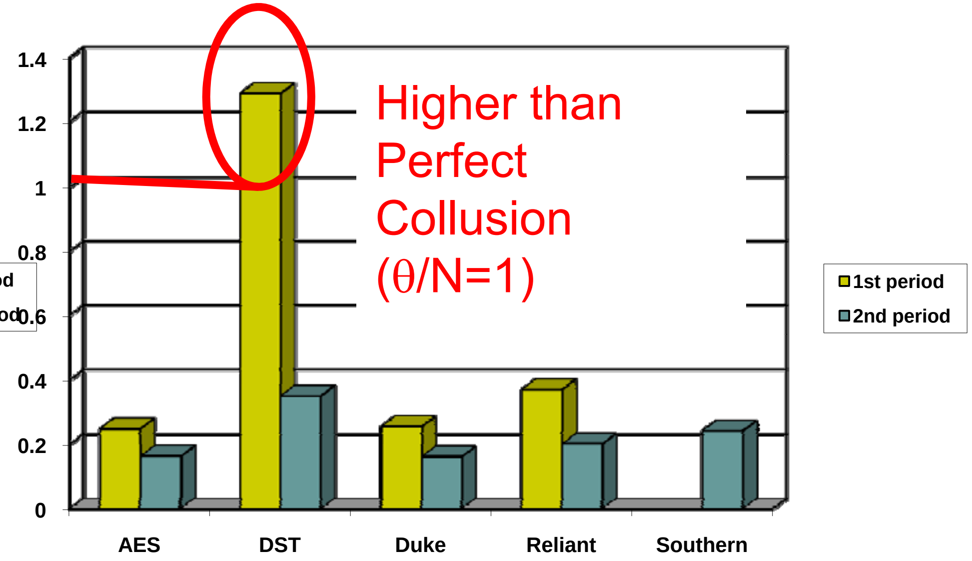


Comparison with Puller's (2007) firm-specific market power estimates

Computed firm-specific market power scores



Puller's (2007) firm-specific market power scores



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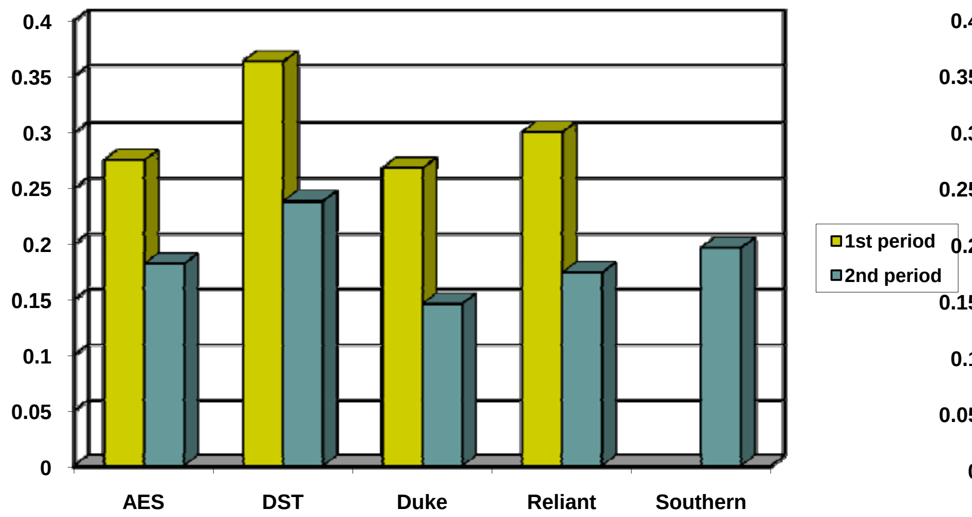
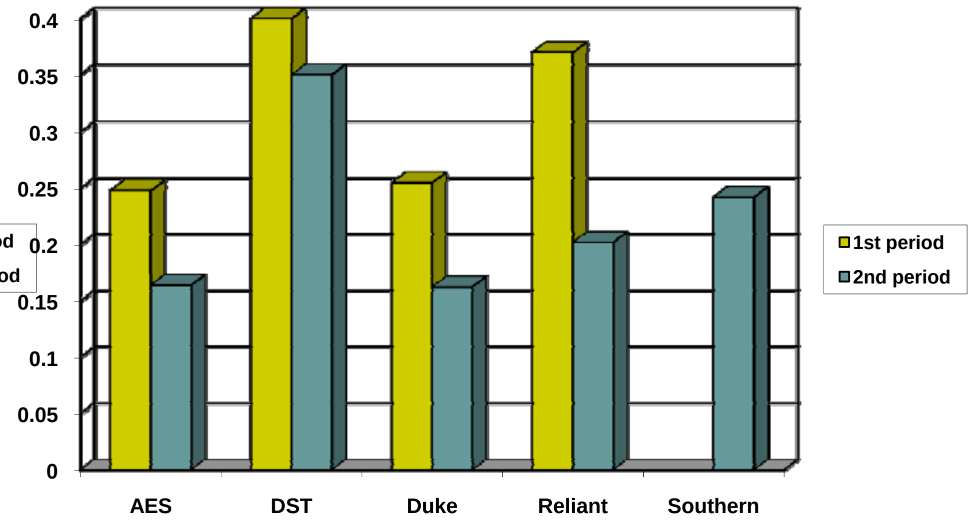
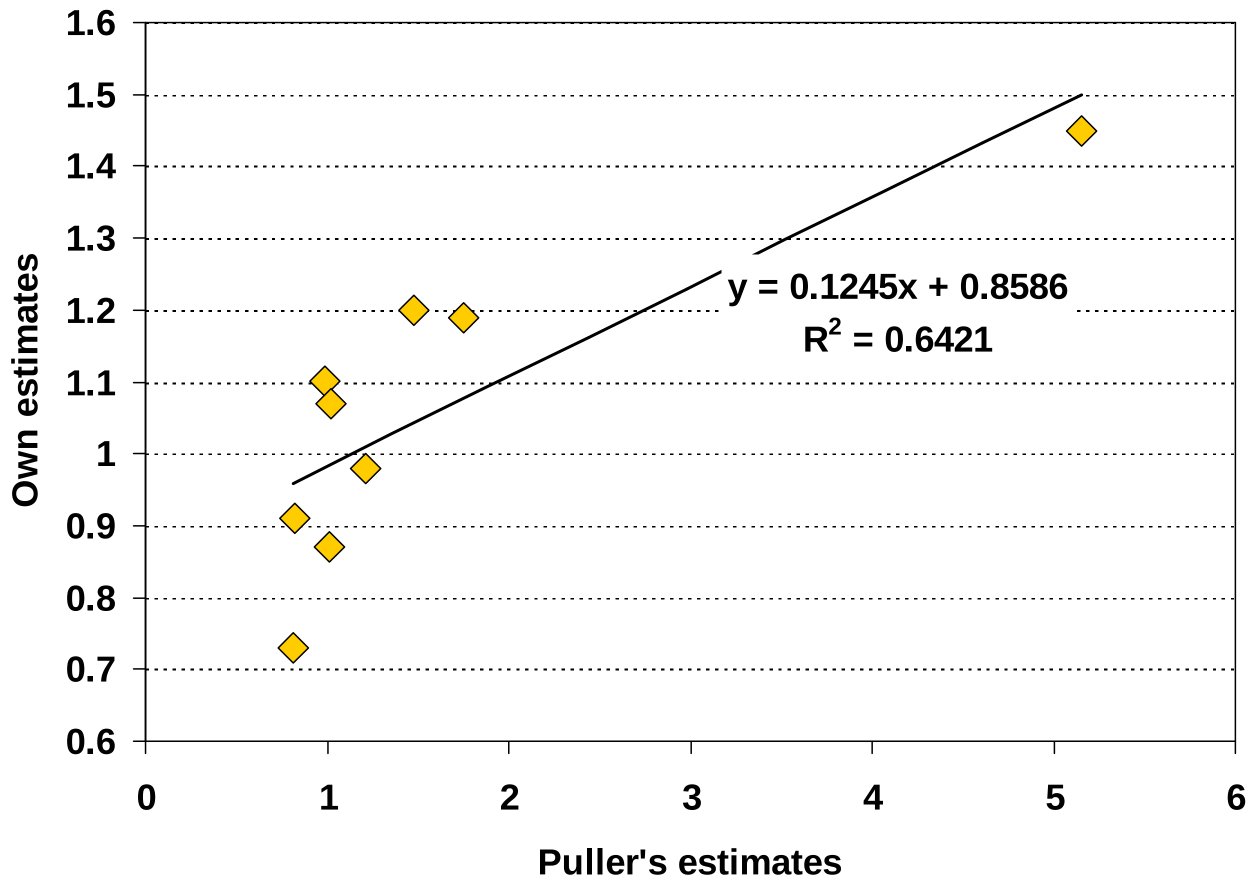


Puller's (2007) firm-specific market power scores

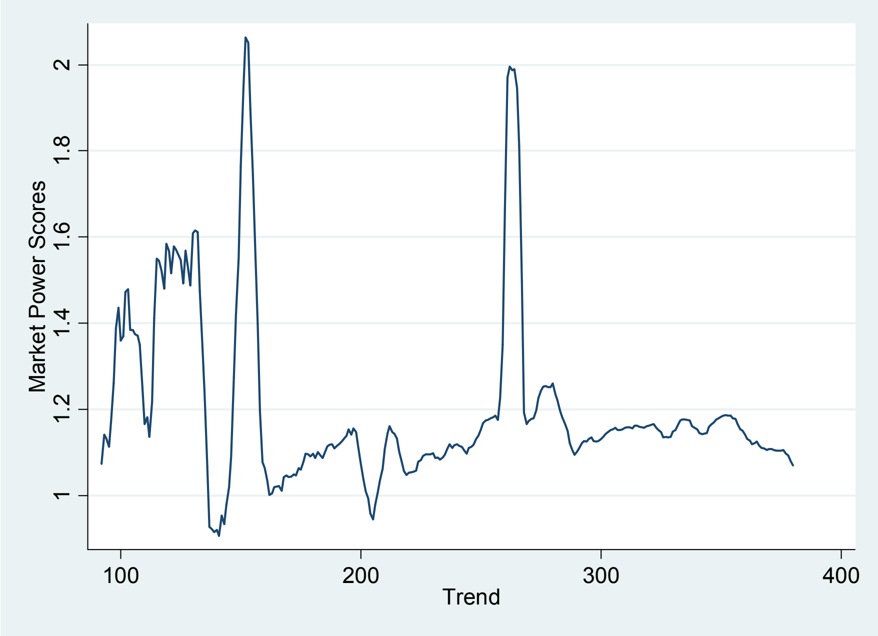


Comparison with Puller's (2007) firm-specific market power estimates

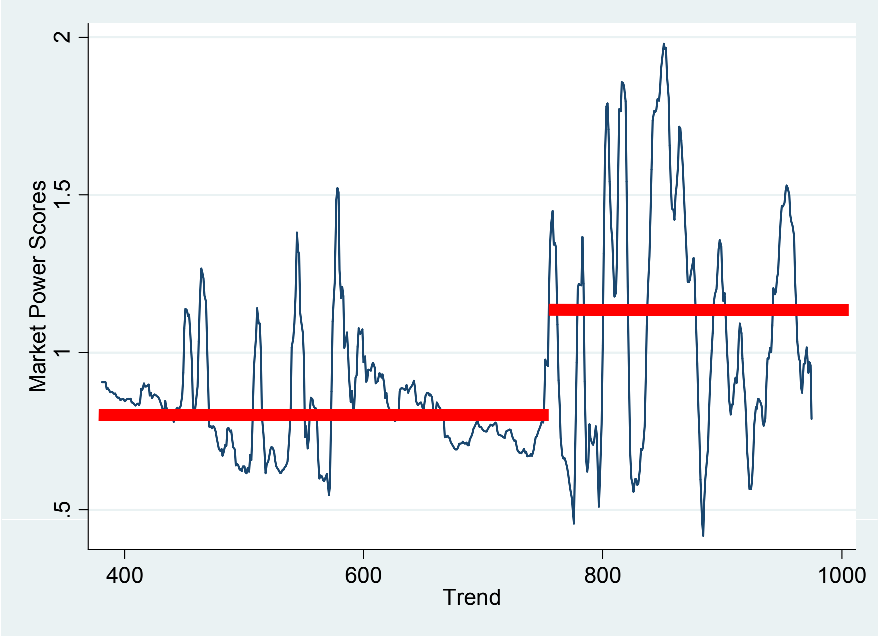


Industry average market power over time

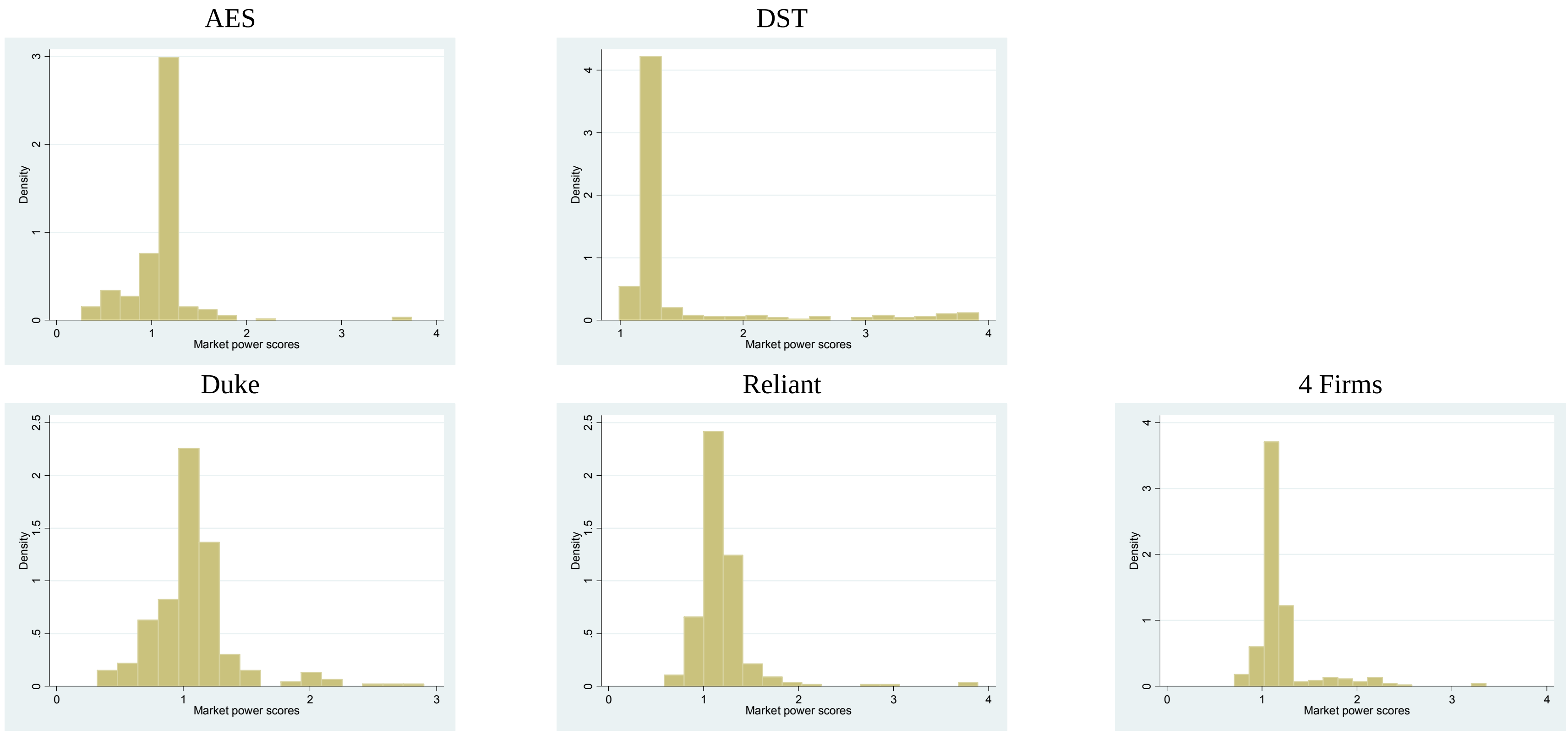
First period
(July 3, 1998 – April 15, 1999)



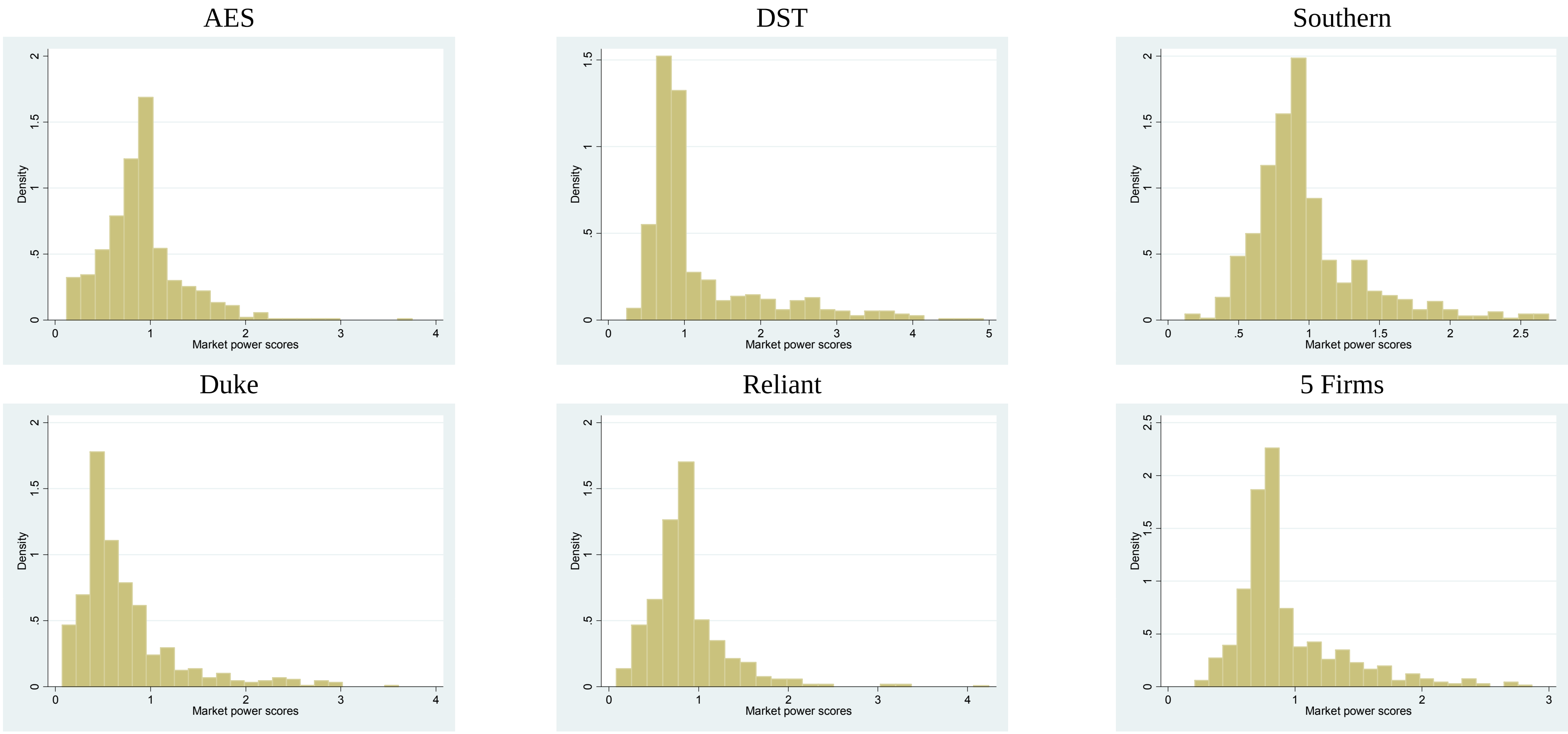
Second period
(April 16, 1999 – November 30, 2000)



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

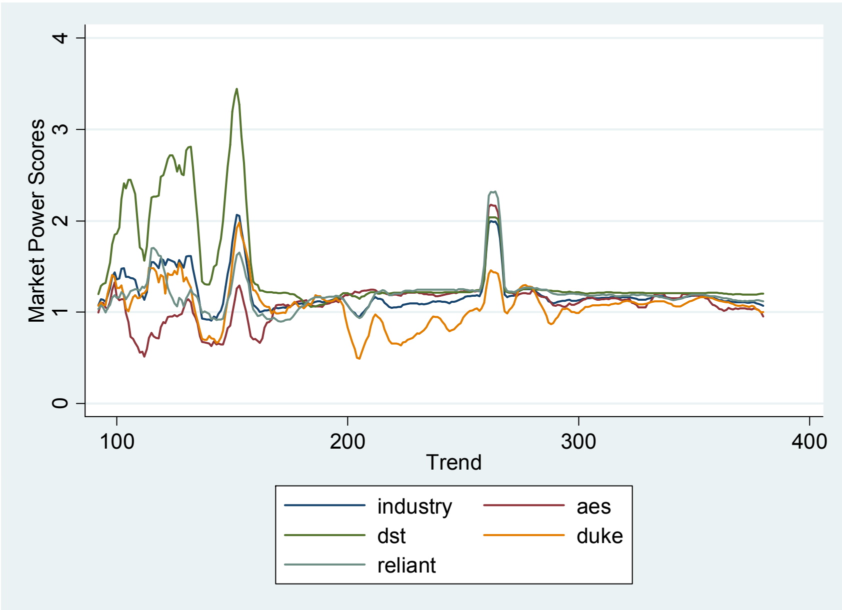


Firm-specific market power scores. Histograms. (April 16, 1999 – November 30, 2000)

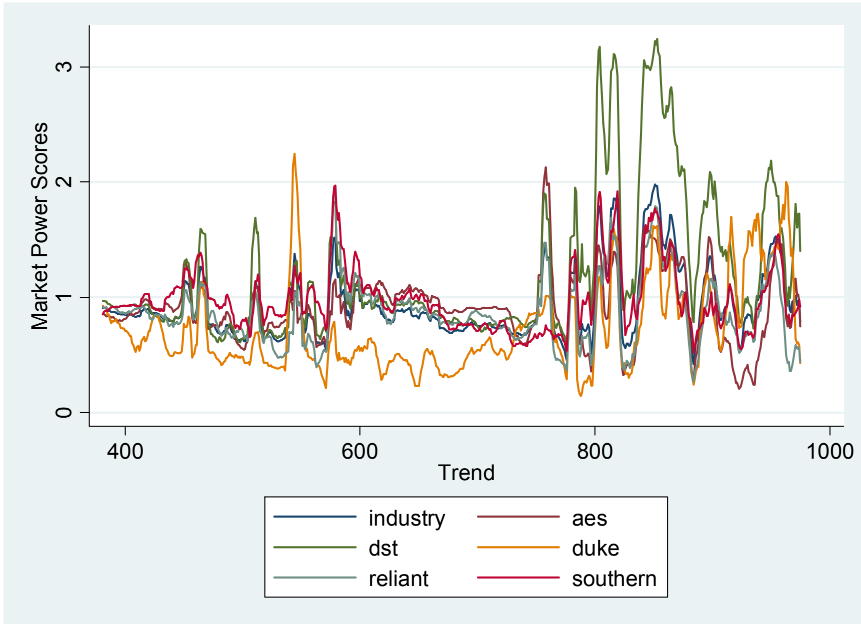


Firm-specific market power scores

First period
(July 3, 1998 – April 15, 1999)



Second period
(April 16, 1999 – November 30, 2000)

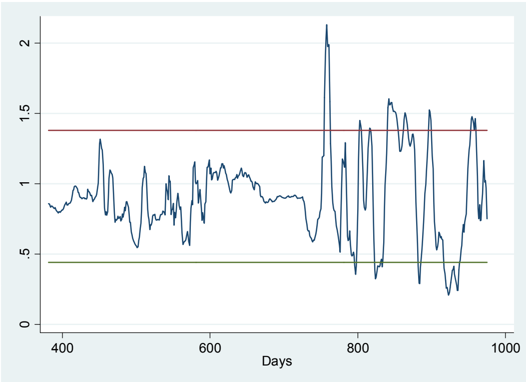


Market power coordination among firms (Coefficients of correlation of market power scores)

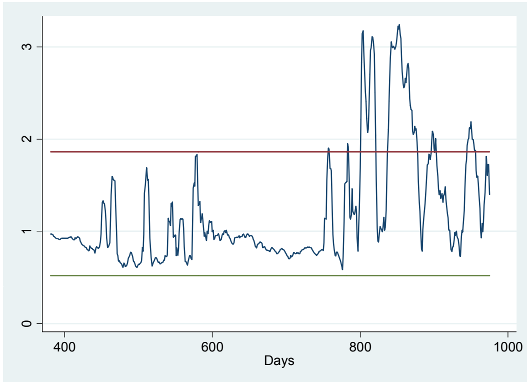
	July 1, 1998 - April 15, 1999						*April 16, 1999 – November 30, 2000*				
	AES	DST	Duke	Reliant	South		AES	DST	Duke	Relian	South
AES	1					AES	1				
DST	0.28	1				DST	0.71	1			
Duke	0.36	0.64	1			Duke	0.30	0.44	1		
Reliant	0.69	0.54	0.57	1		Reliant	0.78	0.76	0.38	1	
South	-	-	-	-	1	South	0.53	0.66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

Screening (Second period)

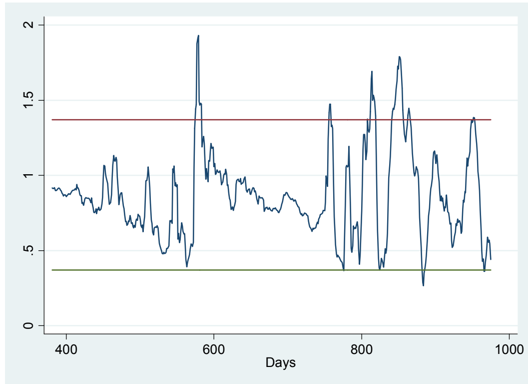
AES



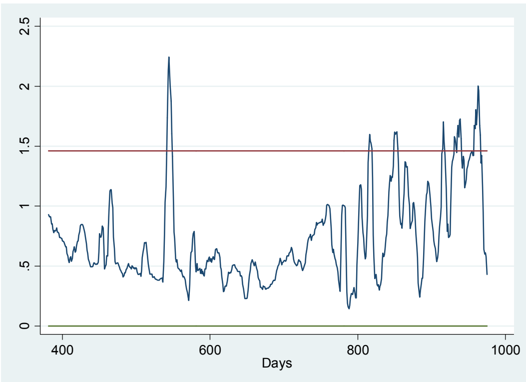
DST



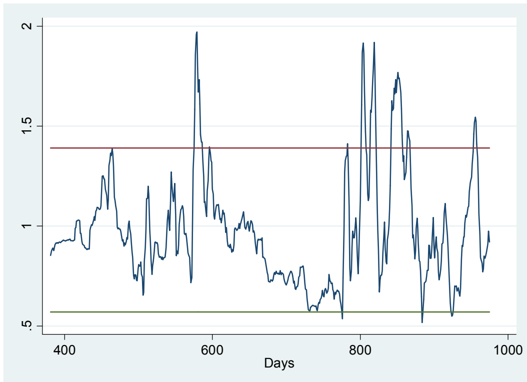
Southern



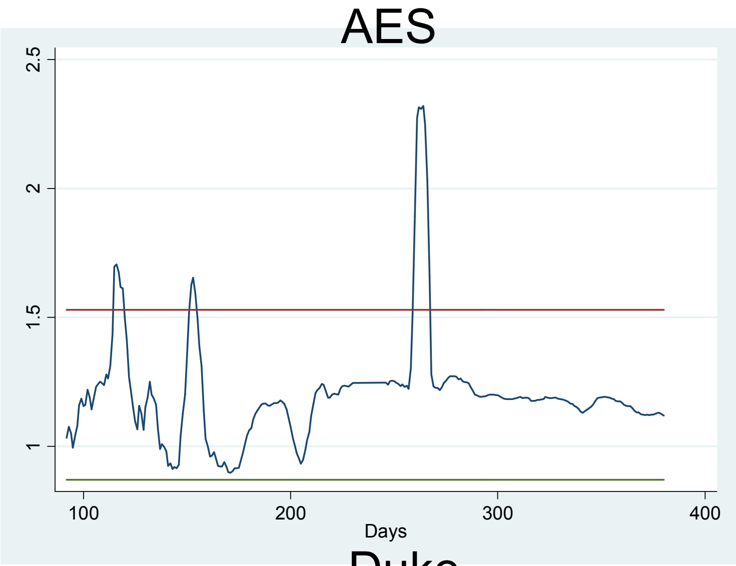
Duke

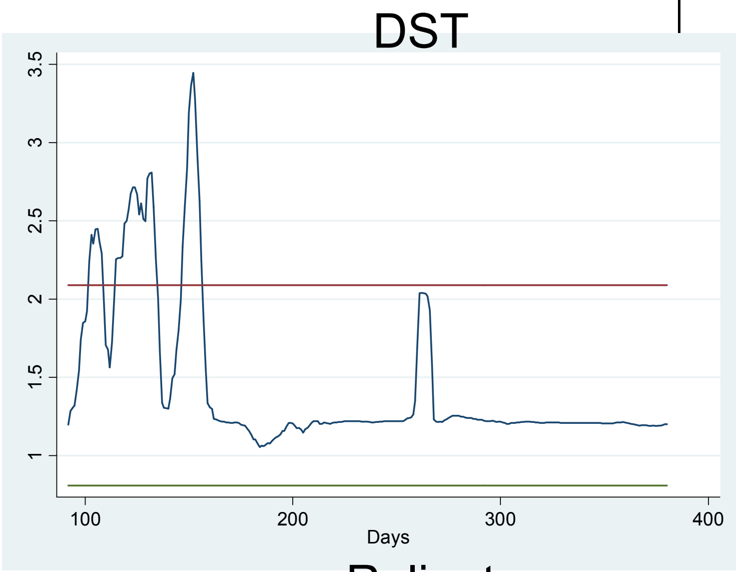


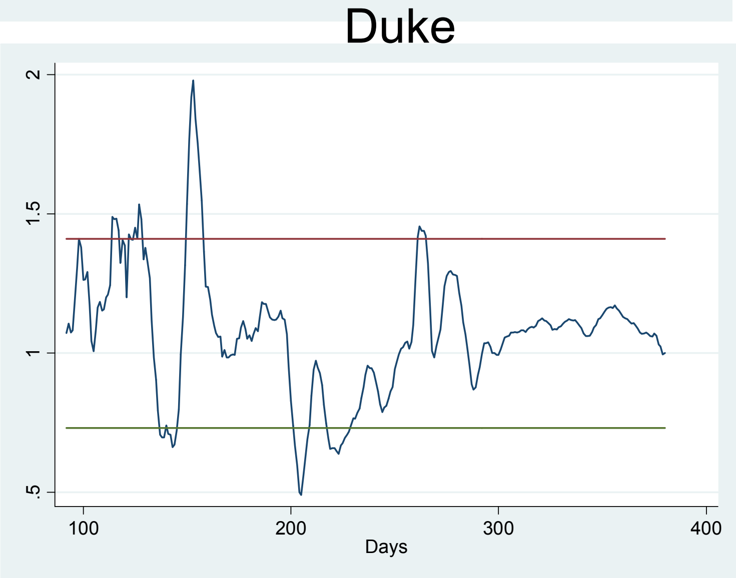
Reliant

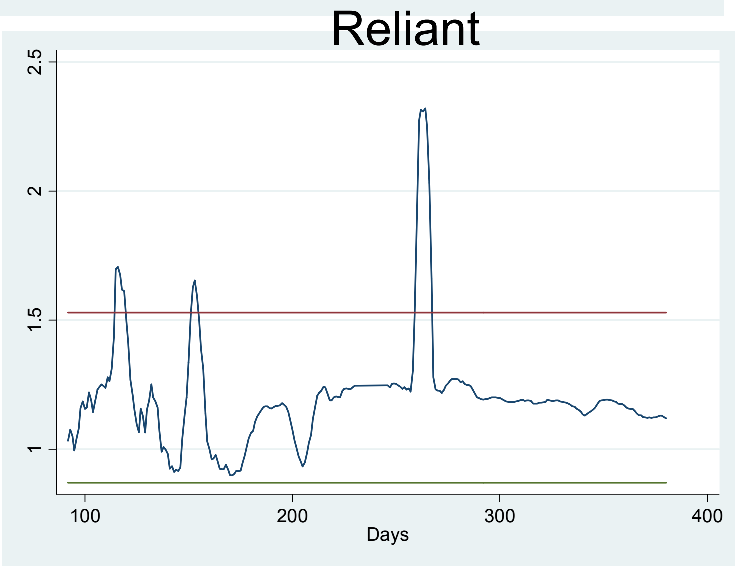


Screening (first period)









5. Summary and conclusions

- Measuring the degree of competition in oligopolistic markets is a key activity in EIO.
- As allowing for the conduct parameter to vary freely, we suggest estimating a “composed error” model where the stochastic part is formed by two random variables.
- 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 distinguish collusion discipline/instability from demand and cost volatility, and to get firm-specific market power scores
- The estimated conduct variation can be used as a measure of the degree of collusive discipline, and the market power scores can be used to detect the creation/decline of collusion episodes.

Continuation...

- Our first-stage results are quite similar to those obtained by Puller (2007).
- Our approach based on the estimated distribution of the random conduct yields similar firm-specific market power scores than Puller (2007) using a fixed-effect approach.
  - This result demonstrates that both approaches are, in practice, equivalent or interchangeable.
- Our procedure has the advantage over Puller's approach that it can be applied with cross-sectional or sort data sets; or when individual pricing equations cannot be consistently estimated with the available instruments.
- Our results suggest that our approach yields more reasonable market power scores than a fixed-effect approach.

THANK YOU FOR YOUR ATTENTION !!!

3rd Workshop on Empirical Methods in Energy Economics
University of Surrey, Guildford, UK
June 24 - June 25, 2010