Empirical Models of Firm-Level Profitability
Based on UK Panel Data

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Working Paper Number 93/16
June 1993

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BELFIELD, DUBLIN 4, IRELAND
EMPIRICAL MODELS OF FIRM-LEVEL PROFITABILITY BASED ON U.K. PANEL DATA

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MAY 1993

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ABSTRACT
Applied Industrial Economics has suffered from the criticism that most of the variables of interest, such as market structure and firm performance are inherently endogenous. We outline the three common approaches to the problem and suggest a fourth which uses panel data. Some simple empirical models of profitability are tested using data on 718 large U.K. companies between 1972 and 1986. Our results suggest that:
(i) Aggregation, firm and time specific heterogeneity and endogeneity are all problems for the older inter-industry cross sectional literature.
(ii) There is evidence of very strong persistence in the profit margins of our 718 firms: not allowing for this in empirical models of profitability can severely bias conclusions reached.
(iii) Both market share and industrial concentration significantly boost profitability. These effects are interpreted as evidence towards the 'market power' rather than the Demsetz hypothesis of differential efficiency.

Keywords: Profitability, Panel data, Instrumental Variables, Persistence.

JEL Classification: L11.

ACKNOWLEDGEMENTS
We would like to thank Steve Machin, Martin Conyon, Costas Meghir, Jonathan Haskel and participants in seminars at IFS and Oxford for helpful comments and members of the Corporate Sector group at the Institute for Fiscal Studies (especially Mike Devereux), and Xeni Dassiou for help in the initial stages of setting up the data. The first author would like to thank the ESRC (under grant no W100281002) and the second author would like to thank the Leverhulme Trust for financial support.
1. INTRODUCTION.

Finally it is important to note that much of the most persuasive recent work [on structure and performance] relies on non-standard sources, particularly panel data....

Schmalensee (1989, Conclusion)

Applied industrial organisation is a discipline in crisis. Historically the roots of the predicament are reasonably clear to trace. The organising theoretical framework of the 'Structure Conduct Performance Paradigm' was replaced by a vigorous application of game theory in the 1980s and it was expected that empirical work would follow this transition. Simply put, the game theoretical critique emphasized the point that the performance and structure proxies used in empirical work were, in a fundamental way, endogenous. Identifying the existence and consequences of market power was far more challenging than observing the significance of concentration in a cross sectional profitability equation at the industry level.

The econometrics of Industrial Organisation has responded in three main ways to the counter-revolution. One could crudely characterise these as the Modest (non-structural) Response, the Ambitious (structural) Response and the Robust Generalisation Response. The first approach is clearly articulated by Schmalensee (1989). Authors in this tradition essentially continued what they were doing before, but treated their results (and reinterpreted the previous literature) in a far more sensitive way. The collection of 'stylised facts', robust correlations across space and time between simultaneously determined variables is all that could be hoped for. Bresnahan (1989), by contrast, puts forward a more ambitious program which still attempts to uncover structural parameters and discriminate between theories. Essentially this means
collecting richer data, most often from very narrowly defined markets - the 'ultra micro study' as it has sometimes been called\(^1\). One problem inherent in single industry studies concerns their policy significance: are the results sufficiently general to yield useful information to policy makers?

In an attempt to deal with this problem of over-specificity of game theoretic models John Sutton (1991) has sought predictions which are robust across a range of model assumptions. The relation between market size and structure seems to hold some promise in this regard, as it should vary systematically with the form of sunk costs\(^2\). These predictions constrain the data quite loosely and the problem remains of how many other theoretical results are invariant to small changes in model specification.

A fourth approach is offered in this paper which lies closest to Schmalensee, but is slightly more ambitious. The endogeneity issue is tackled using Instrumental Variables, using lagged information to identify the effects of market structure variables, rather than relying on arbitrary exclusion restrictions (see, for example, Strickland and Weiss, 1976; Martin, 1979). As a substantive example of this we examine the empirical determinants of profit margins using U.K. firm-level panel data focusing on the econometric methodology: We look at the sensitivity of the results to aggregation, disequilibrium dynamics, and unobserved heterogeneity due to firm and time-specific effects. Our conclusion is that a carefully built model reveals many pitfalls to simple OLS analysis on cross sections, but many of the traditional findings linking fragmentation to lower profitability are upheld.

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\(^1\) The Journal of Industrial Economics had a Special issue in 1987 dedicated to such studies, and other recent examples are Slade (1990) and Hendricks and Porter (1988).

\(^2\) To be more precise, in long-run equilibrium concentration should (weakly) decrease with the size of the market when there are exogenous sunk costs. When sunk costs are endogenous, however, a non-linear pattern emerges and at a certain market size the relationship is reversed.
contrary to some of Schmalensee's stylised facts (Fact No. 4.5).

The structure of the paper is as follows: Section 2 outlines the modeling strategy based around four simple questions; Section 3 discusses data and estimation techniques; section 4 gives the empirical results.

2. MODELING STRATEGY

A generic profitability equation is of the form:

\[ (\Pi/R)_{it} = \gamma_0 + \gamma_1 MS_{it} + \gamma_2 CONC_{jt} + \gamma_3 IMPS_{jt} + \gamma_4 UNION_{jt} + \gamma_5 URATE_{jt} + u_{it} \]

Where the left-hand side variable is the profit-sales ratio which is written as a function of market share (MS), concentration (CONC), import penetration (IMPS), unionisation (UNION) and cyclical factors (captured by the aggregate unemployment rate, URATE). There is a random error \( u_{it} \) where \( i \) subscripts denote firms, \( j \)-subscripts denote industries. A common way to derive an equation resembling (1) is through the first order conditions of a homogeneous product oligopoly (e.g. Cowling and Waterson, 1976; Clarke and Davis, 1982; Machin and Van Reenen, 1993). The problem of relationship between these measures and their theoretical counterparts are well known and it would be tedious to repeat them here (see Geroski, 1988, for a good treatment). Instead, the paper focuses upon four main questions relating to econometric modeling strategy:

QUESTION 1

Are there significant problems attached to using entirely industry-level information rather than firm-level analysis?

Much of the older applied work in industrial economics used aggregate data and it is important to appreciate whether this imparts a significant bias
to their estimates. By aggregating our data to the industry level we can compare these with company-level results and explicitly examine the issue.

**QUESTION 2.**

How large are the biases associated with the assumption that market share (and other right hand side variables) is exogenously determined such that Ordinary Least Squares is an appropriate estimation method for equation (1)?

Given that many studies do use OLS to estimate margins equations this is an important question to ask and is one which has been dealt with in the theoretical literature but, unfortunately, is seldom addressed in empirical work. We use a Generalized Method of Moments estimator due to Arellano and Bond (1991) to tackle the endogeneity problem giving particular attention to the validity of the instruments given the correlation of shocks over time. If the correlated shocks affect all firms similarly (that is they are purely macroeconomic) then replacing URATE with time dummies will be appropriate.

**QUESTION 3**

Is the use of a static model appropriate?

A large empirical literature on the dynamic behavior of margins has emerged in recent years (see, inter alia, Mueller(1986), Geroski and Masson(1987), Levy(1987), Geroski and Jacquemin(1988), Schwalbach et al(1989) and the international series of papers in Mueller(1990a)). A consistent finding is that margins display some persistence and that a model of profitability incorporating dynamics has considerably more explanatory power than otherwise comparable static models. Clearly, in an econometric sense it is only if this lag is completely uncorrelated with the right hand side variables that there will be no omitted bias in estimating equation (1) without lags.
QUESTION 4

Are there time-invariant firm-specific fixed effects (e.g. management style, worker attitudes, union status), the omission of which causes bias in the estimated parameters?

The fact that we use panel data means that we can control for these fixed effects. In the context of equation (1) their importance can be ascertained by allowing each firm to have a separate intercept, say $\gamma_i$. A test of their joint significance amounts to a test of whether one can reject the hypothesis $\gamma_i = \gamma_0$ for all $i$.

Given these considerations the most general model to be estimated will be

$$\begin{align*}
(2) \quad (\Pi/R)_{it} = \gamma_i + \gamma_1^{MS}_{it} + \gamma_2^{CONC}_{jt} + \gamma_3^{IMPS}_{jt} + \\
\gamma_4^{UNION}_{jt} + \gamma_5^{(\Pi/R)}_{it-1} + \text{time dummies} + u_{it}
\end{align*}$$

3. DATA DESCRIPTION AND ESTIMATION METHODS.

The data we use covers 718 large U.K. quoted companies over the period 1972 - 86 who have at least 9 continuous observations in the Datastream databank of company accounts. Industrial data has been matched to the main operating industries of these firms and some descriptive statistics are given in Table 1. Variable definitions and descriptive statistics of the data in levels and first differences are in the upper panel. Correlation matrices for the relevant variables (again in levels and differences) are in the lower one. The dependent variable we use in our analysis is the trading profit margin.

It is assumed that the error term in the most general models takes the form $\eta_i + \nu_t + u_{it}$ where $\gamma_i$ is the firm specific fixed effect, $\nu_t$ is a period specific time effect and $u_{it}$ an idiosyncratic error term. In the more simple models we assume $\eta_i = \eta_0$ for all $i$ and that $\nu_t$ can be approximated by a

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3 The data is described in more detail in Machin and Van Reenen (1993) which also contains a Data Appendix, which is available on request.
cyclical variable like URATE, the aggregate unemployment rate. Using Generalised Method of Moments estimator allows us to efficiently exploit the availability of lagged variables as instruments by allowing the coefficients on the Instrumental Variables to differ from cross-section to cross-section.

In the more general models, first-differencing allows us to control for the fixed effects which then disappear from the model. If $u_{it}$ is serially uncorrelated the residuals from the transformed model should then follow an MA(1) process. We check for this by presenting appropriate tests for second order serial correlation (in the levels models with $\eta_1 = \eta_0$ we also present tests for first order serial correlation). To obtain consistent parameter estimates it is crucial that these tests for serial correlation are satisfied; since autoregressive processes have infinite memory it would be difficult to find lagged regressors that remain uncorrelated with an autoregressive error term.

For computational reasons the instrument set we utilise exploits two moment restriction for each variable - that is, in first-differenced models we instrument an endogenous variable $\Delta X_{it}$ by $X_{i,t-3}$ and $X_{i,t-4}$ stacked by year. For our sample period (1975-86), this generates 24 (12 x 2) instrumental variables (and hence 23 overidentifying restrictions) per firm level variable. Exploiting additional moment restrictions (e.g. $X_{i,t-5}$, $X_{i,t-6}$ if the panel is far enough advanced) did not appear to affect results significantly.\(^4\)

4. ECONOMETRIC MODELS OF PROFIT MARGINS

4.1 Answers to the Four Questions

To examine the aggregation issue we took industry averages of our variables. There were 44 manufacturing industries once one excluded various

\(^4\) In principle one could have used $X_{i,t-2}$, but it was found that the estimates were not stable and diagnostics tests suggested using longer initial lags.
miscellaneous categories. Over the period 1972-86 simple regressions were run using the industry average rate of return regressed on concentration, imports and union density.

\[(\frac{\Pi}{R})_{jt} = 0.970 + 0.015 \text{CONC}_{jt} - 0.024 \text{IMPS}_{jt} + 0.015 \text{UNION}_{jt}\]

\[
\begin{array}{cc}
(0.009) & (0.008) & (0.009) & (0.014)
\end{array}
\]

t = 1972, ..., 1986; j = 1, ..., 44; No of Observations = 660
\[R^2 = 0.016, \text{ Standard Errors in Brackets}\]

The results were consistent with the traditional findings: domestic markets with seller concentration and little foreign competition tended to receive higher profit margins. Only the positive, but insignificant, coefficient on union density is surprising. The results are weak, however, and the explanatory power of the equation is low. Furthermore, when the aggregate unemployment rate is included in the model the significance of the industry variables disappears.

\[(\frac{\Pi}{R})_{jt} = 0.130 + 0.006 \text{CONC}_{jt} - 0.006 \text{IMPS}_{jt} - 0.004 \text{UNION}_{jt} + 0.352 \text{URATE}_t\]

\[
\begin{array}{cc}
(0.010) & (0.008) & (0.009) & (0.013)
\end{array}
\]

\[
(0.046)
\]

t = 1972, ..., 1986; j = 1, ..., 44; No of Observations = 660
\[R^2 = 0.096, \text{ Standard Errors in Brackets}\]

To see if macroeconomic effects really do dominate firm and industry effects we return to the firm level. Column (1) of Table 2 presents the simple disaggregated equivalent of the industry level equation and column (2) its dynamic counterpart. One immediately sees differences suggesting large errors.

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5See Machin and Van Reenen (1993) for exact industry definitions and the SIC/MLH matching)

6Similarly if the lagged industry rate of return is included, it takes a coefficient of 0.827 with a standard error of 0.0167. This raises the R squared to 0.84, but leaves the industry variables insignificant.
in aggregating the data. For example, the effect of concentration is three times larger and significant in column (1) compared to the static industry equation. This is not surprising as the majority of the variance of firm profits margins is within industry.

From column (2) it is clear that controlling for dynamics is extremely important. The coefficient on union density, for example, which appeared positive and well determined in column (1) becomes negative in column (2). The market structure variables, although still well determined have fallen in their short-run effects by about a factor of 10. The long-run effects, however, remain similar (crudely calculated by dividing the short run effect by one minus the coefficient on lagged margins).

Moving to a main focus of the paper, we tried to tackle the endogeneity problem in column (3) by instrumenting the firm level variables (MS and lagged P/R) using the Arellano-Bond method discussed in Section 3. The magnitude of the coefficients does shift around somewhat, but not dramatically. More worryingly, the Sargan Test for instrument validity and the Serial Correlation tests reject $H_0$, suggesting misspecification either in the equation or the instrument set.

The model is first differenced in column (4) to control for fixed effects. This causes the greatest shifts in parameter estimates exhibited so far. In particular the ‘profits persistence’ coefficient on lagged margins falls by half strongly suggesting that it was picking up unobserved firm-specific heterogeneity. The aggregate unemployment rate is significantly negative (rather than significantly positive in columns (2) and (3)) which plausibly reflects pro-cyclical profit margins. The other variables are all significant and in their theoretically expected directions. One might well be tempted to stop here were it not for the fact that the Sargan Test still rejects the null hypothesis of instrument validity suggesting continuing model
misspecification.

The problem lies apparently in the use of a single aggregate variable to reflect the business cycle. That is because much of the macroeconomic effects are not being captured by the aggregate unemployment rate and the unobserved variance is consigned to the error term which becomes correlated with the instruments. To resolve this, URATE is replaced with year-specific time dummies in column (5). Although the Sargan Test cannot reject the hypothesis that we have valid instruments, UNION and IMPS have been statistically insignificant. This does not necessarily mean that these variables are unimportant, but rather that they effect firms in similar way over time that cannot be distinguished from macroeconomic shocks.

The maintained assumption in column (1) is that industry variables are weakly exogenous as they are not choices for the firm. This assumption is clearly dubious for larger firms and so we also tried instrumenting the other industry-level variables in column (6)\(^7\). Apart from increasing the standard errors, the estimates are not dramatically altered. Concentration seems to have been biased downwards by the assumption of weak exogeneity.

Various other experiments were attempted to check for the robustness of the estimates in columns (5) and (6). Extra nonlineairities were allowed for by interacting market share with concentration and other observables - they were invariably qualitatively small and poorly-determined\(^8\). When we allowed the profits persistence term to differ across firms by interacting the lagged dependent variable with the other regressors we found no evidence of such

\(^7\)Given the lower variability of the measures (all firms will have identical values of CONC\(_{jt}\) for example) simple twice lagged differences were used instead of the full GMM method. Experiments showed that GMM actually gave similar results to stacking the instruments in this way.

\(^8\)For example, including the interactions of market share with CONC, IMPS, UNION and (\(\Pi/R\))\(_{t-1}\) in column (5) gave a \(\chi^2(4) = 4.70\) compared to a critical value of 9.49.
effects. These results are interesting in their own right since many of the earlier papers cited find such effects and attempt to discriminate between different theories on the basis of these interactions.

4.2 Interpreting the Results

The main answer to our four questions is that all the potential types of problems affecting industry cross-sectional studies are serious. What still remains true is that the traditional wisdom that firms with higher market shares and/or are in concentrated industries earn higher profits. Using column (6) the short-run elasticity of market share with respect to profitability is about 0.04 compared to an elasticity of 0.50 for industry concentration. The equivalent long-run figures are 0.07 and 0.88 for the long-run. The magnification of the short-run effects highlights the importance of the dynamics of profit persistence. This stands in contrast to the accepted U.S. wisdom that concentration does not have an important independent positive effect on margins (e.g. Ravenscraft, 1983; Kwoka and Ravenscraft, 1986). The U.S. work rarely uses Instrumental Variable techniques on long firm panels, and this may be the source of the discrepancy. Alternatively the U.S. anti-trust framework may be more effective in reducing the ability or benefits of colluding.

Establishing statistical relationships using appropriate econometric techniques is important, but what are the causal interpretations? One popular line of argument (Demsetz, 1973) is that more efficient firms will have higher market shares and this will, at the firm level lead to the positive elasticity of profitability with market share and, at the industry level, a positive association of profit margins with concentration. The fact that a large and

\[ \chi^2(4) \text{ test of } (\Pi/R) \text{ interacted with the observables was 5.15} \]
independent effect of concentration was found lends strongly against the 'Differential Efficiency' interpretation of the data. This is not to say that efficiency is unimportant - some two thirds of the raw variance in profit margins is explained by firm fixed effects and this could be due to differential efficiency.

One could, of course, turn the Demsetz argument on its head and ask whether the market share effect is best explained by dominant firms wielding their power through strategic entry deterrence, predatory pricing and so on. Brenner (1989) suggest that such fears are groundless as high market share firms are those which have been the most innovative. This argument receives little support from a companion paper which matches observed instances of significant innovations into our dataset (Geroski, Machin and Van Reenen, 1993). Explicit controls for firm and industry technological innovations using the Science Policy Research Unit's dataset were introduced into specifications similar to those of our preferred model. The result was that the effects of market share on profitability were reduced only infinitesimally.

5 CONCLUSIONS

In the face of a trenchant theoretical critique of implicit endogeneity assumptions, applied industrial economists have appealed to three different research strategies. One looks to stylised facts, the other the ultra-micro analyses, the third for robust (and elusive) equilibrium generalizations. These are complementary approaches to which we add a fourth. Using panel data we attempt to exploit more convincing instruments to attack the endogeneity issue, the problem of aggregation, of firm heterogeneity and out of equilibrium dynamics.

In a simple exercise we have shown how biases can be large and results
misleading unless one pays careful attention to appropriate techniques. Market share and concentration have positive and significant effects on firm’s profit margins, with the latter being (surprisingly) larger than the former. Given the independent influence of concentration, the controls for fixed effects and the findings of others that the effect of market share does not appear to work primarily through innovation we would reject a ‘Differential Efficiency’ interpretation of our results. Whether this reflects a genuine difference between Britain and the United States or the fact that most U.S. work has rarely used long firm panels and sophisticated instrumenting techniques remains to be seen.
<table>
<thead>
<tr>
<th>Variable Definition</th>
<th>Mean (standard deviation)</th>
<th>Levels</th>
<th>1st-differences</th>
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<td>Trading profit margin</td>
<td>0.102(0.063)</td>
<td>-0.002(0.031)</td>
<td></td>
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<tr>
<td>Market Share</td>
<td>0.026(0.071)</td>
<td>0.001(0.010)</td>
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<tr>
<td>Concentration</td>
<td>0.399(0.180)</td>
<td>-0.006(0.028)</td>
<td></td>
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<tr>
<td>Industry unionisation</td>
<td>0.639(0.114)</td>
<td>-0.002(0.036)</td>
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<tr>
<td>Industry import intensity</td>
<td>0.256(0.147)</td>
<td>0.001(0.032)</td>
<td></td>
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**Correlation Matrix - Levels**

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<thead>
<tr>
<th></th>
<th>II/R</th>
<th>MS</th>
<th>CONC</th>
<th>UNION</th>
<th>IMPS</th>
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**Correlation Matrix - 1st differences**

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TABLE 2: ECONOMETRIC MODELS FOR PROFIT MARGINS

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<td>(0.010)</td>
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<td>(0.002)</td>
<td>(0.013)</td>
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<td>0.960</td>
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<td>(0.028)</td>
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<td>(0.054)</td>
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Firm Level: No, No, No, Yes, Yes, Yes
IVs (GMM): No, No, No, No, No, Yes
IVs (Stacked): No, No, No, No, No, Yes
Dummies: (11), (11)
Sargan: 248.02, 185.98, 100.87, 7.32
Number of Firms: 709, 709, 709, 709
Sample Size: 6834, 6834, 6834, 6834, 6834, 6834
SC1: 26.60, -3.00, -4.920, -6.219, -7.143, -8.548
SC2: 24.40, -3.67, -4.984, -1.679, -1.444, -1.562

Notes:
1. The dependent variable is the trading profit margin, Π/R.
2. Columns (3)-(6) use firm level instruments (MS, Π/R_{t-1}, the investment-sales ratio and dividends) lagged from (t-3) to (t-4). Column (6) uses lags of the industry level variables (IMPS, UNION and CONC) lagged two periods.
3. Asymptotic heteroskedastic standard errors in parentheses.
4. SC1 and SC2 are N(0,1) tests for first and second order serial correlation.
5. Sargan is a χ² test of the overidentifying restrictions (degrees of freedom in parentheses).

\[\text{Notes:}\]
\[\text{1. The dependent variable is the trading profit margin, } \Pi/R.\]
\[\text{2. Columns (3)-(6) use firm level instruments (MS, } \Pi/R_{t-1}, \text{ the investment-sales ratio and dividends) lagged from (t-3) to (t-4). Column (6) uses lags of the industry level variables (IMPS, UNION and CONC) lagged two periods.}\]
\[\text{3. Asymptotic heteroskedastic standard errors in parentheses.}\]
\[\text{4. SC1 and SC2 are N(0,1) tests for first and second order serial correlation.}\]
\[\text{5. Sargan is a } \chi^2 \text{ test of the overidentifying restrictions (degrees of freedom in parentheses).}\]
REFERENCES


Brenner, R. 'Market Power: Innovations and Anti-Trust' University of Montral Discussion Paper 8920


