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THE DYNAMICS OF MARKET STRUCTURE

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In this paper, changes in market concentration are modelled in terms of long-run steady-state levels, and the adjustment towards them. Both the speed of adjustment and the long-run levels of concentration are allowed to vary across industries. Non-linear three-stage least squares estimates for allowing for the endogeneity of profits and advertising for 184 U.S. industries, 1963–67, suggest that both the speed of adjustment and the levels of concentration in the long run are largely determined by minimum efficient scale.

1. Introduction

There have been a number of studies which have tried to explain variations in the level of market concentration across industries, and several more which have focussed on explaining changes in concentration over time [e.g., see Curry and George (1983) for a recent survey]. Martin (1979) in particular, has explicitly modelled changes in concentration in terms of adjustment towards a long-run equilibrium level of market concentration [see also Levy (1985)], suggesting that the process can be parameterized in terms of a steady-state level of concentration, and a speed of adjustment towards that level. As noted by Martin, these two unobservables may have different determinants, and our goal here is to isolate and estimate each in a model which otherwise closely follows Martin's specification. Our results suggest that the level of concentration in the long run is largely technologically determined, and that the failure to distinguish the determinants of steady-state concentration from those of the speed of adjustment seriously biases estimates of how fast market structure adjusts to its long-run level.

*This paper was originally developed to facilitate the simulations reported in Geroski and Masson (1987, sect. 4). We would like to thank the International Institute of Management, Berlin, for support, and Stephen Martin for providing most of the data used in this study.

2. The model

Demand growth, technological change, entry, exit and other endogenous or exogenous disturbances all lead to changes in market structure. Since such effects occur continuously, the actual level of market concentration in any industry i at some time t is as likely to be in a state of adjustment to a new equilibrium as not. Following arguments set out by Martin (1979), we posit that market concentration, $C(t)$, depends on long-run equilibrium levels of concentration, C^*, and a speed of adjustment, λ,

$$C(t) = C(t-1) + \lambda\{C^* - C(t-1)\}, \tag{1}$$

where

$$\lambda = F(PCM(t-1), B, LAG), \tag{2}$$

$$C^* = G(B, G), \tag{3}$$

and where PCM denotes price–cost margin, B is a vector of entry barriers, LAG is the time necessary to construct a new plant, G is growth, and the subscript denoting different industries is suppressed. Clearly λ and C^* are not observable, and so (2) and (3) cannot be directly estimated. However, λ and C^* can be indirectly identified and estimated using (2) and (3) and the non-linear restrictions implied in (1), and this is now we propose to proceed.

The first component of (1) is the speed of adjustment, λ, and it is expected to be affected by PCM because high values of PCM ought to attract entry or fringe expansion, and low values encourage exit or fringe contraction. It seems reasonable to suppose that entry will rise at an increasing rate with increases in PCM above levels at which entry is forestalled (determined by the height of barriers, B). Further, λ should rise when PCM is reduced further below some critical level which induces exit (or fringe contraction).[1] Accordingly, the effect of PCM in determining adjustment speed should be convex, with rapid adjustments most likely when PCM is either very high or very low relative to the level of entry barriers. This suggests that PCM and B should enter eq. (2) in a non-linear, non-monotone fashion. LAG, the time required to plan and construct a new plant should, on the other hand, always slow the adjustment rate, as many adjustments require building new plants. Further, to the extent that greater LAG indicates greater sunk costs, reluctance to exit when price falls below average costs is greater.

The second key component of (1) is C^*. This should be determined mainly

[1]Baldwin and Gorecki (1987) present results which suggest that entry and exit typically occur simultaneously, with higher PCM's simply raising the entry rate and lowering the exit rate. Nevertheless, for the purposes of our tests we employ a maintained hypothesis that, at some critical level determined by the height of entry barriers, net entry and/or fringe expansion shifts from negative to positive.

by minimum efficient scale if markets tend toward technically efficient outcomes in the long run. Another factor affecting C^* may be advertising which, if it reduces entry or fringe firm mobility, may lead to higher values of C^* in the long run. However, new entry or fringe expansion may arise from a firm finding an unexploited niche and using advertising to bring it to the attention of consumers. Hence, the effect of advertising – and product differentiation more widely – is not unambiguous.

In his original work, Martin developed (1)–(3) in his argument, but was constrained to using a linear model for estimation. The empirical model that he used was

$$C(t)=\alpha_0+\alpha_1 PCM(t-1)+\alpha_2 B+\alpha_3 G+(1-\lambda)C(t-1), \tag{4}$$

a formulation which suppresses the interactions between the determinants of λ and C^*. This difference between theory and empirical implementation suggests three lines of inquiry. First, does forcing λ to take a common value for all industries lead to any substantial bias in its measurement? Second, whether or not this is the case, is there a substantial variation in the size of λ across industries? And, finally, do the various determinants of λ and C^* have different and offsetting effects on $C(t)$? Using newer versions of SAS (which provide routines for estimating non-linear three-stage least squares) than were available to Martin, we set out to answer these questions.

Before implementing (1)–(3), it is necessary to specify (2) and (3) somewhat more precisely. In (2), the barriers we deemed relevant were minimum efficient scale divided by the cost-disadvantage ratio,[2] *MCDR*, in conjunction with a regional dummy, *REGION*,[3] and advertising intensity, *AS*, in conjunction with the percent of sales sold direct to consumers, *CONSUMER*. We have written the non-linearity between λ and its determinants as[4]

$$\begin{aligned}\lambda=\mu_1\{PCM(t-1)-[\varepsilon_0+\varepsilon_1 MCDR+\varepsilon_2 REGION+\varepsilon_3 AS\\+\varepsilon_4 CONSUMER]\}^2+\mu_2 LAG.\end{aligned} \tag{5}$$

In specifying (3), we assumed C^* to be linear in *MCDR*, *REGION*, *AS* and *CONSUMER*, and also added the industry growth rate, *G*. Since it seems

[2]We followed Caves et al. (1975) in dividing minimum efficient scale by the cost disadvantage ratio to summarize economies of scale in one variable. Other transformations could have been used, but given the extensive non-linearities already present in the model, it seemed sensible not to introduce further complications and to remain consistent with previous work.

[3]We reclassified 13 industries as regional that were not so classified by Martin.

[4]Any convex function with the potential for an internal minimum could have been used, but quadratic adjustment costs are standard in the literature and do not eat up many degrees of freedom.

possible that both *PCM* and *AS* are endogenous,[5] we added to (1)–(3) essentially the same simultaneous equations system as was used by Martin. Applying non-linear three-stage squares, our estimates are as follows:[6]

$$\begin{aligned}\lambda = \{&\underset{(2.19)}{0.288} + \underset{(1.27)}{0.008}PCMADJ - \underset{(3.55)}{30.016}MCDR - \underset{(0.22)}{0.023}REGION \\ &- \underset{(0.42)}{0.019}\overline{AS} - \underset{(0.68)}{0.133}CONSUMER\}^2 - \underset{(2.06)}{0.022}LAG,\end{aligned} \tag{6}$$

$$\begin{aligned}C^* = {}&\underset{(2.73)}{22.543} + \underset{(3.58)}{8.132}MCDR - \underset{(0.26)}{1.796}REGION - \underset{(0.32)}{1.961}\overline{AS} \\ &+ \underset{(0.62)}{121.126}CONSUMER - \underset{(0.6)}{0.04}G,\end{aligned} \tag{7}$$

$$\begin{aligned}AS = {}&\underset{(1.28)}{1.063} - \underset{(2.03)}{0.068}(\overline{PCM} - 0.07KS) + \underset{(8.77)}{2.990}CONSUMER + \underset{(0.88)}{0.026}\overline{C} \\ &- \underset{(0.77)}{0.0002}\overline{CSQ} - \underset{(0.90)}{0.006}BUYERCONC - \underset{(0.29)}{0.005}IMPORTS \\ &+ \underset{(0.34)}{0.068}DURABLE + \underset{(0.79)}{0.019}G,\end{aligned} \tag{8}$$

$$\begin{aligned}PCM = {}&\underset{(5.31)}{11.923} - \underset{(1.82)}{0.106}\overline{C} - \underset{(0.11)}{0.016}MCDR + \underset{(1.49)}{2.094}REGION \\ &+ \underset{(2.86)}{2.597}\overline{AS} - \underset{(1.95)}{6.233}CONSUMER - \underset{(1.71)}{0.063}BUYERCONC \\ &- \underset{(1.86)}{0.186}IMPORTS + \underset{(4.62)}{0.522}G \\ &+ \underset{(5.67)}{0.105}KS,\end{aligned} \tag{9}$$

[5]The potential for differentiability may be exogenous, whereas actual differentiation and advertising ought to be endogenous. The advertising–sales ratio is generally used as a proxy for the exogenous effect. Martin found endogeneity in his original tests, but Masson and Shaanan (1982) and Geroski (1982) found no traces of endogeneity in other models, and with different data sets.

[6]In these estimates, $t=1967$ and $t-1=1963$. Our sample size of 184 is smaller than Martin's sample size of 209. This is due in large part to our new data on *LAG*. A further nine industries were deleted based on our judgement that the 'industry' was too heterogeneous. The degrees of freedom were too small to permit running the model on a consumers goods sample alone. When the producer goods ($CONSUMER < 50\%$) were run alone the results exhibited some sensitivity to *CONSUMER* and *AS* in the determination of C^*.

where t-statistics are in parentheses below estimated coefficients, $N=184$, the estimated mean square error is 0.362, a bar ($\bar{\ }$) above a variable denotes that it has been instrumented,[7] and the previously undefined variables used in order of first appearance are: $PCMADJ=(t-1)$ value of price cost margins adjusted by subtracting advertising and capital costs (at 6.5% times the capital–sales ratio),[8] KS = the capital–sales ratio, CSQ = concentrated squared, $BUYERCONC$ = buyer concentration, $IMPORTS$ = import intensity, and $DURABLE$ = a durable goods dummy.

We first look at the two traditionally estimated equations, (8) and (9), before turning to estimates of λ and C^*. The results in the PCM equation are fairly standard, with the exception of the negative and insignificant coefficient on $MCDR$. Advertising is not subtracted as a cost in calculating PCM,[9] and so the extent to which higher advertising leads to excess PCM over total costs (including advertising) is measured by the amount that its coefficient exceeds 1, not zero. The t value on this hypothesis is 1.76, significant at the 95% level. Concentration has its expected effect on PCM, and $REGION$ does as well (albeit at only a 10% significance level). The KS variable is also a cost excluded from the PCM measure. If higher capital–sales ratios have no influence on behaviour, then the coefficient on KS is an estimate of the opportunity cost of capital. This is 10.5% as estimated here, somewhat above the 7% measure we impose in estimating the AS equation.[10]

[7]Martin uses exogenous and predetermined variables (and their squares and their interactions) as instruments. We exclude the predetermined variables in linear, squared, or interactive forms because we feel that their measurement errors may not be time independent. Thus, for example, if an excluded variable leads PCM to be high in a specific industry in every period, then the measurement error of $PCM(t)$ would be included in the instruments if $PCM(t-1)$ were used as an instrument. Our instrument set included every other interaction term implied by the λC^* interaction. This included, in some cases, cubic terms.

[8]The measurement of PCM is net of advertising expenditure. The cost of capital measure comes from judgement about bond rates. The 1963 three month Treasury bills yielded 3.16% and Moody's AAA corporate bonds yielded 4.26; the BAA bond yields over 1960–68 were 5.4%. Allowing for slightly more risk, we selected a 6.5% measure of the opportunity cost of total capital (equity and debt) for 1963.

[9]The standard hypothesis is that the PCM above production costs is related to market structure and demand elasticity (i.e., the first-order conditions for profit maximization do not count advertising in marginal costs). As importantly, the Dorfman–Steiner hypotheses for the determinants of advertising are based upon a PCM above production costs (excluding advertising as a cost), but, as noted in Masson and Shaanan (1984), entry should respond to returns above average costs, where costs include advertising costs. This leads to a different formulation for PCM in (6), the λ equation.

[10]Bond rates were about 1% higher in 1967 than in 1963, but we only added 0.5% to the measure of the opportunity cost (see footnote 8) to reflect generally less flexible longer-term rates. The 10.5% estimate here might suggest that we have underestimated the opportunity cost, but it is equally plausible that industries with the identical average production costs, but with higher capital costs, behave differently. For example, higher KS may indicate greater sunk costs (entry risk) or may be acting as a proxy for scale economies. ($MCDR$ is also only a proxy for economies to scale, so if KS captured the barriers effect of economies of scale from $MCDR$, then the coefficient on KS should exceed the opportunity cost on capital.)

Buyer concentration, imports and growth all have expected signs and are significant. The *CONSUMER* coefficient suggests that holding advertising constant, consumer goods have lower margins.[11] The results in the advertising equation not unsurprisingly attributes a major effect to *CONSUMER*. The price–cost margin is also positive and significant determinant of advertising and,[12] although no signs are counterintuitive for the other variables, none are significant.

The first two equations, (6) and (7), are our main focus of interest. The speed of adjustment is positively, albeit insignificantly, related to lagged *PCM* adjusted by subtracting capital and advertising costs. The major barrier to entry slowing the market response to excess profits is *MCDR*. *LAG*, the time required to plan and construct a new plant, is also significant, with a negative effect on adjustment speed, λ. The average value of λ in the sample is 12.3% over five years. Martin's original estimates of λ were 7.6% for producer goods industries and 12.6% for consumers goods industries, but, when his empirical model was estimated on our sample, the estimate of λ was dropped to 5.4%. This answers our first question. It seems to be the case that linearizing (1)–(3) in the manner of (4) generates a substantial downward bias (the estimated value of λ was more than halved) in the estimate of the average speed of adjustment across industries, suggesting much slower market dynamics than is, in fact, the case.[13]

Our second question concerned the extent of the variation in λ across industries. This seems to be substantial. While the average value of λ is 12.3%, one standard deviation on each side of that estimate covers a range from 6.0% to 18.3%. In some cases λ is effectively zero.[14] Clearly for some (but not all) industries, adjustment to long-run equilibrium levels of concentration, C^*, is glacial indeed.

The determinants of C^* appear to be largely technological. The value of

[11]It is worth noting that the range of *AS* is [0.04, 10.71] whereas for *CONSUMER* it is [0, 0.93]. To the extent that *CONSUMER* and *AS* are positively correlated, the positive effect of the 2.6 coefficient on *AS* is much greater than the negative effect of the 6.2 on *CONSUMER*, and this remains true even for the price margin above average costs including *AS* as a cost (e.g., using a coefficient of 1.6 for *AS*). So consumer goods have higher *PCM*'s in general, but lower *PCM*'s conditional on *AS*.

[12]Note that capital costs are subtracted from the (instrumented) *PCM*. In effect, the coefficient on *KS* is constrained to equal (-0.07) times the coefficient on *PCM*. This adds an identifying restriction to the model.

[13]Omitted determinants of C^* are likely to lead to *downward* bias in the estimation of λ since they will lead to estimates that suggest $C^* \neq C(t-1)$ when this is not true, thus giving the impression of very slow adjustment. Hence, this type of specification error does not seem to be a likely explanation of our results.

[14]We did not impose a bound specifically requiring λ to be non-negative. This is partly because of the complicated statistical properties of such bounds, partly because divergence from C^* cannot be ruled out a priori, and partly just to be able to check whether the model predicts reasonably. For nine industries, the predicted value of λ was negative, in four cases with an absolute value exceeding 2% and in one case with an absolute value of 5.3%. The sample maximum predicted was 27%.

MCDR is about 14% greater than minimum efficient scale but, neglecting this, our estimates suggest that the marginal effect of an increase in minimum efficient scale on concentration in the long run is roughly the amount of increase in minimum efficient scale for each of four firms with an average of two plants apiece. Accordingly, the results seem roughly consistent with the view that concentration is technologically determined if there exist some multiplant economies of scale. The average value C^* across the sample was 50.[15] In contrast to others [e.g., Mueller and Hamm (1974) and Mueller and Rogers (1980)] who find that advertising is related to increases in concentration, we find no effect of advertising on C^*. Our third question concerned the possibly offsetting effects that some exogenous variables might have on the two different components of changes in concentration. *MCDR* clearly reduces λ, but it also raises C^*. Some elementary calculations reveal that at the mean values of all exogenous variables (except *REGION* which we set equal to zero to analyze only national industries), the effect of a marginal change of *MCDR* on $C(t)$ at any t is given by $\{0.01[C(t-1)-50]+0.9\}$. Thus, *MCDR* increases predicted $C(t)$ for all feasible $C(t-1)$ values.[16] For $C(t-1)<50$ the reduction in $C(t)$ due to a lower λ is offset by the increases in $C(t)$ due to a higher C^*; for highly concentrated industries, the lower λ and higher C^* induced by increases in *MCDR* both work in the same direction.

3. Conclusions

In analysing changes in market structure, it seems important to examine both the speed of structural adjustment and its steady-state values. Most earlier work has not attempted to disentangle these, and has used linear approximations to model changes in market structure. This suppresses interactions between the two and so may lead to bias. Further, as theory predicts that adjustment will be a convex, non-monotone function of profits, a linear approximation of a convex function with a minimum value which is internal to the data set is likely to show statistical insignificance, even where a strong relationship obtains. Accordingly, we have used non-linear estim-

[15]The value of C^* was not constrained to lie in the interval (0, 100), although changes in concentration equations have been subjected to non-linear bounds in the literature [e.g., see Wright (1978)]. The predicted value of C^* exceeded 100 in 21 industries, it exceeded 150 in 10 industries, and exceeded 200 in four cases. These were all industries with extremely high values of *MCDR* (e.g., at or above 30%). High *MCDR* values were also associated with the low values of λ reported in footnote 13. Very high *MCDR* industries should gravitate to long run equilibria with fewer than four firms, so these values of C^* are not necessarily unrealistic. Bain (1970) reports a 'centripetal tendency' for concentration ratios above 60% to fall, and for those above 40% to rise. His work dealt with 1954–63 and 1954–66, and seems broadly consistent with our estimate of C^*.

[16]Using the linear model (4), the partial derivative of long-run concentration with respect to *MCDR* is 1.75, considerably larger than the effect observed in the non-linear model.

ation techniques in this paper to examine various structural hypotheses with more precision. Our results indicate that while linearization may have led to underestimates of the speed of adjustment, it is nevertheless the case that adjustment is quite slow on average. The estimates presented here also provide independent estimates of steady-state concentration levels, suggesting levels of about 50% on average. These appear to be strongly influenced by minimum efficient scale, a variable which also appears to slow adjustment towards the steady state.

Appendix: Data

LAG = *new plant* construction time (in months) (based on figures ≈1958); this is composed of *two* components: (a) on-site construction, (b) design and procurement. We used the estimate for *large* plants, defined as including those size classes (grouped by number of employees) which collectively produced approximately 80% of the value added by manufacture in the industry. The data is from *Capacity Expansion Planning Factors* by Robert M. Waddell, Philip M. Ritz, John Dewitt Norton and Marshall K. Wood, prepared for Agency for International Development, U.S. Department of State, by the National Planning Association, Washington, D.C., 1966. All the remaining data details can be found in Martin (1979).

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