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"COOPERATION VS. RIVALRY:

PRICE-COST MARGINS BY LINE OF BUSINESS"

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The views expressed here are our own and not necessarily those of the Federal Trade Commission or any of its members. A review has been conducted to ensure that the data in this paper do not identify individual company line of business data. John Kwoka's work was supported by an FTC Bureau of Economic contract; he did not have any access to individual company line of business data. Gratitude is expressed to Bill Long, Mike Scherer and reviewers for a number of helpful comments.

Much of the recent literature on oligopoly price determination has drawn on Cowling and Waterson's (1976) seminal work. Their contribution was to show that a general oligopoly model could be used to motivate cross-sectional studies of industry price-cost margins, employing the Herfindahl-Hirschman (H) index of concentration, the conjectural variation, and demand elasticity. More recently, Clarke and Davies (1982) have shown that the H index is an implication of cost asymmetries, and they propose to parameterize a range of non-competitive behavior among firms in a Cowling-Waterson type model.

The present paper is an effort to take that exercise an additional step forward. In particular, we draw on insights from recent empirical literature to further generalize these oligopoly models, test some of the distinctive features of each, and explore some new implications using data far more disaggregated than previously available. The relevant empirical developments are found in Kwoka (1979) and Ravenscraft (1983). The former work examined the role of individual market shares, rather than concentration, in raising industry margins, and found the possibility of procompetitive rivalry by smaller firms. Ravenscraft uses Federal Trade Commission Line of Business data to demonstrate the powerful effects of a firm's own share and scale economies, and the curious negative effect of four-firm concentration, on line of business operating income.

This study uses market shares to respecify the firm interaction parameter in the theoretical model, thereby broadening the range of estimable behavior. Then empirical evidence is developed which reveals a complex set of effects involving other firms' shares in performance determination, and offers an explanation for the anomalous results involving a negative effect of concentration. Among the important specific results, we find that leading firms' margins in each industry are lower when non-leaders are larger, and non-leaders' margins are diminished in industries where scale economies dictate more dominant leading firms. Despite exceptions, the pervasiveness of this rivalry phenomenon contradicts the traditional presumption that performance levels are shared by all firms in an industry. To that extent, the results are in the spirit of Demsetz's (1973) and Porter's (1979) findings. Further implications of these results for the theoretical model and empirical work are discussed in the last section.

I. Cooperation Models

In this section, we contrast three major approaches to modeling cooperation/collusion: Cowling-Waterson, Clarke-Davies and the "shared asset" model. Our detailed data, described below, permit testing among these alternatives. The results of this testing also constitute the point of departure for the generalization, discussed in the next section, which allows rivalrous behavior among firms.

Cowling and Waterson developed an explicit theory of price determination in an industry j with a constant number of firms (N_j), a homogeneous product price (p_j), and constant marginal costs (c_{ij}). The subscript i permits each firm to have a different constant marginal cost curve. In fact, differences in marginal costs are the sole cause for intraindustry differences in firm size, with larger firms having lower marginal cost. Firm profit (or in the case of a diversified firm, line of business profit) is defined as $\pi_{ij} = p_j X_{ij} - c_{ij} X_{ij}$. Maximizing profits with respect to own output (X_{ij}) yields:

(1) $(p_j - c_{ij}) + p' X_{ij}(1 + \sum_{k \neq i} \partial X_{kj} / \partial X_{ij}) = 0.$

The Lerner index can be derived from equation (1) and is given by:

(2) $L_{ij} = MS_{ij}(1 + \lambda_{ij})/\eta_j$,

where MS_{ij} is the firm's market share, $\lambda_{ij} = \sum_{k \neq i} \partial X_{kj}/\partial X_{ij}$ is its conjectural variation and η_j industry's elasticity of demand. In the spirit of Cowling and Waterson, one can then model oligopoly interaction by hypothesizing that λ_{ij} is an increasing function of some concentration measure C_j. Specifically, we assume a linear function, i.e., $\lambda_{ij} = \gamma C_j$. In actuality, they prefer $C_j = H_j$, the Herfindahl-Hirschman index, and further, aggregate (2) to the industry level to accommodate their data.[1] More directly, however, at the line of business level, their model implies the following estimating form:

(3) $L_{ij} = (MS_{ij} + \gamma C_j MS_{ij})/\eta_j$.

Clarke and Davies extend Cowling and Waterson's model by further specifying the conjectural variation relationship. They interpret perfect cooperation to be the set of λ_{ij}'s which maintain market shares, i.e., $\partial X_{kj}/\partial X_{ij} = X_{kj}/X_{ij}$. Substitution into (2) reveals that this does indeed produce the monopoly solution $L_j = 1/\eta_j$. Then they parameterize the range of behavior from Cournot to cooperation by the industry parameter α_j, where $\partial X_{kj}/\partial X_{ij} = \alpha_j X_{kj}/X_{ij}$ and $0 \leq \alpha_j \leq 1$.[2] From the definition of λ_{ij}, it is straightforward to show that:

(4) $\lambda_{ij} = \alpha_j(1/MS_{ij} - 1)$.

Since α_j represents the degree of industry-wide cooperation, it is natural to represent α_j as an increasing function of concentration C_j. Again assuming this function is linear and substituting it and (4) into (2) yields:[3]

(5) $L_{ij} = (MS_{ij} + \gamma C_j(1 - MS_{ij}))/\eta_j$.

Both the Cowling and Waterson model and the Clarke and Davis adaptation involve some strong assumptions which yield very restrictive specifications. For example, they assume a static environment with a fixed number of firms, a homogeneous product, constant marginal costs and an exogenously determined conjectural variation.[4] A more traditional approach to oligopoly modeling, which has been called the "shared asset" model, acknowledges the difficulty of explicitly specifying the correct functional form and elects a more direct but less rigorous path. It assumes that all firms share in the higher price that results from cooperation. Therefore, profits are assumed to be some positive function of industry-wide concentration. As with the previous models, the functional form is assumed to be linear.[5] Market share is also included to capture scale economies and other possible size-related advantages. Hence, the Lerner index of the $i^{\underline{th}}$ firm in the $j^{\underline{th}}$ industry is:

(6) $L_{ij} = \beta MS_{ij} + \gamma C_{ij}$.

While the role of demand elasticity is acknowledged in this model, no specific interpretation along those lines is given to the estimated coefficients in (6).

Equations (3), (5) and (6) therefore represent three related but different models of oligopoly pricing. They also can be viewed as subsets of the following equation:

(7) $L_{ij} = \beta_1 MS_{ij} + \beta_2 C_j + \beta_3 C_j MS_{ij}$.

All three theories suggest that β_1 will be positive. In addition, the Cowling-Waterson and Clarke-Davies models indicate that it should equal the inverse of the elasticity of demand. Each theory differs with respect to its prediction about the cooperation related parameters β_2 and β_3. The Cowling-Waterson model predicts $\beta_2 = 0$ and $\beta_3 > 0$. Clark-Davies model predicts $\beta_2 = -\beta_3$ or equivalently that the two concentration terms reduce to $\beta_2 C_j(1 - MS_{ij})$. The shared asset model hypothesizes that $\beta_2 > 0$ and $\beta_3 = 0$.

Equation (7) is estimated using an unusually rich data source consisting of 3186 line of business (LB) observations on 258 Federal Trade Commission industry categories for the year 1975.[6] Each "line of business" denotes a firm's operation in one of its industries. The dependent variable is the LB's operating income divided by sales (i.e., a LB's price-cost margin), where operating income is defined to be sales minus materials, payroll, advertising, other selling expenses, R&D, administrative expenses, and depreciation. In addition to the variables in equation (7), the following control variable are included together with a constant term and are assumed to enter the model additively.

MES_j = 1977 industry minimum efficient scale: market share of average plant size in top half of distribution;

$GROW_j$ = industry growth: 1976 divided by 1972 value of shipments;

DS_j = industry distance shipped (in thousands of miles): radius within which 80 percent of shipments occurred;

IMP_j = 1975 industry import penetration: imports divided by apparent domestic consumption;

ADV_j = 1975 industry advertising intensity: weighted sum of LB advertising intensities;

RD_j = 1975 industry R&D intensity: weighted sum of R&D intensities;

CAP_j = 1975 industry capital intensity: weighted sum of LB capital intensity corrected for current capital utilization;

CU_{ij} = 1975 LB capital utilization: smaller of unity or ratio of 1975 LB sales divided by 1974 LB sales.[7]

The results are reported in Table 1. Equation (1) of that table is essentially the model in text equation (7). The positive and significant coefficient on MS_{ij} is consistent with the theoretical prediction of all three models. Its magnitude suggests an average elasticity of demand between three and six, a more elastic estimate than is commonly observed.

The shared asset theory predicts a positive effect of concentration, whereas the regression results reveal a very strong negative association. This theory does, however, appear to be correct in assuming that $CR4_j MS_{ij}$ is not important. The individual t statistic on this variables coefficient is insignificant and an F test reveals that equation (2) in Table 1, which omits the interaction variable, is not significantly different from equation (1).

The Cowling-Waterson model predicts no effect from the linear term $CR4_j$, whereas it is always significant. Further, the general equation loses significant explanatory power when $CR4_j$ is dropped, as the F test for equation (3) demonstrates. The t statistic on $CR4_j MS_{ij}$ is substantially higher in equation (3) than equation (1), suggesting that this interaction term acts as a proxy for the omitted linear concentration term.

Lastly, in addition to a positive effect on MS_{ij}, the Clarke-Davies model predicts equality (in absolute value) of the coefficients on concentration and the concentration-share interaction. Imposing such a constraint, in equation (4) of Table 1, does not significantly reduce explanatory power. Thus, like the shared asset model, there is no evidence against the Clarke-Davies formulation. Given these results, we proceed to use the Clarke-Davies model to develop further theoretical extensions and conduct empirical tests, with the knowledge that the intuitive shared asset approach is likely to yield similar conclusions.[8]

II. Models of Rivalry

The above results support the Clarke-Davies model with one major exception -- the coefficient which estimates the degree of cooperation is negative.[9] To further understand this apparent anomaly, two assumptions employed by Clarke-Davies are relaxed.

First, single summary indexes of market structure, such as the four-firm concentration index and the Herfindahl-Hirschman index, are generalized to allow for the possibility of intraindustry rivalry. Second, the assumption that the α_j's are identical for all firms in an industry is dropped. These changes yield significant insights into the interpretation of the negative coefficient on concentration.

Clarke and Davies offer no theory of oligopoly in the sense of deriving the structural determinants of α_j (or more directly, of λ_{ij}). While most research has used the four-firm concentration ratio, they -- like Cowling and Waterson before them -- prefer the H index, but for reasons that lay outside their theory. As Kwoka has noted, such summary indexes of market structure impose a variety of restrictions on the role of individual market shares and, by implication, on interfirm behavior. For example, the four-firm concentration ratio adds up the top four market shares with equal weight, and ignores all other firms. Empirical evidence in Kwoka and in Lamm (1981) rejects these assumptions, and instead finds unequal weights -- positive on the top two or three shares, followed by a negatively-signed share. This latter result is interpreted as possibly reflecting procompetitive rivalry by third - or fourth -ranked firms, since when such firms are large, industry margins decline. The H index weights each firm by itself, and then takes the summation of those terms. That process, too, embodies assumptions. In particular, it precludes the possibility of a negative, rivalry effect from any firm.

Thus, our first modification will be to relax to some degree these restrictions by letting industry-wide α_j be a simple, linear function of the ordered sequence of market shares in that industry. That is:

$$(8) \quad \alpha_j = \sum_{m=1}^{k} \beta_m Sm_j$$

where k is an empirically determined variable, $1 \leq k \leq N$, representing the subset of firms whose shares "matter", in the sense of having a significant impact on margins. Sm_j equals the m^{th} firm share in the industry, ranked from largest to smallest. Thus, $S1_j$ represents the share of the largest firm in the industry. The hypothesis that cooperation characterizes the relationship between leading firms implies that certain $\beta_m > 0$. If the next one or more firms are strong rivals, cooperation breaks down and all firms' margins decline. In the presence of such firms, α_j is smaller as the result of some $\beta_m < 0$. Finally, if subsequent firms do not matter, margins are determined independent of them and their β_m in equation (8) equals zero.

The general form of interaction in equation (8) by no means precludes conventional measures like the four-firm concentration ratio from emerging. If empirically, $\beta_1 = \beta_2 = \beta_3 = \beta_4$ and $\beta_5 = ,\ldots , \beta_N = 0$, then $\alpha_j = \beta_1 CR4_j$. But we avoid imposing this form a priori. Furthermore, nothing in theory requires that α_j be bounded by zero and unity. Indeed, sufficient rivalry can drive industry margins down to competitive levels. The Cournot equilibrium does not represent the "most competitive" possible outcome in an oligopoly setting.[11]

Secondly, Clarke and Davies rightly observe that nothing requires identical α_j's for all firms in an industry. They note (p. 280), "smaller firms may feel more able to get away with output changes undetected than would larger firms," i.e., smaller firm's conjectures may be closer to Cournot or rivalry. The empirical consequences of such different behavior are suggested by equation (8). That expression assumes identical interactions for all firms with respect to one other, whereas a number of oligopoly theories (dominant firm, price leadership, limit pricing, "strategic groups") would suggest important differences between leading and nonleading firms. We shall test empirically for such differences in α_j's between leaders and followers, along the lines suggested by Clarke and Davies.

Furthermore, the role played by leaders can be expected to differ depending on a number of factors conditioning the firms' environments. Prominent among these in the literature is the degree of scale economies. When economies are great, the price preferences of large leading firms may compress non-leaders' price-cost margins since the latter suffer cost disadvantages. By contrast, in low-scale industries, larger leaders are likely to have a less adverse effect on non-leaders' margins, <u>cet. par.</u> For these reasons, too, the α_j's are predicted to be different, and we shall examine differences between high and low-scale industries.

III. Empirical Evidence

We begin by first exploring the simplest case where the α_j's are identical for all firms in an industry, but α_j depends on k shares according to equation (8). To illustrate the implications, let k = 2, i.e., only S1 and S2 are important to cooperation or rivalry. Then $\alpha_j = \beta_1 S1_j + \beta_2 S2_j$ and substituting into (6), we obtain:

(9) $L_{ij} = (1/\eta_j)(MS_{ij} + \beta_1 S1_j(1 - MS_{ij}) + \beta_2 S2_j(1 - MS_{ij})) + \underline{\beta X} + \varepsilon_{ij}$

where ε_{ij} is a random disturbance term and $\underline{X}$ represents the vector of control variables discussed above. From theory and earlier work it is apparent that we must include own share MS_{ij} plus a term interacting $S1_j$ with one-minus-MS_{ij}. The cooperation hypothesis implies that $\beta_1 > 0$; rivalry, that $\beta_1 < 0$; and "independent" behavior, that $\beta_1 = 0$. In fact, our estimation procedure involves first the examination of the effect of $S1_j$ by itself (in the form specified by the Clarke-Davies model, i.e., interacted with one minus market share). Next, $S2_j$ is added to the equation with $S1_j$, then $S3_j$ is added, and so forth, as long as significant (positive or negative) effects emerge. Thus, we will be performing two-tail tests on ordered sequence of β's.

Table II reports estimates of equation (9) using all 3186 line of business observations, thus far without distinction between leaders and followers. $S1DMS_{ij}$, $S2DMS_{ij}$, etc., denote the interactions of $S1_j$, $S2_j$, etc., with the difference between unity and own share, as specified in equation (9). Observe first that own share MS_{ij}, and minimum efficient scale (MES_j), behave in accordance with theoretical predictions, here and throughout. With respect to other control variables, all statistically significant variables have the expected sign with the sole exception of industry R&D intensity. In addition, the industry advertising and capital intensity variables fail to achieve statistical significance.

The coefficient on $S1DMS_{ij}$ is negative and significant implying that larger leading firms generally lower LB margins. The estimated coefficients on $S2DMS_{ij}$ and $S3DMS_{ij}$ are neither stable in sign nor anywhere near conventional levels of statistical significance. $S4DMS_{ij}$ is positive but also insignificant. The F statistic on $S2DMS_{ij}$ and $S3DMS_{ij}$ taken together is 0.09, far below the 5 percent F value of 3.00. The addition of $S4DMS_{ij}$ to this group raises the F statistic slightly to 0.27, but still well below the critical F value of 2.60. The market shares of nonleading firms do not, in general, seem to affect the price-cost margins of firms in the industry, while the leading firm acts as a strong rival to the smaller firms. Thus, it is the negative effect of S1 which underlies and explains the negative impact of CR4 observed in Table I.

Further insight can be gained by dropping the assumption of identical α_j's for all firms in each industry. As noted in the previous section, reasons exist to believe that leaders and followers in a market are subject to different forces and behave differently. Since the overall sample of LBs is dominated numerically by followers, their behavior dominates the statistical results. That is, followers may be worse off in markets with larger leaders, even while they are better off with larger own share. By contrast, it is not plausible that leaders are somehow worse off with larger shares.

Thus, in accordance with the second modification proposed in Section II, the sample is split into leader firms and follower firms, industry by industry, so as to permit different α_j's. Clearly, such splitting has elements of arbitrariness. Three different definitions of a "leader" were explored: (1) the single largest firm in each industry: (2) the largest firm in each industry plus any second-ranked firms with shares greater that 15 percent and greater than one-half the corresponding top-ranked firm; and (3) the largest firm in each industry only if its share exceeded 10 percent. Since no radical differences emerge in the results under either the broader or narrower definitions, the first definition was adopted as most straightforward and least arbitrary.

Under this definition, the empirical results on the leader sample are presented in Table III. This model is entirely analogous to that in Table II, with the proviso that MS_{ij} now captures the leader's own share directly. The results, however, are quite distinct. The crucial difference, in terms of the cooperation-rivalry theory, is the change in sign and significance of $S1DMS_{ij}$ and $S2DMS_{ij}$. The coefficient on $S1DMS_{ij}$ was negative and significant in Table II while it is positive and insignificant in Table III. This confirms the proposition that leaders are <u>not</u> lowering their own profitability through their rivalrous behavior. The coefficient on $S2DMS_{ij}$, which was insignificant in Table II, has a large significantly negative impact in Table III. A large second firm appears, on average, to induce rivalry with leaders rather than cooperation. In both Table II and Table III, more distant rivals seem to have little impact, with t-values on $S3DMS_{ij}$ and $S4DMS_{ij}$ well below unity. The practical importance of these results would seem to be the lack of evidence of general cooperation or collusion by other firms with the leader.

In Table III, the coefficient on MS_{ij} is considerably smaller than in the overall sample, and statistically insignificant. This change results primarily from the control variables capturing a considerable portion of the explanatory power of the leader's market share.[12] The significantly negative impact of R&D in the overall sample turns positive in the leader sample, while negative effect of distance shipped becomes insignificant. The positive effect of industry advertising and capital intensity, which are insignificant in the overall sample, are significant in the leader sample. The coefficients on almost every control variable are more positive or less negative in the leader sample than in the overall sample.

Similar, but statistically weaker, results were found for subsamples consisting of leaders in consumer goods industries and producer goods industries. An important exception to this pattern emerges in the Food and Kindred Product group (industries in two-digit SIC 20). For this group, a positive and significant coefficient on the second share appears, suggesting cooperation between the top two firms. This result corresponds to other empirical findings of stronger coordination in both food retailing and food manufacturing.[13]

With respect to the follower group, the hypothesized importance of scale economies (see Section II) leads us to split the group according to whether the firms are in the top or bottom half of the MES distribution.[14] In particular, we expect that larger leaders are likely to compress follower margins where the latter are disadvantaged by scale considerations, but in low-scale industries the impact of larger leaders is ambiguous. Table IV confirms these predictions. In high-MES industries, larger leading firms induce rivalrous conjectures and produce smaller follower margins, while leaders have no significant effect in either direction in low-scale industries.[15] An F test reveals that the two subsamples are indeed statistically different. The F statistic, assuming a null hypotheses of similar coefficients for the two subsamples, is 3.32, which exceeds 1.83, the 5 critical F value at the 5% level of significance.

The Clarke-Davies model given in equation (5) implies that the coefficient on market share should equal the inverse of industry demand elasticity for all firms. The estimates are not all that dissimilar for high and low-MES followers, but comparison with Table III for leaders reveals little similarity for the coefficients on MS_{ij}. There is evidence that some portion of the apparent reduction in the role of leaders' market shares is due to colinear factors (see footnote 12). It is also possible that other dimensions of structure, like firm rank itself,[16] or product differentiation need to be more fully represented. At present, this remains a problematic feature of this model.

IV. Summary

The fact that market shares, both own and others', play complicated and interactive roles in determining price-cost margins has become well known. This paper has joined recent theoretical work with empirical research to advance our understanding in certain directions. Substantively, the findings suggest that larger shares for firms in an industry raise their own margins, though for leading firms the effect is bound up in other control variables. A larger leader lowers follower margins in high-scale industries, but has little effect where scale economies are not important. The role of differential cost in determining the pattern of oligopoly interaction seems clear. In addition, larger second-ranked firms can significantly lower leaders' margins. This rivalry phenomenon emerges sooner than in previous studies, which uncovered rivalrous third or forth ranked firms.

These results help interpret some previous findings in the literature. The negative coefficient on four-firm concentration often found (see Ravenscraft (1983) and Mueller (1983)) in individual firm or LB regressions may be due to the mixing of models: Leaders are fewer than followers in most samples, and the latter are disadvantaged by larger leading firms, whose shares are highly correlated with CR4. Similarly, the positive sign of S1's coefficient in industry regressions (see Kwoka (1979) and Lamm (1981)) may be due to aggregation: Larger leading firms comprise more of the weighted average industry price-cost margin. Hence, the positive effect of $S1_j$ on leaders' margins and in general the positive impact of own share will be propagated to the industry level.

Finally, the results have methodological implications. The data have permitted straightforward tests of three models of oligopoly pricing -- Cowling and Waterson, Clarke and Davies and shared asset. All three models result in a negative coefficient on concentration and only the Cowling and Waterson was statistically different from a more general model of oligopoly. We have also noted several limitations of the models. In particular, these models need to incorporate dynamic influences, product differentiation and nonshare related factors which influence cooperation. Even at present, however, the data have illuminated both modeling and empirical issues.

Footnotes

[1]Cowling and Waterson's aggregation of (3) gives industry margins as: $L_j = H_j(1 + \mu_j)/\eta_j$ where $\mu_j = \sum_i \lambda_{ij} X_{ij}^2 / \sum_i X_{ij}^2$.

Thus even before introducing H as a measure of oligopoly behavior (λ_{ij} or μ_j), H appears solely as the result of different market shares. Market shares are in turn the result of cost asymmetries among firms. While Cowling and Waterson's model has often been interpreted as a theoretical justification for using H to represent cooperation, that is not a correct interpretation of the above result. See Clarke and Davies (1982, p. 278).

[2]It follows that:

$$\alpha_j = \frac{\partial X_{kj}/X_{kj}}{\partial X_{ij}/X_{ij}}$$

This is also the measure of cooperation proposed by Dickson (1982) and Long (1982).

[3]Note, substituting only equation (4) into (2) yields:

$$L_{ij} = (MS_{ij} + \alpha_j(1 - MS_{ij}))/\eta_j.$$

With $\alpha_j = 1$, $L_{ij} = 1/\eta_j$ which implies that each firm within the industry must have the same price-cost margin. But, the Clarke and Davies model assumes homogeneous products and different constant marginal costs, implying <u>different</u> price-cost margins for each firm. Thus, there appears to be a contradiction in this model. This problem is similar to the case of a monopolist with two constant marginal costs plants. The solution is for the most efficient plant (or firm) to produce all the output. In general, with nonidentical costs, collusive equilibrium in a conjectural variation model may require negative outputs from high-cost firms and side payments. It is true, however, that except for close approximations to cooperation ($\alpha_j = 1$) with dramatically different costs, the model encounters no such problems and on that basis we proceed. We thank the referee for this insight and Bill Long for helpful discussions.

[4]Some of the assumptions have been made less restrictive in recent work by Clarke, Davies, and Waterson (1984) and Long (1982).

[5]Initial work explored several nonlinear specifications including discontinuous concentration ratios and a squared concentration term. The discontinuous concentration ratios resulted in signs and significance levels similar to the linear concentration variables. Furthermore, neither the nonlinear nor the discontinuous terms added any significant explanatory power to the linear term regressions.

[6]At the time of estimation, only 1974-1976 line of business data were available. The results reported in this paper are for 1975. Initial estimation also employed 1974 and 1976 data and these years yielded similar results.

[7]Most of these variables appear in Ravenscraft (1983). The import variable comes from Benvignati (1984). Except for the capa-

city utilization variable, industry rather than LB-level versions of the variables are employed. Ravenscraft's results suggests that for many variables the industry intensity values better characterizes the context within which each line-of-business operates.

[8]In fact, all of the equations presented in the paper have been run using the shared asset model and for all these runs the qualitative results were similar to the Clarke-Davies model.

[9]Daskin (1983) argues that concentration's coefficient may be biased downward because of the omitted demand elasticity. Long and Ravenscraft (1984), however, present evidence which contradicts this cla

[10]A similar procedure was used to generalize the H index. Specifically, individual coefficients were estimated for each Sm_j^2 variable. This disaggregation of the H index yielded similar, but statistically weaker, results relative to those in Table 1.

[11]The idea that the Cournot solution represents the lower bound has gained credibility more from repetition than from economic theory or empirical evidence. The supposed analogy to "competitive independence" is fallacious. For example, with identical firms the competitive solution is $\lambda_j = -1/(N_j-1)$, not zero. Equation (7), therefore, can imply a negative α_j for large MS_{ij}. Only as N_j approaches infinity does the competitive solution approach the Cournot solution. This latter result suggests that equation (7) should not contain a constant term. We acknowledge a referee's assistance for this last point

[12]Note, when the control variables are omitted, MS_{ij} becomes significantly positive and the t-statistic on $S1DMS_{ij}$ increases to 1.42. The sign and significance of $S2DMS_{ij}$ and MES_j remain the same.

[13]See Connor et. al. (1985) for a review of these studies.

[14]That is, the 258 industries were divided in two using the median value of MES_j. This naturally leads to a moderately unequal number of LB observations in the top and bottom halves of the MES distribution, since there will tend to be fewer firms in the high MES industries.

[15]The negative coefficient on $S1DMS_{ij}$ in the high MES sample stems mainly from the producer goods industry subsample. The coefficient on $S1DMS_{ij}$ is positive in high MES consumer and Food and Kindred product goods industries. In low MES industries, the coefficient on $S1DMS_{ij}$ is positive for producer and Food and Kindred product groups and negative for consumer goods industries. Note, the only estimated subsample for which no rivalry is observed is Food and Kindred product group. However, in all cases the coefficient on $S1DMS_{ij}$ is insignificant. On the other hand, MS_{ij} is positive and significant for all subgroups, except low MES producer goods and high MES Food and Kindred products industries.

[16]A variable measuring firm rank was added to the regression in Table II equation (2). Its inclusion did not significantly increase the regression's explanatory power.

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Table I -- Three Specifications of the Profit-Cooperation Relationship

Dependent Variable - LB Operating Income/Sales

Independent Variables*	1	2	3	4
MS_{ij}	.2851 (2.93)	.1947 (4.90)	.3223 (3.34)	.1657 (4.40)
$CR4_j$	-.0422 (-2.65)	-.0470 (-3.10)		
$CR4_j MS_{ij}$	-.1545 (-1.02)		-.2743 (-1.89)	
$CR4_j(1-MS_{ij})$				-.0464 (-2.97)
R^2	.0837	.0834	.0817	.0832
F statistic**		1.03	7.04	1.77

Notes: t statistics are in parentheses.
The number of observations is 3186 lines of businesses.
*Also includes nine other control variables (including a constant term). The regression statistics for these variables are contained in Table II.
**The F statistic is a test of the linear restrictions imposed in equations (2), (3) and (4).

Table II -- Individual Share Components of Concentration Ratios

Dependent Variable - LB Operating Income/Sales

Independent Variables	1	2	3	4
$S1DMS_{ij}$	-.1004 (-3.69)	-.1084 (-3.14)	-.1095 (-3.17)	-.1063 (-3.06)
$S2DMS_{ij}$		.0250 (0.38)	-.0122 (-0.13)	-.0123 (-0.13)
$S3DMS_{ij}$			.0773 (0.57)	.0039 (0.03)
$S4DMS_{ij}$				.1450 (0.78)
MS_{ij}	.1696 (4.50)	.1694 (4.49)	.1696 (4.49)	.1694 (4.49)
MES_j	.2602 (3.56)	.2536 (3.37)	.2473 (3.25)	.2398 (3.13)
$GROW_j$	.0590 (8.34)	.0589 (8.32)	.0584 (8.19)	.0579 (8.08)
DS_j	-.0200 (-2.99)	-.0200 (-2.99)	-.0204 (-3.03)	-.0201 (-2.97)
IMP_j	-.0605 (-2.09)	-.0607 (-2.10)	-.0587 (-2.01)	-.0597 (-2.05)
ADV_j	.1194 (1.35)	.1196 (1.35)	.1188 (1.34)	.1114 (1.25)
RD_j	-.3724 (-2.51)	-.3682 (-2.47)	-.3643 (-2.44)	-.3647 (-2.45)
CAP_j	-.0010 (-0.08)	-.0006 (-0.05)	-.0017 (-0.14)	-.0028 (-0.23)
CU_{ij}	.1912 (11.08)	.1911 (11.07)	.1912 (11.07)	.1914 (11.08)
CONSTANT	-.1812 (-9.17)	-.1818 (-9.17)	-.1812 (-9.12)	-.1819 (-9.15)
R^2/F	.0846 (29.33)	.0846 (26.67)	.0847 (24.47)	.0849 (22.63)

Notes: t statistics are in parentheses, except in R^2 column which contains F statistics testing for the significance of the linear model. The number of observations is 3186 lines of businesses.

Table III -- Leading Firm Analysis

Dependent Variable - LB Operating Income/Sales

Independent Variables	1	2	3	4
$S1DMS_{ij}$	-.0904 (-1.33)	.0167 (0.20)	.0136 (0.16)	.0155 (0.18)
$S2DMS_{ij}$		-.3015 (-2.23)	-.4175 (-2.16)	-.4157 (-2.14)
$S3DMS_{ij}$			.2462 (0.84)	.2192 (0.58)
$S4DMS_{ij}$				.0455 (0.11)
MS_{ij}	.0231 (0.51)	.0288 (0.64)	.0301 (0.67)	.0302 (0.67)
MES_j	.3145 (2.81)	.3113 (2.81)	.2995 (2.68)	.2974 (2.62)
$GROW_j$	.0525 (3.54)	.0507 (3.44)	.0500 (3.38)	.0498 (3.35)
DS_j	-.0079 (-0.57)	-.0081 (-0.59)	-.0080 (-0.58)	-.0079 (-0.57)
IMP_j	-.0917 (-1.79)	-.0920 (-1.81)	-.0915 (-1.80)	-.0918 (-1.80)
ADV_j	.7176 (4.08)	.7122 (4.08)	.7163 (4.10)	.7150 (4.07)
RD_j	.3428 (1.07)	.2865 (0.90)	.3092 (0.96)	.3112 (0.97)
CAP_j	.0493 (2.27)	.0473 (2.19)	.0438 (1.99)	.0435 (1.96)
CU_{ij}	.1210 (2.42)	.1246 (2.51)	.1256 (2.53)	.1262 (2.52)
CONSTANT	-.1413 (-2.62)	-.1322 (-2.47)	-.1336 (-2.49)	-.1344 (-2.48)
R^2/F	.2056 (6.39)	.2214 (6.36)	.2236 (5.88)	.2237 (5.41)

Notes: t statistics are in parentheses, except in R^2 column which contains F statistics testing for the significance of the linear model. The number of observations is 258 lines of businesses.

Table IV -- Follower Firm Analysis

Dependent Variable - LB Operating Income/Sales

Independent Variables	LOW MES	HIGH MES
$S1DMS_{ij}$	-.0544 (-1.39)	-.1229 (-2.86)
MS_{ij}	.2480 (2.06)	.2396 (2.42)
GRO_j	.0467 (5.45)	.0840 (5.65)
DS_j	-.0226 (-2.58)	-.0114 (-0.86)
IMP_j	-.1025 (-1.89)	-.0466 (-1.07)
ADV_j	.0577 (0.56)	.1538 (0.75)
RD_j	-.5785 (-2.39)	-.2787 (-1.22)
CAP_j	.0353 (2.11)	-.0566 (-2.49)
CU_{ij}	.1880 (9.22)	.1972 (5.57)
CONSTANT	-.1812 (-7.66)	-.1756 (-4.22)
R^2/F	.0779 (17.51)	.0948 (12.15)
# OF OBS.	1874	1054

Notes: t statistics are in parentheses, except in R^2 column which contains F statistics testing for the significance of the linear model.