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THE EFFECT OF MARKET SHARES AND SHARE

DISTRIBUTION ON INDUSTRY PERFORMANCE

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A central proposition of industrial organization is that the extent of seller concentration in an industry is an important determinant of that industry's profitability. Although this thesis underlies much public policy and popular thinking, a great deal remains unknown about the exact relationship between industry structure and performance. The present study brings wholly new data to bear on this issue and permits examination of much more detailed structural correlates of performance than heretofore possible.

This research is predicated on the explicit recognition of two opposing forces within industries - the advantages of greater output control by leading firms, versus the difficulty of agreement among more numerous firms. At least potentially, output control confers the power to set and enforce above-competitive prices for the benefit of the industry. Much depends, however on <u>who</u> controls output, since the number of core firms influences the strength of collusive or cooperative agreements. Larger numbers weaken their sense of interdependence, produce more differences of opinion, and multiply the sheer number of understandings required. [15, pp. 183 - 186] Such factors reduce chances for success, but must be balanced by the need for control over sufficient industry output.

None of this helps identify what number of firms is "too large" or what amount of output control is "sufficient." Particular theories of oligopoly offer some insights, but no specific and consistent conclusions emerge. Thus the Cournot theory predicts that industry price varies inversely with the number of firms. Chamberlin claimed that industries were competitive until some critical level of output was controlled by leading firms, at which point a monopoly-type result ensued. Stigler focused on the problem of enforcing interfirm agreements and concluded that both fewness of firms and wide disparity in sizes (features summarized in the Herfindahl index) make successful cooperation more likely.

Empirical tests of the structure-performance relationship, which originated with Bain some twenty-five years ago, shed some additional light. [1] Bain hypothesized, and found, that high values of the eight-firm concentration ratio were systematically associated with above-average profit rates, and that the relationship was discontinuous (much as Chamberlin had argued) at a critical value of about 70 percent output control. An enormous number of subsequent studies - using different measures of performance, periods of time, explanatory variables, etc. - have confirmed this fundamental conclusion, with some modifications. [6, pp. 184 - 233] Many have failed to find the discontinuity that Bain's data revealed. [14, p. 90] Virtually all have produced better statistical fits using the four-firm concentration ratio rather than the eight-firm or more inclusive versions. [8] This suggests that the number of relevant firms in determining industry price and performance is quite small, a conclusion also implicit in a few studies focusing on other features of firm size distribution [10; 11; 17]. One study even detects a depressing effect on industry profitability from larger shares for the fifth through eighth firms in an industry, presumably the result of increased rivalry under such circumstances. [12]

Most studies have been forced to use simple concentration ratios as the relevant dimension of industry studies, largely due to the unavailability of more disaggregated data on individual firm shares. This has perhaps been the most serious obstacle to improved understanding of the structure-performance relationship. The use of the simple sum of the four or eight largest shares - the concentration ratio - obscures much of interest about firm size distribution, and may cause us to underestimate the

the importance of structure in general. Nothing in theory, for example, predicts that exactly four firms are crucial to industry performance. Nothing predicts that they are equally important as is implicit in their summation. Given their dependence on detailed data, these issues have been beyond the reach of previous research.

This study is not bound by these usual limitations. A novel data source provides estimates of individual firm shares by four-digit SIC industries. When linked to information from the 1972 Census of Manufactures, these data provide a unique opportunity to examine new and specific relationships between industry structure and performance. We shall demonstrate that the number of firms important in determining an industry's performance is smaller than previously realized, that their relative importance is a complex matter, and that industry coordination appears to be effective at relatively modest levels of output control. In the process, we also demonstrate that the conventional concentration ratio can be substantially improved upon, that the relationship is clearly discontinuous when the appropriate structural characteristics are used, and that industry structure is considerably more important to performance than other analyses reveal. But before describing these results in detail, we must begin with a sketch of our new data source.

II

Market share information is derived from data developed by Economic Information Systems, Inc., on 120,000 manufacturing plants employing twenty or more persons. 1/ Their data were designed for use by businesses in identifying competitors, suppliers, and customers, a fact reflected in the nature and organization of the original data set. The sources for this compilation includes the Census Bureau's County Business Patterns, Census of Manufactures data on industrial productivity, and a private mailing to 300,000 manufacturing establishments, all supplemented by a variety of public sources--annual reports, Dun and Bradstreet, trade association information, etc.

The creation of the EIS data set begins with County Business Patterns statistics on employment by SIC for each county. Employment is allocated to individual plants in the county identified primarily through the mailing list. Plants under twenty employees are excluded as having data too costly or unreliable to compile. EIS then uses Census of Manufactures data on value of shipments per employee for various employment size classes of plants in each four-digit industry to estimate shipments for each plant. The use of different productivity (shipments/employee) factors captures some scale effects and technology differences among plant size classes, but of course cannot account for individual plant-by-plant variations. Thus the data tend to underestimate the output of high productivity establishments, and overestimate that for low productivity plants. Additional error is introduced by assigning all plant employment and output to its primary SIC industry (though the existence of secondary activity is noted).

We will be using a modified form of this data set, one created by the Bureau of Economics of the Federal Trade Commission for its special needs. This version combines data on all plants of the same company operating in each four-digit SIC industry. From this we can obtain individual market share data by industry for all firms with at least one establishment of twenty or more employees.

The significance of the deficiencies of EIS data depends on the uses to which it is put. In our version where data are combined into firm aggregates, the possible inaccuracies associated with individual plant statistics tend to be less severe. Some corrobation of this can be derived by comparing 1972 Census concentration ratios with those ratios calculated by summing EIS market share data. For example the Census four-firm concentration ratio (CR4) has a mean of .4088 and a standard deviation of .2199, while its EIS counterpart averages .3983 with a standard deviation of .2190. Their simple correlation coefficient of .922 indicates that while they are not completely identical, they reflect essentially the same property of industry structure. At the eight, twenty, and fifty firm levels, their correspondence is, if anything, even closer. Regressions performed below lend further weight to this conclusion, and we are generally satisfied that the EIS data are quite adequate for our purposes.

This modified data set is linked to the 1972 Census of Manufactures according to four-digit SIC industry. Of the 451 "industries" comprising the Census, seventy denoted as "miscellaneous" or "not elsewhere classified" were deleted as not representing true industries. Other problems resulted from the fact that the corresponding EIS data used "old" SIC definitions, while Census data were organized on the basis of a major revision of SIC industries. Of the 381 remaining Census industries, 77 differed significantly between the data sets. Twenty-four could be accounted for by combining Census data so as to reconstruct eleven "old" industries, but the remaining 43 defied any such process. The final data base consists of 314 industries, still a very large number for data of this scope.

III

Since our present purpose is to explore the structural features of industries which are relevant to performance, we shall adopt an accepted methodology for such analysis and introduce selected alternatives to the conventional concentration ratio. In this section we review the basic model and perform some preliminary regressions as the context for the more detailed analysis to follow.

As a measure of industry performance, the price-cost margin has both sound theoretical roots and considerable practical advantages. The various threads of oligopoly theory seem more consistent in predicting that concentration raises price (relative to cost) than profits [6, p. 199]. In addition, margin data are available for all four-digit SIC industries, and is measured more accurately than profitability [3, p. 272]. In recent years a substantial literature has developed relating these margins to industry structure [2; 3; 6; 14; 16] and it is this metholology that we follow below.

Industry price-cost margin (PCM) is readily calculated from the Census of Manufactures [19] as industry value added minus payroll, divided by value of shipments. This yields a percentage margin of revenue over direct cost, which is regressed on a number of corrective and causal variables. Foremost among the latter, of course, are alternative structural characteristics of the industry. A brief description of the other factors and their rationale follows.

(1) Inter-industry differences in capital intensity would be associated with differences in PCM, since the latter subtracts out only current

or direct production costs. A capital-output ratio is therefore included as an independent variable. KO is calculated as the gross book value of assets from the Annual Survey of Manufactures, divided by value of shipments 2/

(2) Similarly a correction must be made to reflect the discrepancy between the national data compiled in the Census and the geographical extent of true economic markets. The most widely available and best performing variable continues to be Collins and Preston's geographical dispersion index, defined as the sum of absolute values of the differences between the percent of all manufacturing value added and a particular industry's value added for each of four Census regions of the country. 3/ Thus if production is widely dispersed, this variable (GE) would be small; markets are probably local or regional in scope, and price-cost margins larger, cet. par.

(3) Theory predicts industry performance will be positively associated with the extent of unanticipated growth experienced. Hence we define GR as the percentage change in industry shipments between 1967 and 1972 [19], and include it as an independent variable.

(4) Finally theory suggests that product differentiation, characteristic of consumer goods, may act as an entry barrier raising industry margins. Also since advertising expenditures have not been accounted for in the margin calculation, PCM in consumer goods industries (where such expenditures are concentrated) may be systematically overstated. For these reasons a dummy variable DUM equal to one (1) for consumer goods industries

and zero (0) for producer good industries is included in the regression. 4/

Regression analyses of the sort just described have tended to give substantial support to the concentration-performance relationship, and Equations (1a) and (1b) of Table I duplicate these regressions for 1972 Census data. In both the bivariate and multivariate formulation, the four-firm concentration ratio has a positive significant effect on price-cost margins, and all other variables are significant and bear the expected sign. In this respect these results conform to similar conclusions based on 1958, 1963, and 1967 data. But these results are considerably weaker than in other years. For example, analogous bivariate regressions in 1967 yielded a t-ratio over 7 and $\bar{R}^2$=.121, and multivariate results produced a t-ratio on CR4 over 5 and $\bar{R}^2$=.234. [14] In addition the magnitude of the coefficients on CR4 in both regressions on 1972 data are somewhat smaller.

All of this suggests a smaller and less decisive role for the four-firm concentration ratio in 1972 than in past years. Likely reasons are not hard to find. That year and the preceding one were years of considerable inflation, a period of time thought to obscure the effect of structure on performance as concentrated industries lag in response to price increases. [6, p. 200] In addition the Freeze-Phase system of price controls during that time were clearly tilted against concentrated industires and may have led to more restrained behavior on their part. In light of these considerations, the weaker structure-performance relationship found in 1972 is not very surprising.

Equations (2a) and (2b) display results of analogous regressions employing the four-firm concentration ratio derived from EIS market share data (labeled C4 to distinguish it from Census CR4). It is reassuring to find that C4 behaves much like its counterpart in both regressions--and indeed somewhat better. Since most of our subsequent analysis is based on EIS data, the equations using C4 provide a more consistent standard against which to judge our results than do Equations (1a) and (1b). Finally, we report a curiosity: The much praised and little-used Herfindahl index (defined as the sum of squared market shares in an industry) is computed from EIS data and substituted into the basic regressions. In both bivariate and multivariate formulations of Equations (3a) and (3b), respectively, H performs slightly better than CR4 but worse than C4. While the Herfindahl is implied by one theory of oligopoly [17] and is often claimed to be a superior index, present evidence provides no special support for that theory or belief.

IV

Previous discussion suggested that industry margins are increased when quite small numbers of firms dominate an industry. The abundance of data in the EIS compilation permits us to answer questions concerning the exact number, relative importance, and necessary size of the largest firms in determining industry performance. We have therefore selected for examination and testing the shares of the ten largest firms in each four-digit industry, denoted S1, S2,........S10. A priori beliefs outlined above suggest that this number is sufficiently inclusive to capture important structural influences. Table II provides information about mean, maximum, and minimum values for these share data, as well as the number of industries (N) where a firm of that rank exists at all. The EIS tabulation procedure, as noted before, tends to miss very small firms, and five of 314 industries have less than ten firms by their count.

Our procedure will be to introduce successive market share data into the price-cost margin regression to see if significant additional explanatory power is achieved. That is, we shall begin simply with S1 as the independent variable (plus the other non-structure factors described above) and add S2, then S3, and so forth. 5/ If these subsequent shares are statistically significant, we conclude that they are important structural influences on industry performance. Collinearity among successive shares, however, may preclude the converse proposition. Nevertheless, where coefficients fall <u>very</u> far short of conventional significance levels, we may have some confidence that such firm shares do not play important roles. And of course we are exploring an ordered set, since there is no rationale for including a given share without all larger shares present.

The regressions which result from this process are given in Table III. Part A focuses on structural elements alone, and Part B includes the several other variables predicted by theory. Equations (1a) and (1b) demonstrate that the share of the largest firm S1 is positively and significantly related to industry price-cost margin. In addition, all other variables are strongly significant and have the expected signs, as they do throughout. This regression would be of special interest if only the largest firm mattered to industry performance, i. e., if coordination was generally impossible even among two firms. Our next result demonstrates a rather different conclusion.

Equations (2a) and (2b) add S2 to the preceding regression and obtain a positive and clearly significant coefficient on the additional structural variable. In addition, $\bar{R}^2$ has risen to .089 in the simple regression (2a) to .163 in the complex version (2b), each well in excess of its counterpart in Equations (1) and well in excess of the fits reported using four-firm concentration ratios (see Table I). We tentatively conclude that a large second firm share contributes to industry price-cost margin, and does so in a manner not captured by C4.

A somewhat different effect is obtained from the next extension of this approach as reported in Equations (3a) and (3b). The third leading share appears to have a negative, or depressing, effect on industry margins, but its coefficient falls a bit short of conventional significance levels. The t-values on S3 are significant only at the .13 and .065 levels, although $\bar{R}^2$'s have risen in these regressions. While S3's correlation with S2 (.780) may account for its failure to achieve significance, we cannot draw any conclusions from its negative sign at this time. We shall return to this interesting, if ambiguous, result in the next section of this paper.

The inclusion of S4, as shown in Equations (4), yields clearer results. Its t-value is very small and there appears little doubt that the fourth largest share is truly insignificant. $\bar{R}^2$'s fall in its presence, and other estimated coefficients remain relatively unaffected. This formulation with the four largest shares is of special interest, however, since it constitutes a disaggregated version of the four-firm concentration ratio. By summing these shares, C4 implicitly assumes equal coefficients on S1 through S4. We can test this linear restriction directly by comparing error sum of squares in the separate regressions with C4 and with S1 through S4. [18, pp. 143 - 4] The resulting test statistic for the simple structural equations is $F(3, 309)=2.56$, and for the complex specification will all variables $F(3, 305)=3.04$. The latter clearly implies rejection of the linear restriction at the 5 percent level. Although the former is just short of significance ($F(3, 309)=2.60$ at

5 percent), the complex specification is theoretically preferable and in any event this test is overly strong in the presence of statistically insignificant coefficients. 6/ We therefore conclude that the linearity assumption implicit in the four-firm concentration ratio is invalid, and much useful information is secured by disaggregating into share form.

The remaining market shares, S5 through S10, can be discussed together, since their behavior and impact are similar. The results of the successive inclusion of S5 and S6 (in Table III) can best be described as weak, erratic, and statistically insignificant. $\bar{R}^2$'s fall in their presence, and an F-test on the entire set of shares S4, S5 and S6 confirm that they jointly contribute insignificant explanatory power to the regression. 7/ Similar tests were performed on the variables S7, S8, S9, and S10, with qualitatively identical results. We therefore conclude that none of the remaining market shares, either individual or collectively, adds sufficient explanatory power to justify its inclusion in these performance regressions.

Let us now return to the "proven" regressions for a closer examination of the economic significance of the statistical results. One rather striking result is the important role played by the second leading firm. It has a large, positive, and highly significant impact on industry price-cost margin, suggesting that quite apart from the size of S1, the second firm can enhance and solidify the domination of an industry and its ability to raise price-cost margins above competitive levels. Larger shares for subsequent firms appear incapable of improving on this result, and there is even some suggestion that a larger third firm hinders it. These results imply that the coordination difficulties associated with larger firm numbers set in very early.

A final point concerns the relative importance of S1 and S2. In Equations (2) and (3) the coefficient on the second leading share is considerably larger than on S1. Examination of either the corresponding beta coefficients [5, p. 197 - 8] or the simple multiplication of the estimated coefficients with mean values of S1 and S2 (since they are similarly scaled) implies that S2 is approximately twice as "important" an explanator of industry price-cost margin. As previously noted, these differences are statistically significant. In the next section we shall cast additional light on this result, and clarify the role of S3 as well.

V

Having established how few in number are the import t firms, we turn to the second major question - the form of the relationship between structure and performance. The preceding results are based on continuous effects, but some theories of oligopoly (e. g. Chamberlin) and some previous studies, including Bain's suggest a "critical value" at which collusion or cooperation become effective. We test for such a discontinuity with a lengthy process of fitting the data to the relevant alternative structural representations. The results are simply too extensive to report here, and except for a small number of conclusive regressions, we shall confine ourselves to a verbal description of the general procedure and results.

Zero-one dummy variables are defined for each whole percent value of S1 between .12 and .32 inclusive, S2 between .09 and .22, S3 between .05 and .20, and S4 between .02 and .16. These ranges encompass the mean values of the respective market shares, generally extend nearly to the maximum value, and capture the region within which performance effects peak. Our strategy is to examine successive shares (i. e., first S1, then S2, etc.) to see whether a continuous or dichotomous variable provides the better fit. 8/ If the latter, the single best value in the range is used to define the zero-one dummy for that share and is denoted DS1, DS2, etc. Then various slope dummies and continuous variables are tested. Finally with multiple dummies, a "space" in the matrix of possible critical values is re-examined to ascertain that the best overall fit has not been overlooked by this sequential procedure.

The results of this process appear in Table IV. The search procedure for the leading firm share produced the best overall fit and largest t-ratio at a critical value of S1=.26. These test criteria fell off rather sharply to either side of that value, in a pattern which was regular except for a slight local maximum at S1=.21. DS1 is therefore defined as unity when S1$\geqslant$.26, and zero otherwise, and Equations (1) reveal this relationship has considerably greater explanatory power than the continuous form of S1 reported in Table III. Industry margins are 23 percent when leading firm share is small, but for the seventy-one industries where S1$\geqslant$.26, margins rise to 29 percent. This difference has a high degree of statistical significance.

Furthermore, in the presence of this intercept dummy, neither a slope dummy nor leading share itself is significant. This implies that there is no slope to the relationship between S1 and PCM but only a simple breakpoint at the critical value .26. This conclusion is corroborated by separate regressions on subsets of industries above and below that value. In neither case was S1 itself statistically significant, though the values of the intercepts and PCM clearly differed between the two. 9/

Next, using DS1, the S2 range was similarly searched. T-ratios and $\bar{R}^2$'s were maximized at a critical value of S2=.15, and in Equations (2)

DS2 is defined as unity for S2$\geq$.15 and zero otherwise. Again, the results show a very regular pattern with respect to S2, and in addition, a large space (a 13x15 matrix around S1=.26, S2=.15) was re-examined to be certain that this point was the true overall maximum.

The economic significance of these results in Equations (2) are straightforward. If S1 is at least .26 <u>or</u> S2 at least .15, industry price-cost margins is increased from 23 percent to somewhat over 27 percent. The magnitude of the effects of S1 and S2 in this formulation are statistically indistinguishable, the test statistic for a significant difference (t=.127) being well below conventional levels. This result seems more plausible than our previous finding that in continuous form the second largest share S2 is more important than the first. Note of course that if S2$\geq$.15, S1 must be at least as large and hence they jointly comprise .30 or more of the industry. If both S1$\geq$.26 and S2$\geq$.15, as occurs in 37 cases, they total at least .41 of the industry and margins rise to nearly 32 percent. The explanatory power of this dummy formulation is considerably greater than the continuous form in Table III, and again suggests that underlying relationships are dichotomous.

Given DS1 and DS2, the S3 range produced a strong, negative, and signficant value of the dummy at .16. Equations (3) report the results of including DS3, defined as unity for S3$\geq$.16 and zero otherwise. A rather large region in the three-space of S1-S2-S3 dummy values was re-examined <u>10/</u> to insure that these values yielded the overall maximum. The t-value on DS3 and the jump in $\bar{R}^2$ suggest an importance of the third leading share which was largely obscured in the earlier continuous formulation (see Table III).

Equations (3a) and (3b) indicate that whenever the third market share becomes at least .16, industry margins fall by 13 percent - 15 percent. An S3$\geq$.16 implies a total share for the top three of at least .48, of course, and this result emphasized the difference it makes as to how that total is distributed among the three. Greater equality appears to increase industry rivalry and drive margins down by a considerable amount. It must be emphasized that this effect is based on a small number of observations, however, for only five industries have DS3=1, i.e. S3$\geq$.16. 11/ Additional tests for possible effects of S3 (e. g. on the subset of industries where S3<.16, using slope dummies and S3 itself) yielded no statistically significant results. The only effect of this leading share appears to be a negative one in these extreme cases.

Similar efforts with respect to S4 produced no significant relationship in the dichotomous formulation, 12/ and we have no reason to alter our previous conclusion that shares past the third have no systematic effects on industry price-cost margins. 13/ The effects of the first three, however, are quite considerable and substantially greater in dichotomous than in continuous formulations. The third leading share appears to have a role limited to the few cases where it becomes very large, while S1 and S2 have separate and more frequently encountered discontinuities with respect to industry price-cost margins. These complex size and distritution effects probably explain the generally weak and erratic results of searches for a discontinuity in the four-firm concentration ratio.

VI

The simplicity and intuitive appeal of the conventional concentration ratio raise a question of the possibility of combining relevant firm shares into some summary statistic. For the present ignoring the limited role of S3 and smaller shares, we note that S1 and S2, at least in dummy form, are of roughly equal importance. This suggests a very simple summary measure - the sum of the two largest shares, or the "two-firm concentration ratio." Here we briefly report the results of statistical tests of this concentration ratio compared to the share formulation.

As shown in Equation (1) of Table V, the two-firm ratio C2 produces a t-value of 5.49 and 4.78 in bivariate and multivariate regressions, leaving no doubt about its relationship to industry price-cost margins. The $\bar{R}^2$'s are .085 and .160, respectively. Comparison with Equations (2) in Table III reveal that the two-firm concentration ratio is almost as good an explanator as its individual share components. This perhaps suggests some usefulness for C2, but would not seem to justify dispensing with the share formulation. Note the somewhat clearer advantage of C2 over the four-firm concentration ratio (Table I), as would be expected from our understanding of the roles of S3 and S4.

In addition, the form of the functional relationship between C2 and margins was explored. Previous share results in fact suggest the possibility of a dual break in the two-firm concentration ratio, one mirroring the critical value on the leading share S1, and the other reflecting the similar property of S2. 14/ An extensive data fitting process examined single and dual dummies, conbinations of dual dummies, intercept dummies, and continuous values for C2. The results showed a rather clear break at C2=.35, and in Equations (2) of Table V, D1C2=1 when C2$\geq$.35. Industry margins are about 23 percent below that point and rise by 5.8 percentage points for the 91 industries above. The explanatory power of this dichotomous formulation rises to $\bar{R}^2$=.183 from .160 in the multivariate regression (but still below analogous share versions). A second critical value was sought, and the best fit was produced by defining D2C2=1 when C2≥.49. Equations (3) show that its coefficient falls somewhat short of conventional significance levels, and we are left without clear and convincing evidence of the existence of the second discontinuity. Little doubt, however, surrounds the first critical value at C2=.35, although none of these results constitutes an argument for substituting the two-firm concentration ratio for the more informative market share data.

VII

Almost all previous literature relating industry structure to performance has focused on the four-firm concentration ratio. For reasons already suggested, such an arbitrary, summary statistic is incapable of establishing exactly what features of industries are important, how important they are *in toto*, and what their relative importance is. The analysis in this paper demonstrates that the four-firm concentration ratio contains one irrelevant firm share (S4) and another with the wrong sign (S3). Large market shares for the two leading firms appear to be most decisive for industry price-cost margins, with a depressing effect from a sufficiently large third share. Moreover, these effects are discontinuous, with rather clear breaks at S1=.26, S2=.15, and S3=.16. 15/ The figures imply that industry margins are unaffected until output control by one or two firms reaches 25 - 35 percent, that past some point further domination by them has no affect on performance, and that three-firm coordination problems are so severe as to make the third largest firm more likely a rival.

As a crude and heuristic measure of the worth of this whole approach, we note that the original four-firm concentration regressions had an $\bar{R}^2$=.076 for the bivariate form and $\bar{R}^2$=.151 for the multivariate form (see Table I). Simple share formulations, reported in Table II, raised these to .093 and .170 respectively, and the intercept-dummy version of the share regressions (Table IV) further improved the fits to $\bar{R}^2$=.173 and $\bar{R}^2$=.230. While such comparisons do not constitute statistical tests, it is significant that a close examination of detailed structural features has raised $\bar{R}^2$'s by 8 to 10 percentage points. This constitutes a doubling of the explanatory power of structural features alone, and implies that industry structure is a far more important - and complex - determinant of performance than previously recognized.

Table I

	Structural Variable	KO	GE	GR	DUM	CONST.	$\bar{R}^2$
1a	.1064 CR4 (4.91)					.2290	.069
1b	.0919 CR4 (4.14)	.0794 (4.25)	-.0356 (2.59)	.0488 (2.54)	.0370 (3.46)	.2039	.145
2a	.1126 C4 (5.19)					.2277	.076
2b	.0972 C4 (4.40)	.0776 (4.16)	-.0338 (2.49)	.0469 (2.46)	.0392 (3.70)	.2021	.151
3a	.3117 H (5.08)					.2481	.073
3b	.2694 H (4.36)	.0802 (4.34)	-.0339 (2.50)	.0460 (2.40)	.0392 (3.70)	.2189	.150

Table II

Variable	Mean	Min.	Max.	N
S1	.175	.011	.687	314
S2	.100	.008	.334	314
S3	.070	.007	.214	314
S4	.053	.006	.169	314
S5	.042	.005	.121	314
S6	.034	.003	.095	314
S7	.028	.001	.060	314
S8	.024	.000	.054	312
S9	.020	.000	.046	311
S10	.018	.000	.043	309

Table III

		S1	S2	S3	S4	S5	S6	KO	GE	GR	DUM	CONST	$\bar{R}^2$
A	1a	.1911										.2391	.067
		(4.86)											
	2a	.0791	.3072									.2278	.089
		(1.45)	(2.92)										
	3a	.0882	.4378	-.2973								.2339	.093
		(1.61)	(3.23)	(1.52)									
	4a	.0872	.4364	-.2552	-.0646							.2347	.090
		(1.58)	(3.21)	(.92)	(.22)								
	5a	.0872	-.4384	-.2495	-.1623	.1490						.2330	.088
		(1.58)	(3.22)	(.90)	(.38)	(.33)							
	6a	.0927	.4325	-.2501	-.1571	-.1059	.3857					.2299	.086
		(1.66)	(3.16)	(.90)	(.37)	(.17)	(.62)						
B	1b	.1643						.0822	-.0330	.0446	.0407	.2098	.146
		(4.16)						(4.45)	(2.42)	(2.32)	(3.83)		
	2b	.0656	.2794					.0773	-.0348	.0464	.0382	.2023	.163
		(1.23)	(2.74)					(4.20)	(2.58)	(2.44)	(3.62)		
	3b	.0750	.4313	-.3520				.0817	-.0352	.0437	.0384	.2091	.170
		(1.41)	(3.31)	(1.86)				(4.43)	(2.62)	(2.30)	(3.65)		
	4b	.0729	.4287	-.2788	-.1134			.0822	-.0348	.0439	.0384	.2102	.168
		(1.36)	(3.28)	(1.05)	(.39)			(4.44)	(2.59)	(2.31)	(3.65)		
	5b	.0734	.4314	-.2721	-.2338	.1857		.0820	-.0354	.0436	.0386	.2084	.166
		(1.37)	(3.29)	(1.02)	(.58)	(.43)		(4.41)	(2.61)	(2.28)	(3.66)		
	6b	.0784	.4254	-.2709	-.2288	-.0444	.3485	.0812	-.0352	.0444	.0387	.2054	.164
		(1.44)	(3.23)	(1.01)	(.57)	(.08)	(.59)	(4.36)	(2.59)	(2.32)	(3.67)		

Table IV

	DS1	DS2	DS3	KO	GE	GR	DUM	CONST	$\bar{R}^2$
1a	.0674 (6.03)							.2573	.101
1b	.0600 (5.36)			.0788 (4.35)	-.0359 (2.68)	.0416 (2.20)	.0381 (3.64)	.2294	.175
2a	.0482 (3.93)	.0455 (3.51)						.2528	.133
2b	.0434 (3.58)	.0415 (3.30)		.0725 (4.04)	-.0362 (2.75)	.0445 (2.39)	.0353 (3.42)	.2280	.200
3a	.0481 (4.01)	.0578 (4.43)	-.1490 (4.02)					.2528	.173
3b	.0435 (3.66)	.0520 (4.10)	-.1309 (3.60)	.0719 (4.09)	-.0348 (2.69)	.0350 (1.89)	.0319 (3.13)	.2305	.230

TABLE V

	Structural Variable	Structural Variable	KO	GE	GR	DUM	CONST	$\bar{R}^2$
1a	.1515 C2 (5.49)						.2308	.085
1b	.1532 C2 (4.78)		.0780 (4.24)	-.0346 (2.56)	.0448 (2.36)	.0394 (3.74)	.2047	.160
2a	.0652 D1C2 (6.48)						.2526	.116
2b	.0579 D1C2 (5.66)		.0714 (3.90)	-.0341 (2.57)	.0456 (2.43)	.0374 (3.59)	.2264	.183
3a	.0520 D1C2 (4.08)	.0282 D2C2 (1.69)					.2526	.121
3b	.0461 D1C2 (3.65)	.0257 D2C2 (1.59)	.0705 (3.86)	-.0350 (2.64)	.0456 (2.44)	-.0360 (3.46)	.2277	.187

FOOTNOTES

1/ In 1972, plants with twenty or more employees accounted for 35.2 percent of all manufacturing establishments by number but 94.4 percent by value added [19, MC72 (1), p. 5].

2/ One problem with this measure is the presence of industry price itself in the value of shipments figure, but no satisfactory alternatives appear to exist. Starting in 1972, assets data are reproduced in the Census of Manufactures [19, MC72 (2)].

3/ See [2;3], and for unsuccessful effort to truncate it, see [14]. Data are from [19, MC72 (2)].

4/ Data are an update by the author of [4].

5/ The literature dealing with the analogous problem of marginal concentration ratios appears to have concluded that shares or share groups cannot be included directly because each is constrained to be less than its predecessor or the remainder of the industry, whichever is smaller [12; 7; 2; Weiss in 6]. That, however, does not constitute a sufficient reason for transforming share data if theory predicts that such shares or groups of shares are indeed the appropriate causal varibles. Furthermore, the transformation most often used [8; Weiss in 6] is in reality a very specific interaction term between such share groups which lacks any apparent justification. I would like to thank Darius Gaskins and Michael Lynch for pointing this out.

6/ This is because the inclusion of insignificant variables like S4 scarcely raises the regression sum of squares while it constitutes an additional linear restriction, i. e., it costs a degree of freedom in the test statistic. Proliferation of such variables lowers the resulting F-statistic even if preceding variables were pairwise statistically distinct. For example, t-tests on the differences between the coefficients of S1 and S2 in Equations (4) or Equations (3) all give values in excess of 2.00, leading to the conclusion that they are not identical. See [9, p. 371 - 2].

7/ For this test, see [9, pp. 370 - 1]. The remaining regressions are not reported here due to space limitations and lack of comparability. The latter occures since industries must be omitted from the sample when they lack firms of low enough rank for the regressions. For example, the industry with only seven firms cannot be included in the equation using S10, S9, S8, or even S7, since its seventh share is redundant in the presence of the side condition that all shares sum to unity. In any event, none of these remaining regressions can do more than confirm the irrelevance of lower-ranked firms, since S4 has already been excluded.

8/ Tests for this procedure are described in Kmenta [9,pp. 409ff.]. Rhoades and Cleaver [14] perform some analogous tests, but do not use their results to clarify functional forms.

9/ This result is inconsistent with simple dominant firm behavior where margins would rise with the share of the leading firm, cet. par.

10/ The 8x8x8 space consisted of all combinations of the following: S1=.20, .22, .24, .26, .28, .30, .32, .34; S2=.07, .09, .11, .13, .15, .17, .19, .21; S3=.06, .08, .10, .12, .14, .16, .18, .20. The results show great regularity in the pattern of explained sum of squares (or $\bar{R}^2$, or F), and leave little doubt as to the validity of the reported result.

11/ The five industries are: SIC 2296, Tire Cord and Fabric; 2823, Cellulosic Manmade Fibers; 3333, Primary Zinc; 3482, Small Arms Ammunition; and 3672, Cathode Ray Picture Tubes.

12/ It is interesting that dummies for S4 equaling .15 and .16 were large, negative, and had t-values as high as 1.22. This again reflects some tendency for very large lower-rank shares to drive down industry margins, but is based on only a small number of observations.

13/ This of course does not imply that such firms never play a role in industry conduct and performance. The limitations of structural analysis and of large cross-sectional studies, for particular industries, are obvious.

14/ In addition, some outlying cases may occur when S3 is very large, according to earlier results. The two firm concentration ratio, however, has no way of coping with that possibility.

15/ Particular conclusions about share values apply to relevant markets, and hence national Census or EIS figures need careful interpretation.

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