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"Sales-at-Risk": A Test of the Mutual Forbearance Theory of Conglomerate Behavior

I. Introduction

In seeking to understand the implications of the large amount of diversification and conglomeration that has occurred in the United States since the mid-1960s, some economists have revived the "mutual forbearance" hypothesis first presented by Edwards (1955). Several papers have attempted to formalize or test this hypothesis, which states that multimarket contacts (MMCs) among firms have the potential for facilitating collusion in one or more of the markets where these contacts occur.[1] Using 1976 data from the Federal Trade Commission's Line of Business study, an earlier paper (Feinberg 1982) developed a framework for evaluating MMCs and in-

This paper tests the mutual forbearance theory of conglomerate behavior at both company and industry levels, using 1976 data from the Federal Trade Commission's Line of Business program. This theory states that companies meeting rivals in more than one market will be able to facilitate collusion in one or all of those markets. At the company level the evidence supports the theory, showing sales-at-risk, a measure of the importance of multimarket contacts, to increase price-cost margins in the moderate range of concentration where collusion is feasible but difficult to achieve without mutual forbearance. The industry-level results are weaker, casting some doubt on the hypothesis.

* Associate professor of economics, Pennsylvania State University. This paper was begun while I was a consultant to the Line of Business program at the Federal Trade Commission. The Manager of the Line of Business program has certified that he has reviewed and approved the disclosure avoidance procedures used by the staff of the Line of Business program to insure that the data included in this paper do not identify individual company line-of-business data. Views expressed here are my own and not necessarily those of the Federal Trade Commission. I would like to thank William Long, George Pascoe, David Ravenscraft, Melvin Reder, and an anonymous referee for their help on this project.

1. These studies often refer to terms other than mutual forbearance (e.g., "spheres of influence," "extended interdependence"). They include Adams (1974), Reynolds (1976), Heggestad and Rhoades (1978), Areeda and Turner (1979), Strickland (1980), Feinberg (1982, 1984), Scott (1982), and Feinberg and Sherman (1985).

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vestigated their importance in U.S. manufacturing industries. In this paper I go further and examine the effect of "sales-at-risk"—a measure of the importance of MMCs—on price/cost margins. This is done by two separate statistical analyses, one at the company level, the other at the industry level.

The mutual forbearance theory may be viewed as an extension of traditional oligopoly theory, which stresses the possibility of cross-market conjectural variations. One firm meeting another in more than one market will anticipate (or conjecture) a potential reaction by the other firm, in all of the markets in which they meet, to an action undertaken in any one of them. Feinberg (1982) shows that, given cross-market conjectural variations, the more important MMCs are to a company, the less competitive that company's output and price performance will be.[2]

Although a recent experimental study (Feinberg and Sherman 1985) provides some support for this hypothesis, previous tests of the mutual forbearance hypothesis that used actual business data have produced mixed results. Heggestad and Rhoades (1978) studied 187 major banking markets and found that "multimarket meetings between dominant banks do adversely affect the degree of rivalry within markets" (p. 532). However, their measure of competitive performance—instability in leading-firm shares—is peculiar; more important, it is unclear how their results, which focus on geographic market extension in a regulated, financial sector, would generalize to broader types of diversification and to nonregulated and manufacturing sectors of the economy. Strickland (1980) examined 408 four-digit SIC manufacturing industries for 1963 and found an unexpected *inverse* relationship between measures of MMC and average price/cost margins. However, Strickland's study has three problems. First, 1963 seems too early in the conglomerate wave to pick up significant mutual forbearance effects (if they exist); second, the listing of markets in which firms operate, and their shares of those markets, had to be estimated from plant employment data; finally, the industry-level measures of MMC are based solely on the activities of 195 large firms, with likely severe understatement of multimarket links among U.S. manufacturing firms.

It is difficult to evaluate either multimarket operation (diversification) or MMC using publicly available data. Companies are often reluctant to reveal all of their market affiliations and still more secretive about their shares of these markets. However, the Federal Trade Commission's Line of Business (LB) program has compiled data for 1976 on the domestic operations of 466 U.S. manufacturing companies (including the 250 largest) within 273 industry categories;[3] some of these com-

2. For a detailed theoretical discussion, see Feinberg (1982: 5–10; 1984).
3. These categories correspond to three- to four-digit SIC classifications.

panies operate in only one industry, some have activities in more than 40—the average company has eight LBs. These companies accounted for about 50% of U.S. manufacturing sales in 1976. The study described in this paper is based on the FTC LB data.

In Feinberg (1982), I constructed a measure of MMC, called sales-at-risk, from the FTC LB data. I argued that the individual LB was the appropriate level for evaluating the importance of MMCs, that the measure used should capture both the number of markets in which contact occurs with other companies and the number of multimarket rivals, and, finally, that sales-at-risk (SAR) was the theoretically and intuitively best measure of the *importance* of multiple market links among companies.

The SAR measure weights MMCs by the sales that are at stake in the markets in which MMCs occur. For a particular LB, say company j's operations in industry i,

$$\mathrm{SAR}_{ij} = \sum_{k \neq i} (M_{ki} - 1) S_{kj}$$

where M_{ki} = the number of companies operating in both industry k and industry i, and S_{kj} = company j's sales in industry k. SAR does not distinguish between MMCs due to conglomerate diversification and those due to vertical integration, but this is no defect; both types of contact should provide opportunities for facilitating collusion. Accordingly, in the empirical studies described below I employ SAR as the measure of potential mutual forbearance behavior.[4]

With few exceptions, previous studies based on the FTC LB data have used the individual LB as the unit of analysis (e.g., Weiss and Pascoe 1981; Ravenscraft 1983). This choice allows for a tremendous increase in degrees of freedom in statistical tests; it also permits us to include variables measured simultaneously at the LB, industry, and company levels that may help disentangle efficiency and collusive effects of certain structural variables.[5] However, such an analysis implicitly assumes an independence of observations (and, by implication,

4. Scott (1982) has employed these data to examine MMC from a somewhat different perspective from that used here. He finds that a significant amount of such contact is "purposive," in that it is more than would be expected if diversification occurred randomly. Of course, such purposive MMCs could reflect a search for either efficiency or market power, but Scott finds that when combined with high industry concentration, high MMC implies larger company profit rates even after controlling for market share. As we would expect market share to capture efficiency effects on profits, Scott's results suggest a collusive, or mutual forbearance, link between MMC and profit rates. However, it should be noted that Scott's measure of MMC (1) can be calculated only at the industry level, not at the LB or company level; (2) is based only on the MMCs between two sampled companies in each industry, and therefore cannot differentiate between situations in which two firms meet in several markets and (say) 10 firms meet in those same markets; and (3) weights all MMCs equally.

5. For a discussion of the latter point, see Ravenscraft (1983).

of decision making) across LBs within a company. Since the mutual forbearance theory requires that there be a company-level decision-making process coordinated across LBs, a more aggregated company-level analysis is appropriate here. SAR is aggregated over all LBs (included in the data file) for a company, expressed as a multiple of that company's domestic unregulated sales (plus transfers) and used to explain an average company-wide price/cost margin (over all included LBs).

Although there have been several company-level structure/performance studies using disaggregated data other than the FTC LB data (e.g., Dalton and Penn 1971, 1976; Imel and Helmberger 1971; Gale 1972; Shepherd 1972), none has tested the mutual forbearance hypothesis, as is done in the analysis reported in Section II. Section III reports an analogous study at the industry level. The need for an industry-level study is twofold: (i) to the extent that mutual forbearance occurs, its effects should be reflected in cross-industry differences in behavior; (ii) such a study is needed to compare the results to those of other structure/performance studies, most of which have been conducted at the industry level. For this purpose SAR is aggregated over all company LBs in an industry and normalized by industry sales. Section IV summarizes the key results of the paper.

II. A Company Study of Mutual Forbearance

As noted above, the FTC LB data for 1976 cover 466 companies. However, the 14 nonmanufacturing categories and 16 of the 259 manufacturing industry categories were deleted from the data file after a determination that they represented too broad a product definition.[6] I further deleted all companies that produced in fewer than two of the included industries or had less than 50% of their domestic unregulated sales in the included industries. Failing such deletions, these companies were likely to have SAR seriously understated in my calculations. The 391 companies that remain have 84% of their domestic unregulated sales in the included industries and represent 89% of all manufacturing sales covered in the 1976 LB data (about 45% of all U.S. manufacturing sales).

The performance variable employed here is a company's weighted-average price/cost margin (PCM) over all its domestic unregulated LBs, using sales plus transfers as weights.[7] PCM is defined as operating income divided by sales plus transfers. Operating income equals sales minus the sum of materials, payroll, advertising, other selling expenses, and general and administrative expenses.

The following are included as explanatory variables:

6. See Feinberg (1982) for details on criteria for exclusion.

7. It should be noted that qualitatively identical results were obtained in regressions using a profit rate on *assets* as the dependent variable.

1. SHAREA, sales-weighted average market share. From previous studies I expect a positive coefficient on this variable, regardless of whether the "cause" is greater market power, scale economies, or both.

2. SALESA, average sales per market. I expect a positive sign on this variable, which I attribute to scale-economy advantages of larger size within each market.[8]

3. CR4A, sales-weighted average four-firm seller-concentration ratio. A positive sign on the coefficient of this variable would be due to enhanced opportunities for collusion in more concentrated markets.[9]

4. DIV, diversification as measured by the distribution of a company's sales over its LBs. This measure, described by Berry (1975), equals $1 - \Sigma_{i=1}^{m} s_i^2$, where a company operates in m markets and has a share of its total sales equal to s_i in the ith market. To the extent that economies of multimarket operation exist, this variable should have a positive estimated coefficient. In the absence of a separate measure, DIV may also capture efficiency effects of vertical integration.

5. CAPINT, assets divided by sales, is included primarily to capture "normal" returns to capital not deducted from PCM, with a positive coefficient anticipated. However, large values of CAPINT may also be associated with excess capacity or the problems of colluding where fixed costs are high. Such associations would make for a negative coefficient but, on balance, I believe that these latter forces will be outweighed.

6. ADS, advertising as a percentage of sales, is included both to control for returns to "goodwill" and to reflect any price effect of product differentiation. On both counts a positive sign is predicted.

7. SAR, sales-at-risk per dollar of company sales, measures the importance of multimarket contacts to the company.[10] A positive sign is expected, reflecting more mutual forbearance behavior, especially at higher levels of CR4A (which allow for more strategic behavior on the part of the firm). Interaction terms with CR4A will be included.[11]

8. When "total domestic unregulated sales" was included in regression equations in place of this variable the results were virtually unchanged.

9. While there are numerous other industry-level variables that could be averaged in this way, my primary concern here is with company characteristics. Regression runs (available from the author on request) including weighted-average industry sales growth and consumer sales shares produced results, for the variables of primary interest here, similar to those reported below.

10. The App. to this paper gives a detailed example of how SAR and related variables are calculated.

11. Originally interactions of SAR with both SHAREA and CR4A were included. However, the high zero-order correlation between SHAREA and CR4A (.52) led to finding both interaction terms insignificantly different from zero; as will be seen below, the interactions with CR4A were found to be significant when only that interaction was included, and the estimated standard error was reduced as well. As an alternative, SARX, measuring SAR only where CR4A exceeds 30, will be employed in some regression equations. Using either method of interacting SAR and CR4A improves the regression fit compared to results (not reported here) including SAR in isolation.

TABLE 1 Descriptive Company Statistics

Variable	Mean	Standard deviation
PCM (%)	8.6	4.6
SHAREA (%)	7.6	7.8
SALESA ($ million)	175.1	294.5
CR4A (%)	43.0	13.5
DIV	.67	.21
CAPINT (%)	69.0	21.2
ADS (%)	1.5	2.3
SAR	18.3	17.5
SARX	12.0	13.0
SARIA	14.7	14.8

	Frequency Distribution of SAR							
Cell boundaries	0–10	10–20	20–30	30–40	40–50	50–60	60–70	70–100
Frequency	167	88	60	32	18	10	7	9
Relative frequency	.43	.23	.15	.08	.05	.03	.02	.02

NOTE.—$N = 391$, but $N = 389$ for SARIA (see n. 12).

8. SARIA, sales-weighted average *industry* sales-at-risk (including only SAR from industries with CR4 > 30), will be included in some regressions to try to distinguish between company and industry effects of MMCs on company performance. It might be argued that a large SAR reflected management efficiency in diversifying in a particular direction (the same type of diversification adopted by rivals), while SARIA was more likely to pick up purely collusive effects of MMC. A positive sign is anticipated.[12]

Descriptive statistics are presented in table 1, a correlation matrix in table 2, and regression results in table 3. The first regression equation uses the truncated sales-at-risk measure, SARX, to capture any interaction with concentration. While SARX has the expected positive effect on profit margins, this effect is very small (an elasticity at mean values of .03) and not significant at conventional levels. Of the other variables, average market share (SHAREA), capital intensity (CAPINT), and advertising intensity (ADS) all have the hypothesized positive impact on PCM and are significantly different from zero. However, company diversification and average concentration show no significant effect, while average sales per market (SALESA) has an unexpected negative and statistically significant (though small) effect on PCM.

In equation (2) I replace SARX with two interaction terms, SAR*CR4A and SAR* $(CR4A)^2$, which are included along with SAR;

12. All regression equations are estimated on 391 observations except where SARIA is included; in order to link this variable to the company file, two observations had to be deleted and 389 remain.

TABLE 2 Company Correlation Matrix

	SARX	SAR	ADS	CAPINT	DIV	CR4A	SALESA	SHAREA
PCM	.05	.05	.18	.30	−.04	.17	−.01	.25
SHAREA	−.06	−.14	.13	.05	−.33	.52	.37	
SALESA	.23	.23	−.09	−.03	−.10	.28		
CR4A	.18	−.03	.08	.24	−.08			
DIV	.39	.40	.04	.03				
CAPINT	.11	.08	−.03					
ADS	−.02	−.08						
SAR	.90							

NOTE.—N = 391.

these terms permit mutual forbearance to have an impact at moderate levels of concentration while being ineffective (or unnecessary) at either very low or very high levels of concentration. The fit of (2) is better than that of (1) (i.e., reduced standard error of estimate) while all other coefficient estimates are similar to those of equation (1).[13] However, in (2) the total effect of SAR is significant (i.e., $F = 5.05$, in testing the simultaneous effect of all three variables involving SAR) as compared with the insignificance of SARX in (1).[14] The total effect of SAR is positive for average four-firm concentration ratios between 15 and 51, with the largest positive impact (an elasticity of .11, at the mean values of SAR and PCM) at CR4A = 33.

At this point, I digress briefly to interpret further the relationship between SAR and PCM. It was argued in Feinberg (1982), and briefly above, that "pure" economies of multimarket operation should be reflected by a measure of diversification such as DIV, while strategic advantages of multimarket contact among firms predicted by the mutual forbearance theory would be associated with SAR. However, it has been argued that SAR reflects "purposive" diversification and may be due either to a search for economies or to collusive motives.[15] To counter this argument, I have constructed a variable, SARIA, which is a weighted average of the industry sales-at-risk measure (truncated to zero where CR4 < 30), averaged over all of a company's LBs included in my data file. To the extent that SARIA affects company PCM, it must be through collusive effects.[16]

13. Including the quadratic interaction term also improves the regression fit, as compared with results (not reported here) interacting SAR with CR4A alone.

14. As an example of feasible movements in SAR, in the six mergers among FTC LB sample companies during 1974–76, the average SAR of acquiring companies increased by 34%, from 25.8 to 34.6.

15. Although he uses a different measure, Scott (1982) makes essentially this argument.

16. I also take account here of the fact that foreign and regulated sales of the companies analyzed are not included in the data; while on average these (omitted sales) represent only 14% of total company sales, there are some companies in the sample with

TABLE 3 Company Regression Results

	1	2	3	4
Constant	3.37	2.34	3.95	2.87
	(2.82)	(1.77)	(3.23)	(2.11)
SHAREA	.16	.18	.20	.22
	(4.60)	(5.12)	(5.23)	(5.65)
SALESA	−.0017	−.0017	−.0012	−.0011
	(2.00)	(1.94)	(1.31)	(1.19)
CR4A	−.012	.026	−.038	−.001
	(.61)	(1.04)	(1.86)	(.03)
DIV	−.52	−1.06	−.71	−1.17
	(.43)	(.87)	(.57)	(.94)
CAPINT	.064	.057	.061	.057
	(6.10)	(5.46)	(5.65)	(5.23)
ADS	.31	.28	.33	.30
	(3.19)	(2.97)	(3.23)	(3.01)
SARX	.022	...	−.011	...
	(1.20)		(.51)	
SAR	...	−.122	...	−.091
		(1.07)		(.76)
SARCR4A	...	.0106	...	.0083
		(2.04)		(1.51)
SAR(CR4A)^2	...	−.00016	...	−.00014
		(2.62)		(2.10)
SARIA	...	...	.062	.051
			(3.32)	(2.75)
R^2	.19	.21	.22	.24
Standard error	17.6	17.0	17.0	16.6
F	12.4	11.5	12.4	11.1
N	391	391	369	369

NOTE.—Dependent variable = PCM; t-statistics in parentheses below estimated coefficients.

Equation (3) simply adds SARIA to equation (1). As before, SHAREA, CAPINT, and ADS have significant positive effects on PCM and the coefficient of DIV is not significantly different from zero. Average sales per market (SALESA) no longer has a significant impact, but concentration now has a negative effect on PCM, significant at 10% and of reasonable size (an elasticity of −.19 at mean values). However, of primary interest here is the strongly significant positive coefficient of SARIA and the insignificant impact of SARX. At mean values of SARIA and PCM, an elasticity of .11 between those two

much larger omitted shares, which implies that a large number of contacts, those in foreign or regulated markets, may have been missed. To circumvent this difficulty, I have deleted from the remaining analysis of this section all companies whose 1976 domestic unregulated sales represented less than 50% of their total sales. This deletion of 20 companies, combined with the loss of two (as noted earlier) in order to calculate SARIA, leaves a sample of 369 companies. As an alternative procedure (to deletion), the percentage of a company's sales included in the 1976 FTC LB data file was explicitly included in regression equations (3) and (4), both in isolation and interacted with SAR. All results were similar to those reported.

variables is implied by the regression equation. Increasing SARIA from 14.7 to 22 (a 50% increase) implies, ceteris paribus, an increase in PCM from 8.6% to 9.1%.[17]

In equation (4) I attempt to improve the fit of the regression by adding SARIA to equation (2) (again, with the reduced sample of 369) and continue to find a strong positive effect of average market share on company profit margins, with an estimated elasticity (at the means) of .19. Average sales per market and diversification have negative, but not significant, effects on PCM. Capital intensity and advertising intensity have the expected positive effects. While the magnitude of the estimated coefficient of SARIA is somewhat smaller than in equation (3), it is still highly significant and has an effect (in elasticity terms, evaluated at the means) about half that of market share on PCM. In this specification, as in (2), SAR has a significant effect on PCM; the F-test on the simultaneous inclusion of SAR, SAR*CR4A, and SAR*$(\text{CR4A})^2$ yields a value of 3.28, significant at 5%, though weaker than in (2). However, the effect of company sales-at-risk is positive only for CR4A between 14 and 47 and reaches a maximum elasticity of .18 at CR4A = 31.

As for the impact of concentration on PCM, an F-test on the equation with and without variables involving CR4A finds that their inclusion adds significantly to the explanatory power of the equation, at 1%. The partial effect of CR4A on PCM is negative for CR4A greater than 30 and, at mean values of SAR, CR4A, and PCM, implies an elasticity of $-.30$.

The major results of this section are as follows: (1) SAR seems to have a positive effect on company price/cost margins, and as *company* sales-at-risk is generally dominated by average *industry* sales-at-risk, support is given to a mutual forbearance (or collusive) rather than efficiency-based view of SAR. (2) Recent studies finding market share to dominate concentration as a structural variable, at both the LB and the company level, are supported. (3) Some recent work finding a *negative* effect of concentration on profit margins is also given (weak) support.

17. More complete descriptions of the calculation of sales-at-risk are given in the App. and in Feinberg (1982), but an illustration may be useful here. Suppose a company's "average" or "typical" industry consisted of 10 firms, with equal market shares of 10%. If six of those firms met initially in five *other* markets and their sales were identical in all markets, they would each have sales-at-risk from the perspective of the "typical industry" equal to 10% × (5 markets) × (5 other rivals) = 250% of industry sales in the typical industry. Industry SAR would simply be 250% × (6 multimarket firms) = 1,500%, or 15 times industry sales. If just one more firm in the typical industry diversified into those five other markets, industry sales-at-risk would increase to (7 multimarket firms) × 10% × (5 markets) × (6 other rivals) = 2,100% or 21 times industry sales. To any company in the typical industry, whether a multimarket firm or not, SARIA would have increased from 15 to 21.

III. An Industry Study of Mutual Forbearance

It was noted earlier that the 14 nonmanufacturing categories and 16 of the 259 manufacturing industries were deleted from the data file in calculating SAR. In addition, two other industries were deleted because they contained only one (sampled) company each. For the purposes of this section, I have deleted 47 industries in which the sales of companies included in the data represented less than 25% of total industry sales. For the 194 industries remaining, more than 71% of total sales are included. Despite the deletions made, the industries to be analyzed contributed more than 90% of all manufacturing sales in the FTC LB data.

The traditional structure/performance paradigm is employed here, but augmented by a measure of sales-at-risk to explain the industry-level price/cost margin. While most of the variables employed are calculated for entire industries, the measures of PCM and SAR are based solely on the companies included in the FTC LB data file; therefore an exact replication of other studies using census or other whole-industry sources should not be expected. PCM is defined as in Section II, except that it is now a weighted-average price/cost margin for an industry, averaged over all LB observations for that industry in the data file.

The following are included as explanatory variables:

1. CR4, the 1972 four-firm seller-concentration ratio, adjusted from census data by Weiss and Pascoe (1982); both traditional collusion theories and more recent work viewing this variable as a proxy (at the industry level) for company market shares (e.g., Ravenscraft 1983) predict a positive effect on PCM.

2. DIV, a sales-weighted average (over all companies—in the FTC LB data file—in an industry) of the diversification index defined in Section II; economies of multimarket operation would imply a positive effect.

3. CAPINT, assets of all company LBs divided by all sales plus transfers of company LBs in an industry. As in Section II, a positive coefficient is expected.

4. ADS, advertising expenditures traceable to all company LBs divided by all sales plus transfers of company LBs in an industry. As in Section II, a positive sign is expected.

5. SAR, an estimate of sales-at-risk as a multiple of total industry sales.[18] A positive effect on PCM is predicted by the mutual forbearance hypothesis.

6. GRO, the rate of growth in industry shipments, 1976 shipments divided by 1972 shipments, with data taken from the 1972 *Census of Manufactures* and the 1976 *Annual Survey of Manufactures*. This

18. Total industry sales is estimated by adjusting census shipments data to FTC LB definitions. See U.S. Federal Trade Commission (1982), pp. 62–66.

proxy for demand growth is expected to have a positive impact on profit margins.

7. IMP, imports as a percentage of domestic consumption, derived from the 1972 input/output table of the economy. This functions as a measure of ease of entry and potential competition; a negative effect on PCM is anticipated.

8. CON, the ratio of consumer demand to total demand (from the 1972 input/output tables). This variable is interacted with CR4 and a positive sign is predicted. Collusion should be more effective in sales to consumers than to industrial users, as cartel cheating is less likely when firms face small dispersed buyers.

9. MES, minimum efficient scale, the average plant size of the plants in the top 50% of the plant size distribution as a percentage of industry sales, from census data. Considered either as an entry barrier or as a measure of efficiency (or both), this variable is predicted to have a positive effect on PCM.

10. CDR, cost-disadvantage ratio, defined by Caves et al. (1975) as the ratio of value added per worker in plants supplying the bottom 50% of industry value added to value added per worker in larger plants supplying the top 50% of industry value added.[19] This is a proxy for the slope of the long-run average-cost curve below MES, and a negative impact is expected (i.e., as smaller plant sizes are at a greater disadvantage, CDR falls and PCM is expected to rise).

Descriptive industry-level statistics are presented in table 4, a correlation matrix in table 5, and estimated regression coefficients in table 6. From equation (1) it appears that all estimated coefficients have the predicted signs except that of CR4. However, the deviant coefficient is not significantly different from zero. Moreover, the positive and significant coefficient of CON*CR4 implies that (i) concentration has a positive effect on PCM in industries with CON greater than 11 (43% of the sample), and (ii) as consumer demand becomes a larger part of an industry's total demand, an increase in concentration leads to a larger increase in PCM (or a smaller decrease, for CON less than 11).[20] At mean values of CR4, CON, and PCM, the implied elasticity of PCM with respect to CR4 is 0.05.[21]

While the other coefficients have the predicted signs, only those for CAPINT, GRO, IMP, and CDR are significant at levels of 10% or less. SAR has a weak positive effect (elasticity, evaluated at the means, of

19. Like Caves et al. (1975), I truncate CDR at a maximum value of 1.0 rather than view higher values as representing diseconomies of scale. However, nearly identical results were obtained in a regression using CDR without the truncation.

20. Although CR4 and MES are highly correlated (+.48), removing MES from the regression has no major effect on the magnitude, sign, or significance of the CR4 coefficient.

21. For an industry with all of its sales to consumers, this elasticity (at the means of CR4, PCM) is 0.28.

TABLE 4 Descriptive Industry Statistics

Variable	Mean	Standard Deviation
PCM (%)	9.4	5.1
CR4 (%)	46.6	18.2
DIV	.70	.13
CAPINT (%)	68.4	21.8
ADS (%)	1.8	2.9
SAR	18.9	24.3
GRO	1.53	.33
IMP (%)	6.7	8.5
CON (%)	26.1	33.4
MES (%)	4.0	3.5
CDR	.88	.13

Frequency Distribution of SAR*

Cell boundaries	0–10	10–20	20–30	30–40	40–50	50–70	70–100	100–130	130–160	160–190
Frequency	90	41	28	12	12	4	3	2	1	1
Relative frequency	.46	.21	.14	.06	.06	.02	.02	.01	.01	.01

NOTE.—N = 194. The 11 industries in the upper tail of this distribution, with SAR > 50, are (1) industrial inorganic chemicals, except industrial gases and inorganic pigments; (2) plastics materials and resins; (3) industrial organic chemicals, except gum and wood chemicals; (4) fertilizers; (5) pesticides and agricultural chemicals, not elsewhere classified (n.e.c.); (6) explosives; (7) valves and pipe fittings, except plumbers' brass goods; (8) lighting equipment, n.e.c., including wiring devices; (9) electron tubes, receiving and transmitting types; (10) electronic capacitors, resistors, coils and transformers, connectors and components, n.e.c.; and (11) combat vehicles, tanks.

0.024) that is not significantly different from zero.[22] An interaction term between SAR and CR4 was included in a regression run; the fit of the regression equation worsened (as measured by the standard error), the interaction coefficient was not significantly different from zero, and an F-test indicated that the two variables SAR and SAR*CR4 did not significantly increase the equation's explanatory power.

Examining the correlation matrix in table 5 reveals that SAR is positively correlated with both DIV (.24) and GRO (.22). Neither of these correlations is surprising: the former reflects the obvious relationship between multimarket operations and multimarket contacts; the latter can be explained by already-diversified firms entering rapidly growing industries and, in the process, greatly increasing the SAR in those industries. These correlations make it difficult to identify an independent effect of SAR on PCM.

When we remove both GRO and DIV, as in equation (2), SAR is now seen to have a weak but significant (at 10%) positive effect on PCM

22. At the suggestion of a referee, this regression equation was rerun, deleting the 11 industries with the largest values for sales-at-risk (see table 4). While all the other coefficient estimates (and their significance levels) are nearly identical to those shown in table 6, col. 1, the coefficient of SAR is estimated to be −.0038 (an elasticity, at mean values, of −0.006), and not significantly different from zero (t = 0.13). When GRO and DIV are removed, as in col. 2 of table 6, SAR has a weak *positive* effect, but it is not significantly different from zero.

TABLE 5 Industry Correlation Matrix

	CDR	MES	CON	IMP	GRO	SAR	ADS	CAPINT	DIV	CR4
PCM	−.19	.22	.11	−.09	.24	.04	.27	.23	−.02	.18
CR4	−.03	.48	.08	−.15	−.01	−.10	.07	.08	−.16	
DIV	.02	−.05	−.15	−.10	−.08	.24	−.05	−.04		
CAPINT	.15	.08	−.24	.17	.08	−.01	−.02			
ADS	−.17	.19	.60	−.03	−.10	−.16				
SAR	.12	−.10	−.25	−.15	.22					
GRO	.13	−.09	−.21	−.06						
IMP	−.10	.20	.13							
CON	−.14	.19								
MES	−.11									

NOTE.—N = 194.

TABLE 6 Industry Regression Results

	1		2	
CONSTANT	4.38	(1.20)	11.08	(4.09)
CR4	−.007	(.33)	−.007	(.31)
CON*CR4	.00065	(2.66)	.00065	(2.58)
SAR	.012	(.87)	.025	(1.77)
DIV	1.57	(0.62)	...	
CAPINT	.067	(4.30)	.072	(4.50)
ADS	.187	(1.34)	.160	(1.11)
GRO	3.88	(3.92)	...	
IMP	−.099	(2.39)	−.106	(2.49)
MES	.186	(1.63)	.164	(1.39)
CDR	−8.83	(3.57)	−8.90	(3.48)
R^2	.31		.26	
Standard error	19.1		20.5	
F	8.4		8.0	

NOTE.—Dependent variable = PCM. N = 194. t- statistics are in parentheses beside the estimated coefficients.

with an estimated elasticity, at the means, of 0.05.[23] All other coefficients remain essentially the same as in equation (1). The results of equations (1) and (2) illustrate the difficulty of disentangling the effects of multimarket contacts from those of other industrial-structure variables, but also offer some encouragement to the conjecture that when these effects are better isolated, additional support will be given to the mutual forbearance hypothesis.

IV. Conclusions

In this paper I have tested the mutual forbearance theory of conglomerate behavior at both the company and industry level, using 1976 data from the Federal Trade Commission's Line of Business Program. This theory states that companies meeting rivals in more than one market will be able to facilitate collusion in one or all of those markets. At the company level, sales-at-risk, a measure of the importance of multimarket contacts, was found to have a significant effect in increasing price/cost margins in the moderate range of concentration where collusion is feasible but difficult to achieve without mutual forbearance. In addition, an industry measure of sales-at-risk (averaged over a company's lines of business) has a strong effect in increasing margins, an effect more suggestive of collusion than of efficiency.[24]

Some doubts about the mutual forbearance hypothesis are raised at the industry level. The effects of sales-at-risk seem harder to isolate

23. A collinearity problem does not seem to be behind the insignificant coefficient of DIV, as this remained insignificant when SAR was deleted from the equation.

24. It should be noted that in a preliminary regression run on 2,661 observations at the LB level, the industry-level measure of SAR retains a strong positive effect on LB PCM.

from those of other structural measures, in particular diversification and market-demand growth. However, some (admittedly weak) support for the mutual forbearance hypothesis is found here as well.

Further work investigating the nature and effects of multiple-market rivalry among companies is likely to be fruitful, especially if it uses data as rich as those collected under the FTC's Line of Business program. To the extent that a time series of these data can be obtained, important work investigating the causes and patterns of multimarket contacts can be pursued. Given the prominence of the conglomerate firm in the U.S. economy today, no research investigating the determinants of economic performance can afford to ignore this cross-market rivalry.

Appendix

Example of Calculating SAR Variables

There are three industries (1, 2, and 3) and 18 companies (A,B,C, . . . , R).

Industry 1 (CR4 = 100)		Industry 2 (CR4 = 95)		Industry 3 (CR4 = 25)	
Company	Sales	Company	Sales	Company	Sales
A	20	A	50	A	10
B	20	B	30	B	10
C	20	D	100	·	·
		E	5	·	·
	60	Q	10	·	·
		R	5	·	·
				P	10
			200		160

At the LB level:

$$SAR_{A,1} = (50 \times 1) + (10 \times 2) = 70;$$

$$SAR_{A,2} = (20 \times 1) + (10 \times 3) = 50;$$

$$SAR_{A,3} = (20 \times 2) + (50 \times 3) = 190;$$

$$SAR_{B,1} = (30 \times 1) + (10 \times 2) = 50;$$

$$SAR_{B,2} = (20 \times 1) + (10 \times 3) = 50;$$

$$SAR_{B,3} = (20 \times 2) + (30 \times 3) = 130;$$

$$SAR_{C,1} = 10 \times 2 = 20;$$

$$SAR_{C,3} = 20 \times 2 = 40;$$

$$SAR_{D,2} = 10 \times 3 = 30;$$
$$SAR_{D,3} = 100 \times 3 = 300;$$
$$SAR_{E,2} = 10 \times 3 = 30;$$
$$SAR_{E,3} = 5 \times 3 = 15;$$

all others = 0.

At the industry level:

$$SAR_1 = \frac{SAR_{A,1} + SAR_{B,1} + SAR_{C,1}}{60}$$
$$= 140/60 = 2.3;$$
$$SAR_2 = 160/200 = 0.8;$$
$$SAR_3 = 675/160 = 4.2.$$

At the company level:

$$SAR_A = \frac{SAR_{A,1} + SAR_{A,2} + SAR_{A,3}}{20 + 50 + 10} = \frac{310}{80} = 3.9;$$

$$SARX_A = \frac{SAR_{A,1} + SAR_{A,2}}{80} = \frac{120}{80} = 1.5;$$

$$SARIA_A = \frac{(20 \times SAR_1) + (50 \times SAR_2)}{80} = 1.1;$$

$$SAR_B = \frac{230}{60} = 3.8, \; SARX_B = \frac{100}{60} = 1.7, \; SARIA_B = \frac{70}{60} = 1.2;$$

$$SAR_C = \frac{60}{30} = 2.0, \; SARX_C = \frac{20}{30} = 0.7, \; SARIA_C = \frac{46}{30} = 1.5;$$

$$SAR_D = \frac{330}{110} = 3.0, \; SARX_D = \frac{30}{110} = 0.3, \; SARIA_D = \frac{80}{110} = 0.7;$$

$$SAR_E = \frac{45}{15} = 3.0, \; SARX_E = \frac{30}{15} = 2.0, \; SARIA_E = \frac{4}{15} = 0.3;$$

$$SAR_Q = 0, \; SARX_Q = 0, \; SARIA_Q = 0.8;$$

$$SAR_R = 0, \; SARX_R = 0, \; SARIA_R = 0.8;$$

all others = 0.

Here SARX and SARIA are truncated measures; industry 3 is dropped, since CR4 < 30.

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