Strategic Management Journal, Vol. 17, 653–664 (1996)

MARKETS VS. MANAGEMENT: WHAT 'DRIVES' PROFITABILITY?

JAIME A. ROQUEBERT, ROBERT L. PHILLIPS and PETER A. WESTFALL
College of Business Administration, Texas Tech University, Lubbock, Texas, U.S.A.

This study addresses the issue of the relative degree of variance in ROA accounted for by industry, corporate, and SBU effects while controlling for the business cycle and the interaction between the business cycle and industry. Two key articles, Schmalensee (1985) and Rumelt (1991), are discussed in detail. Research results on a recent data base (COMPUSTAT), using variance components analysis (VARCOMP) are presented that not only confirm most of the Rumelt (1991) findings, but also suggest the existence of a corporate effect, heretofore undetected.

The debate between researchers in industrial organization economics (IOE) and the field of strategic management (SM) concerning the question of the principal source of profits (markets or organizational behavior) has been going on for more than 50 years. Perhaps the term 'debate' is somewhat strong in that there has not been so much of a debate as a case of neglect. The key question of the principal source of profits appears to have had very little influence on the further development of theoretical orientations in both the IOE and the SM fields, each acting as if its view were dominant—industry for IOE, management for SM. Only recently have researchers from both fields gone 'head-to-head' so to speak.

The present research attempts to build on the 'head-to-head' research by (1) contrasting and comparing key methods and findings on the topic, (2) investigating the issue further by pitting the IOE model against the quintessential SM model, using a relatively recent, broad SBU panel spanning 7 years, and (3) exploring possible reasons for any divergence with previous research findings.

Key words: ROA; industry effect; corporate effect; profitability

The paper has three sections that parallel the above purposes. First, we briefly review the theoretical background, followed by an extensive comparison of the two head-to-head articles on the topic. Next, we present the results of our empirical analysis. Finally, we suggest a possible reconciliation of differing findings and extend the theoretical relationship between corporate diversification and corporate effects on SBU profitability.

THEORETICAL BACKGROUND

Ed Mason, the 'father' of IOE, argued in the late 1930s that there was a rather deterministic association between market structure and profitability (Mason, 1939). The logic of the argument rested on the premise that structural characteristics of the industry or market, typically operationalized through summary measures such as concentration (Lenz, 1981), placed constraints on the conduct (or strategies) firms could pursue. The constrained conduct, in turn, led to differential performance among firms according to the industry in which the firm operated (Mason, 1939).

Within the IOE field, firms in an industry were

CCC 0143-2095/96/080653-12

Received 4 April 1994
Final revision received 5 December 1995

thought to be alike in all strategically important respects except for scale, and therefore, the focus or unit of analysis was the industry (Weiss, 1971; Rumelt, Schendel, and Teece, 1994). The early industrial organization economic work was also concerned with capturing complexity; consequently, explanations were based upon detailed and extensive industry studies (Porter, 1991).

It should be pointed out that Mason was not the only theorist commenting on the subject. Even at the time, there were theorists arguing what we might now suggest belongs to the genre of the resource-based theory of the firm. Nourse and Drury (1938) suggested that influences specific to the firm determined performance; i.e., management basically determined firm advantages and firms were not simply at the mercy of industry factors. Over 50 years have passed since Mason's (1939) proposition with apparently little dampening of the industry élan'. Montgomery and Porter (1991: xiv–xv) affirm the importance of industry effects:

> Present research continues to affirm the important role industry conditions play in the performance of individual firms. Seeking to explain performance differences across firms, recent studies have repeatedly shown that average industry profitability is, by far, the most significant predictor of firm performance. It is far more important than the extent of a firm's diversification . . . In short, it is now uncontestable that industry analysis should play a vital role in strategy formation.

(Note: Montgomery and Porter, 1991, used a single article to support the above quotation—Schmalensee, 1985, which will be discussed in detail later).

In contrast to the basic theoretical orientation of IOE, the strategy field seems to have germinated in the early 1960s out of the case study tradition at Harvard (Teece, 1990). Learned *et al.* (1969) and Andrews (1971) constituted for the most part the organizing framework that guided the lines of inquiry (Barney, 1991).

In the classic strategy model, a firm's competitive advantage was gained from a combination of external and internal factors, known as opportunities and strengths applied against threats and weaknesses. The early literature was developed around broad principles, reflecting an orientation toward prescriptions for practitioners and the 'recognition, indeed the preoccupation, with the fact that competition was complex and highly situation-specific' (Porter, 1991: 97). It was implicitly assumed that managers' perceptions and choices largely accounted for the variance in companies' performance. The emphasis on taking a general manager's perspective led to a largely process-oriented, as opposed to a content-oriented stream of research (Porter, 1981).

Investigation of the evolution of organizational theory models suggests a somewhat 'in-between' view of the world. As in industrial organization economics, performance models in organizational theory have been largely deterministic (White and Hammermesh, 1981). However, until recently the theory and measures of environmental (industry) influence have been distinct from those employed in industrial organization economics. Further, and more importantly, the 'determinism' was not only from the influence of the external environment, but also from the organization structure itself. In essence, the organizing principle was that the structure of the organization and its fit to the environment determine the relative degree of profitability.

There were major shifts during the decades of the 1970s and 1980s in the strategic management and industrial organization economics fields, with respect to the unit of analysis, the reevaluation of assumptions, and the relative focus across fields. The reasons for shifting theoretical orientations appear to have been the inability of neoclassical economics to explain intraindustry profitability differences, the lack of rigor and inductive nature of case studies, and perhaps a 'healthy' cross-fertilization between fields.

Mason's deterministic approach implied that 'comparisons across industries would be valid', while Nourse's hypothesis supported the notion of intraindustry heterogeneity (Bass, Cattin, and Wittink, 1977: 194). Further, the feedback loops of cause–effect–cause relationships regarding environment, conduct, and performance would render purely deterministic theories unreconcilable.

Recently, a 'new' stream of research has reemerged by the name of resource-based theories, which propose that firm idiosyncrasies in the accumulation of unique and inimitable resources create sustained competitive advantage (Barney, 1991; Collis, 1991; Conner, 1991; Lippman and Rumelt, 1982; Rumelt, 1984). It should be kept in mind that the seeds of this notion were present at the birth of the field (e.g., Nourse and Drury, 1938). This rapidly developing body of literature argues that the forgotten half of Andrews' model ('the marshaling of internal resources to develop distinctive competencies') needs to be brought back into the core of strategy (Bartlett and Ghoshal, 1991: 8–9). A clear implication of resource-based theory is the obvious choice of unit of analysis; namely, that it requires a focus on the individual firm.

A highly important second implication relates to the methodologies suitable for organization studies. Since idiosyncratic attributes represent a source of competitiveness, a reliance on detailed case studies, or at least in-depth analysis, appears to be required. It does not suggest, at least at first glance, that resource-based theory should supplant the traditional and well-established IOE frameworks, but rather that it supplements them.

What we have seen then, in essence, is the strategic management field coming almost full circle in terms of what early policy researchers 'identified as the basis for good strategy formulation' (Collis, 1991: 65).

The deterministic vs. choice orientation of the effectiveness research does not account solely for differences in units of analysis (as shown by part of the organization theory literature), but rather each approach brings with it different perspectives, biases, and methodologies. As Rumelt (1974: 560) points out:

> ... the mismatch arises because policy researchers and economists have been interested in substantially different phenomena. The central concerns of business policy are the observed heterogeneity of firms and firm's *choice* of product–market commitments. By contrast, the basic phenomena of interest in neoclassical theory is the functioning of the price system under norms of decentralized decision making.

It should also be added that economists 'tend to see firms as players in a multifactor economic game, and their interest is in the game and its outcomes, rather than in the particular play or performance of individual firms' (Nelson, 1991: 61).

From the foregoing discussion, it is apparent that there are opposing assumptions about the strength of environmental forces (choice or determinism) seen in different literatures. Second, each set of assumptions implies justification of different units of analysis. In light of these two arguments, the strategy field has recently tried to answer the question 'what is the relative impact of industry factors vs. firm effects on financial performance?'

Of all the past research, however, two studies dominate the literature. First is the classic article by Schmalensee (1985), cited earlier by Montgomery and Porter (1991) in support of their emphasis on industry factors. Schmalensee (1985) investigated estimates of the relative importance of firm (corporate), market (industry), and market share on business unit profitability. He used the Federal Trade Commission (FTC) line of business (LB) data for 1975 and both regression analysis and an analysis technique that was then unique to the IOE literature—variance components analysis. (See Appendix 1 for further discussion).

Schmalensee (1985) concluded his regression and variance component analyses with four propositions, two of which are relevant to the present work. The relevant propositions state that (1) firm effects do not exist, and (2) industry effects exist and are important, accounting for at least 75 percent of the variance of industry rates of return on assets (Schmalensee, 1985: 349).

The second major work to address the relative variance question was that of Rumelt (1991), who explored the variance accountability issue of industry vs. other factors. Because Rumelt (1991) was concerned with Schmalensee's (1985) use of a single year's data, he extended Schmalensee's (1985) methodology to cross-sectional and time-series data by using 4 years' worth of data, and included a term in his equation not only for corporate management (what Schmalensee, 1985, called firm effects), but for SBU level management also.

COMPARING SCHMALENSEE (1985) TO RUMELT (1991)

Schmalensee (1985) used the FTC LB data for the year 1975. SBU returns on assets (ROAs) were decomposed by an equation in the form:

$$r_{ij} = \mu + \alpha_i + \beta_j + \gamma S_{ij} + \epsilon_{ij} \qquad (1)$$

where r_{ij} is the rate of return of firm i's operations in industry j (SBU ROA); S is the market share; α are firm effects, β are industry effects, μ and γ are constants; and ϵ are disturbances.

Schmalensee (1985: 343–344) stated that

whereas none of the coefficients in the specified equation could be given a 'defensible structural interpretation' the model taken as a whole could address 'the relative merits of at least the extreme versions of the classical, revisionist, and managerial positions'. The relative magnitudes of the variables would suggest support or lack of support for each.

Schmalensee (1985: 344) tested for the existence of industry effects (nonidentical β), corporate effects (nonidentical α), and share effects (nonzero γ), using ordinary least squares and the 'usual F-statistics'. The results indicated that corporate effects 'simply do not exist' (Schmalensee, 1985: 346). In contrast, tests for the existence of industry and share effects were significant at least at the level of 0.045. Schmalensee (1985) reformulated his basic model leaving out the term representing corporate effects, i.e., the αs (see Equation 1), and applied the variance component analysis. His results allocated less than 1 percent of the variance to share effects, 19.5 percent to industry effects, and the remaining variance (80%) to error.

It should also be noted that Schmalensee (1985: 345) addressed the issue of whether or not it is 'defensible' to work with industry-level data, i.e., examining the average SBU ROA by industry. By so doing, his basic equation then became

$$R_j = \mu + \beta_j + \text{'terms in } \alpha\text{s, } S\text{s, and } \epsilon\text{s'} \quad (2)$$

where R_j is the average SBU ROA for industry j. He then suggested that industry-level analysis would seem to be sensible if estimates of the variance of β (industry effects) are large relative to the cross-section variance of the R_j (Schmalensee, 1985: 345). It was through the latter analysis that he found that the industry effects in Equation 2 accounted for over 75 percent of the variance.

As indicated above, Rumelt (1991) used the same data as Schmalensee but added to it the data for the years 1974, 1976, and 1977. Rumelt (1991) then postulated the following model:

$$r_{ikt} = \mu + \alpha_i + \beta_k + \gamma_t + \delta_{it} + \phi_{ik} + \epsilon_{ikt} \quad (3)$$

where r_{ikt} represents the SBU ROA for a given SBU of corporation k in industry i in year t; α are industry effects, β are the corporate effects, γ represent the year effects, δ are the industry by year interactions, ϕ represent the SBU effects, and ϵ represent error. Variances associated with particular effects are, respectively, σ^2_α, σ^2_β, σ^2_ϕ, σ^2_ϕ, and σ^2_ϵ.

Since Schmalensee (1985) used only a single year's worth of data, if we were to 'translate' Schmalensee's model using Rumelt's specification ($t = 1$ year) we would have

$$\begin{aligned} r_{ik1} &= \mu + \alpha_i + \beta_k + \gamma_1 + \delta_{i1} + \phi_{ik} + \epsilon_{ik1} \quad (4) \\ &= (\mu + \gamma_1) + (\alpha_i + \delta_{i1}) + \beta_k + (\phi_{ik} + \epsilon_{ik1}) \\ &= \mu' + \alpha'_i + \beta_k + \epsilon'_{ik} \end{aligned}$$

As pointed out by Rumelt (1991), it is clear that persistent effects (α_i and ϕ_{ik}) are not estimable when only 1 year of data is considered; time-series data is needed to isolate their effects.

In Schmalensee's (1985) model, 'industry effects' are the combined effects of industry and industry–time interaction in Rumelt's (1991) model. It can also be seen that Schmalensee's 'error effects' are the combined effects of error and the persistent SBU effects of Rumelt's model. The corporate effects are the same in both models. It should be noted that Schmalensee considered a market share variable in the variance component analysis; however, its contribution to variance explained was negligible (less than 1 percent), and will not be included in the remainder of the discussion. Assuming that all effects are independent, the variances are related as follows (anything with a prime refers to Schmalensee's model): $\sigma^2_{\alpha'} = \sigma^2_\alpha + \sigma^2_\delta$ and $\sigma^2_{\epsilon'} = \sigma^2_\phi + \sigma^2_\epsilon$. The theoretical corporate variance, σ^2_β is identical in both models.

Thus, Schmalensee's (1985) industry effects (about 20 percent; from Table 1, p. 348) corresponds to the sum of Rumelt's (1991) 'industry–year interaction' plus 'industry' variance components (about 16 percent), as given in Rumelt's (1991) Table 3, p. 178. (Note: Rumelt, 1991, drew two samples, A and B. Sample A closely followed Schmalensee's, 1985, selection procedure and, among other things, excluded all SBUs with sales less than 1 percent of the FTC industry total sales for a given year. Sample B was an expanded Sample A through the addition of smaller SBUs).

Schmalensee's estimate of σ^2_ϵ (error) is about 80, whereas Rumelt's estimate of $\sigma^2_\phi + \sigma^2_\epsilon$ (combined error and SBU effects) is 83 percent—

rather a remarkable agreement (see Table 4 for a comparison of findings). The agreement suggests, of course, had Schmalensee (1985) used more than 1 year's worth of data and, had he included an SBU term in his equation, he might well have arrived at a similar value for the amount of SBU variance accounted for as Rumelt (1991) found. (The comparison is clearly pointed out in Rumelt's, 1991, Table 4, p. 179).

Let us now focus our attention on the major differences between Schmalensee (1985) and Rumelt (1991) on their respective findings concerning industry averages. Recall from Equation 2 above, the equation for examining the average profitability of industries. The percentage accounted for by industry effects was estimated to be approximately 75 percent by Schmalensee (1985), but only 48 percent for Rumelt (Table 5, 1991: 11). There are at least three possible reasons for the discrepancy.

First, as indicated above, the industry term of Schmalensee's (1985) model encompasses both the persistent and nonpersistent industry effects, i.e., includes the industry effects and industry by year interactions of Rumelt's (1991) model, which was pointed out by Rumelt (1991).

Second, two sets of data were used which yielded a different number of observations per industry. The variance decomposition procedure is very sensitive to such differences.

Third, the two theorists calculated the industry averages in a different way. Schmalensee (1985) computes the average return for all corporations in the given year, then considers a cross-sectional variance. Rumelt (1991) calculates the average over all corporations *and years*, then considers variance of the time-series averages.

It appeared that some of the difference might be due to the differing methods of average calculations; thus, we examined Rumelt's (1991) findings on the decomposition of variance of industry averages using both calculating methods. (See Appendix 1 for a detailed, mathematical discussion and comparison of the two methods of average calculations). In conclusion, the discrepancies between the 75 percent (Schmalensee) and the 50 percent (Rumelt) may be the result of the *overall precision* with which the industry effects are estimated. This precision may be more related to a particular data base used than it is to the actual ROA values—one can obtain drastically different variance decompositions through different subsets of the data, or by considering differing numbers of years in a longitudinal study. Compounding this difficulty is the fact that there is no unique 'variance' measure for industry averages. We have described two possibilities: the time-series vs. cross-sectional methods.

Further, by analyzing industry averages, one implicitly suggests that the appropriate estimate of the industry effect is the average of all units within the industry. Such an implication leads to an erroneous conclusion. If the random effects model is considered valid, then the industry averages are inefficient estimates of industry effects. The appropriate estimates are the best linear unbiased predictors (or BLUPs, see Searle, Casella, and McCulloch, 1992).

Thus, to avoid the difficulties associated with choice of data base, choice of variance measure for industry average, and choice of estimation of industry effects themselves, we recommend the decomposition of the *actual* ROA variance (the r_{ikt}), rather than the variance of the industry averages, as the primary vehicle for assessing the relative importance of factors. Such a decomposition then may be used for determining decompositions for variances of averages (cross-sectional or time-series), or for other estimates (e.g., BLUPs), if desired.

THE CURRENT RESEARCH

We wanted not only to compare and contrast the Schmalensee/Rumelt differences, but also to enter the debate using a more up-to-date data base while employing a variance components analysis similar to Schmalensee (1985) and Rumelt (1991). Thus, our mathematical model was as follows:

$$r_{ikt} = \mu + \alpha_i + \beta_k + \gamma_t + \delta_{it} + \phi_{ik} + \epsilon_{ikt}$$

where r_{ikt} represents the SBU ROA for a given SBU of corporation k in industry i in year t; α are industry effects, β are the corporate effects, γ represent the year effects, δ are the industry by year interactions, ϕ represent the SBU effects, and ϵ represent error.

Since we were conducting a longitudinal study, we expected to obtain results similar to Rumelt, i.e., a high SBU effect, a low industry effect, and probably a zero or near zero corporate effect since both Schmalensee's (1985) and Rumelt's (1991) corporate effects were trivial, at best.

Data base

In the present effort, we selected the COMPUSTAT® Business Information Industry Segment Data as the population from which to sample. In addition to the financial information at the consolidated corporate level, COMPUSTAT compiles information required by the Securities and Exchange Commission (SEC) and the Financial Accounting Standards Board (FASB) Statement Number 14. Corporations are required to provide information on their principal lines of business (industry segments). In the data base, each corporation is required to report information on segments which account for 10 percent or more of consolidated sales, operating profits, or assets.

Before proceeding, it may be well to compare the COMPUSTAT data to the FTC data used by both Schmalensee (1985) and Rumelt (1991). Table 1 presents key aspects of the two data bases. As can be seen from Table 1, there are important differences between the two data bases. The COMPUSTAT data base is:

- more recent (1985–91) vs. FTC (1974–77);
- broader in scope (746 manufacturing SICs vs. 260 for FTC);
- for a greater time period (7 years of data vs. 4 years for FTC);
- larger (almost 3000 corporations involved in manufacturing vs. fewer than 500; over 6000 manufacturing lines of business vs. fewer than 4000 for the FTC data);
- less restrictive (includes smaller corporations—average SBUs per corporation of 1.95 vs. 9.17 for the FTC data).

To be sure, both data bases have their advantages.

Table 1. Comparison of the COMPUSTAT and FTC data bases

	Average of FTC sample	COMPUSTAT
Industry categories	259	942
Corporations	458	6,873
Lines of business (LOB)	4,193	13,398
LOB per corporation	9.17	1.95

The FTC data were designed to obtain data from only the corporations with the greatest market share and therefore might be considered the 'successful' corporations. On the other hand, there may be an advantage in looking at a sample that not only better represents businesses in general, but is much more recent. Despite the above advantages, it must be acknowledged that the FTC data were collected under regulatory force whereas the *COMPUSTAT* data are taken from data that companies provide in their respective statements.

Sample selection and statistical procedure

In order to parallel Schmalensee (1985) and Rumelt (1991) we restricted our sample to 4-digit SIC codes connected with manufacturing (codes 2000–3999). Second, we only selected those corporations with two or more SBUs. Third, we eliminated all SBU ROAs greater than four standard deviations from the mean in order that extreme values did not have undue influence on the analysis.

Of the four estimation procedures in the SAS/STAT® package for the variance components analysis (PROC VARCOMP), we selected the maximum likelihood procedure because of certain advantages. One benefit is that the asymptotic covariance matrix of the parameter estimates is readily available as a by-product of the estimation procedure. The square roots of the diagonal elements of the covariance matrix are standard errors of the parameter estimates which can, in turn, be used to create asymptotically valid confidence limits on the parameters. In other words, we can estimate the significance levels of the resulting *t*-values. We must, however, add a caveat. The validity of the asymptotic approximation requires that the true underlying parameter be nonzero. That the use of these standard errors for testing the hypothesis of the parameter equals zero is, strictly speaking, not valid for hypothesis testing. Nevertheless, it is useful to supply the standard errors along with the estimates to provide a measure of accuracy. Further, the order of magnitude of the parameter (expressed as a percentage of the total variance accounted for) can be used as an indicator of the likelihood that the underlying true value is nonzero—that is, the greater the parameter, the more likely the basic assumption is met.

A second benefit is that the maximum likelihood estimation scheme is an iterative procedure which incorporates the relative magnitudes of the estimates at each step of the iteration. The alternative is to use single-step (noniterated) quadratic estimates which do not account for the relative magnitudes of the variance components, and such estimates lose efficiency relative to the iterated estimates, particularly in large samples (see Searle *et al.*, 1992, for further discussion).

Due to computational constraints with the maximum likelihood method, we employed a random sampling procedure, without replacement. Ten samples of 100–150 corporations were analyzed. Each sample, on the average, contained 100–150 corporations in over 160 industries. The 10 samples resulted in 16,596 different SBU ROAs (all that met the selection criteria in the data base) being analyzed. The average number of SBUs per corporation was 4.01. Table 2 presents the descriptive statistics for each sample.

In order to further investigate the robustness of the procedure, we used the MIVQUEO estimates, which are more easily computed (but less efficient than the maximum likelihood estimates), allowing us to analyze the entire data set with a single run.

Results

Table 3 shows the results for each sample, including the parameter estimates for the various effects, the percentage of total variance each parameter represents, the value of the diagonal of the asymptotic covariance matrix, and the estimated significance level.

As can be seen from Table 3, our results produced a high degree of agreement with the Rumelt (1991) results of the FTC data base in percent variance accounted for by both industry and SBU effects. The results of the MIVQUEO analysis provided the same relative order of variance accounted for, but as expected due to reasons discussed earlier, produced smaller values for the parameters and a much larger value for the error term (industry = 4.6%; corporate = 7.0%, SBU = 32.6%; industry by year interaction = 2.9%; and error = 52.6%). We suggest that the relative size of the parameters of the MIVQUEO results tend to support the maximum likelihood parameter estimates.

However, there is a significant divergence between the present results and both the Schmalensee (1985) and Rumelt (1991) results. Specifically, we estimate a nontrivial corporate effect, i.e., 18 percent of variance for us vs. less than 2 percent for Rumelt (1991) and near zero for Schmalensee (1985). See Table 4 for a comparison of Schmalensee's (1985), Rumelt's (1991), and current results. (Note: we compare our results to Rumelt's, 1991, Sample B as that was the sample that was less restrictive with respect to the size of SBU market share and, thus, more comparable to our data).

TOWARD A POSSIBLE RECONCILIATION

It should be acknowledged that Schmalensee (1985) recognized that 80 percent of the variance

Table 2. Descriptive statistics for each sample

	Sample Size	Average ROA	S.D. ROA	Minimum ROA	Maximum ROA	Levels Industry	Levels Corporation	Levels SBU
Sample 1	1,752	11.34	22.53	−138.24	132.39	223	114	437
Sample 2	1,773	10.52	19.73	−137.60	149.38	266	108	451
Sample 3	1,711	11.04	20.35	−131.87	135.59	240	108	432
Sample 4	1,457	10.96	21.79	−138.47	128.35	232	94	387
Sample 5	1,603	10.36	22.75	−134.38	145.16	225	105	415
Sample 6	1,512	11.96	20.90	−131.22	146.46	230	98	403
Sample 7	1,699	10.03	22.27	−144.68	121.74	258	102	443
Sample 8	1,800	12.99	20.55	−147.06	142.41	241	113	–
Sample 9	1,721	11.42	18.19	−138.68	143.10	235	99	411
Sample 10	1,568	9.29	23.48	−143.22	144.67	225	110	403
	16,596	11.00991		−147.06	149.38	237.5	105.1	421.4

Table 3. VARCOMP results for each sample

		Industry	Corporation	SBU	Year	Industr. × Yr.	Error	Total
Sample 1	Variance component estimate	75.90	103.58	173.56	2.51	0.39	237.17	593.12
$n = 1752$	Percent of total	12.8%	17.5%	29.3%	0.4%	0.1%	40.0%	100.0%
	Estimate variance (diagonal)	515.12	940.45	694.58	4.16	30.04	126.71	
	Significance level	3.34	3.38	6.59	1.23	0.07	21.07	
Sample 2	Variance component estimate	100.34	92.12	155.20	0.85	20.55	116.76	485.81
$n = 1773$	Percent of total	20.7%	19.0%	31.9%	0.2%	4.2%	24.0%	100.0%
	Estimate variance (diagonal)	928.60	709.56	700.35	0.84	37.31	50.75	
	Significance level	3.29	3.46	5.86	0.93	3.36	16.39	
Sample 3	Variance component estimate	39.98	99.11	147.78	6.31	5.25	169.67	468.11
$n = 1711$	Percent of total	8.5%	21.2%	31.6%	1.3%	1.1%	36.2%	100.0%
	Estimate variance (diagonal)	392.60	773.66	504.31	16.49	27.42	71.30	
	Significance level	2.02	3.56	6.58	1.55	1.00	20.09	
Sample 4	Variance component estimate	14.22	73.99	281.99	0.88	0.00	201.97	573.05
$n = 1457$	Percent of total	2.5%	12.9%	49.2%	0.2%	0.0%	35.2%	100.0%
	Estimate variance (diagonal)	1064.15	876.13	2096.78	1.29	0.00	81.23	
	Significance level	0.44	2.50	6.16	0.78	0.00	22.41	
Sample 5	Variance component estimate	102.82	162.59	125.70	1.56	17.85	198.47	608.98
$n = 1603$	Percent of total	16.9%	26.7%	20.6%	0.3%	2.9%	32.6%	100.0%
	Estimate variance (diagonal)	605.61	1635.77	449.24	2.28	67.39	123.80	
	Significance level	4.18	4.02	5.93	1.03	2.17	17.84	
Sample 6	Variance component estimate	48.49	105.60	145.97	0.42	13.82	173.81	488.11
$n = 1512$	Percent of total	9.9%	21.6%	29.9%	0.1%	2.8%	35.6%	100.0%
	Estimate variance (diagonal)	431.20	920.70	557.78	0.85	102.43	140.30	
	Significance level	2.34	3.48	6.18	0.45	1.37	14.67	
Sample 7	Variance component estimate	79.95	173.91	173.00	0.88	0.00	200.31	628.05
$n = 1699$	Percent of total	12.7%	27.7%	27.5%	0.1%	0.0%	31.9%	100.0%
	Estimate variance (diagonal)	460.28	1652.84	590.27	1.09	0.00	72.12	
	Significance level	3.73	4.28	7.12	0.84	0.00	23.59	
Sample 8	Variance component estimate	44.55	50.53	317.25	5.52	44.78	82.13	544.77
$n = 1800$	Percent of total	8.2%	9.3%	58.2%	1.0%	8.2%	15.1%	100.0%
	Estimate variance (diagonal)	380.20	682.58	1263.39	12.18	56.42	36.94	
	Significance level	2.28	1.93	8.93	1.58	5.96	13.51	
Sample 9	Variance component estimate	0.00	40.52	198.17	2.73	12.74	139.02	393.18
$n = 1721$	Percent of total	0.0%	10.3%	50.4%	0.7%	3.2%	35.4%	100.0%
	Estimate variance (diagonal)	0.00	284.42	489.49	3.91	35.55	60.55	
	Significance level	0.00	2.40	8.96	1.38	2.14	17.87	
Sample 10	Variance component estimate	56.59	86.24	276.19	1.08	0.00	237.12	657.22
$n = 1568$	Percent of total	8.6%	13.1%	42.0%	0.2%	0.0%	36.1%	100.0%
	Estimate variance (diagonal)	870.46	1496.55	1507.75	1.70	0.00	101.79	
	Significance level	1.92	2.23	7.11	0.83	0.00	23.50	
Average percent of total		10.1%	17.9%	37.1%	0.4%	2.3%	32.2%	100.0%
Significant runs ($t > 2$)		7	9	10	0	4		
Weighted average percent $N = 16{,}596$		10.2%	17.9%	37.1%	0.5%	2.3%	32.0%	100.0%

in the ROAs of SBUs was in his analysis unrelated to industry, share, or corporate (firm) effects. Thus, it should come as no surprise that when both we and Rumelt (1991) include an additional term in the equation (SBU effects), some of the previously unexplained 80 percent would be accounted for.

Also, it is interesting to note that Rumelt concluded his section on corporate effects with the observation that it was surprising to find only a 'vanishingly small' corporate effect. He further suggested that both his result and that of Schmalensee 'remains a puzzle and deserves further investigation' (1991: 182).

Table 4. Comparison of results (percent of variance accounted for)

Variable	Schmalensee	Rumelt 'B'	Current
Industry × Year	n.a.	5.38	2.3
Market share	0.6	n.a.	n.a.
Industry	19.5	4.03	10.2
Corporation	n.a.	1.64	17.9
Business unit	n.a.	44.17	37.1
Error	79.9	44.79	32.0
Total	100.0	100.00	99.5

Three possibilities immediately come to mind in order to explain the difference in the corporate parameter between the present research and the results of both Rumelt (1991) and Schmalensee (1985). First, time must be a consideration. Perhaps the world shaped up a bit differently in the late 1980s and early 1990s vs. the mid-1970s. Second, the difference in methods, although minor, might have something to do with it. Finally, we must consider the differences in the data bases. Recall that the FTC data base contained a much higher number of SBUs per corporation (Table 1). Thus, diversification of the corporation may have something to do with the differing results.

There is not much we can immediately do with respect to the first speculation—the world-has-changed hypothesis. And, the differences in methods, in our judgment, should not have made that much of a difference in outcomes (recall we used both an iterative and noniterative method). But, we could investigate the third speculation—diversification of corporation. Rumelt (1991), citing a working paper from Kessides (see the citation on Kessides, 1987), reported that Schmalensee's data was reanalyzed in which all corporations which were active in fewer than three industries were excluded. The results produced a 'statistically significant' corporate effect (Rumelt, 1991: 170). The implication is, of course, the greater the diversification the greater the corporate effect since Schmalensee (1985), who included the less diversified corporations, found no significant corporate effect.

The average number of lines of business per corporation for Rumelt's (1991) Sample B was 6.07. Our average number of lines of business per corporation was 4.01. Thus, we began to perform sensitivity analysis on the analytical results by successively increasing the required number of SBUs per corporation to be included in the analysis. We went from a minimum of two SBUs per corporation to three, then four, etc. We were able to increase the SBU requirement through six. After a minimum of six SBUs per corporation, our statistical power trailed off precipitously. However, the minimum of six SBUs per corporation resulted in an average number of SBUs per corporation of 7.82. Figure 1 presents the results of our diversification sensitivity analysis together with a power function extrapolation.

As can be seen from Figure 1, there is a strong relationship between the number of SBUs per corporation and the percentage of SBU ROA variance accounted for by the corporate effect. What is particularly puzzling is our result which suggests the corporate effect is inversely related to diversification is exactly the opposite of the result obtained by Kessides (1987).

On the other hand, if we use a power function to model the diversification sensitivity results and then plot the average number of SBUs per corporation in Rumelt's (1991) 'B' sample (the larger sample), we obtain a value for the corporate effect of about 9 percent (see the vertical axis of Figure 1). Although we have not completely converged with Rumelt's (1991) results of 1.64 percent, we have narrowed the gap from about 16 percent (2% vs. 18%) to about 7 percent (2% vs. 9%). In the variance component analysis

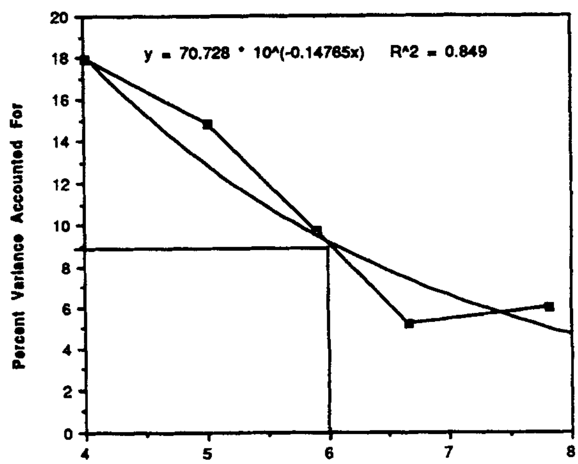

Figure 1. Size of corporate effect vs. degree of diversification

procedure, using differing data bases from different time periods, and somewhat different variance component techniques, 7 percent may not represent a great deal of divergence.

CONCLUSIONS AND RECOMMENDATIONS FOR FURTHER RESEARCH

It was anticipated that the dominant presence of SBU effects discovered by Rumelt (1991) in the FTC data base might be replicated in the more recent data; however, it was not expected that we would also find a nontrivial corporate effect. To be sure, these findings provide additional evidence that strategic management theory has an important role to play, as certainly even corporate managers in the general case might have a significant impact on SBU profitability. We suggest that the variance component results on the recent data base, especially when considered in conjunction with Rumelt's (1991) results, provide strong support for the study and theory development of strategic management concepts. Note that our combined variance accountability of corporate and SBU effects is 55 percent.

Further, if we reexamine Rumelt's (1991) five implications of his concluding paragraph, it appears that our results support four of the five (1, 2, 3, and 5): (1) 4-digit industries are more heterogeneous than homogeneous; (2) SBU ROA do not greatly differ by size; (3) the impact of industry effects on SBU ROA can only account for about 8 percent of the variance (in our case, 10%); (5) SBU ROA is the appropriate unit of analysis in lieu of industry averages. However, we differ with respect to Rumelt's fourth implication concerning corporate effects. We suggest the following modification: corporate effects may range from approximately zero to about 20 percent of the variance in SBU ROA, depending on (among other things) the diversification of the corporation—the greater the diversification, the less the corporate effect.

If such is the case, then we have introduced a further puzzle in that our findings are counter to those of Kessides (1987) (see the discussion on page 661). How could Kessides go from an insignificant to a significant corporate effect by restricting Schmalensee's FTC data to only those corporations with more than two SBUs? Frankly, we do not know. Since Kessides (1987) remained an internal working paper and was not published, at least to our knowledge, we have no way of determining the detailed procedures used.

In any future research, probably the first order of business would be to examine the 'why' of the diversification effect. Perhaps as the number of SBUs increase in a given corporation, the greater the tendency for the corporation to act as an internal capital market rather than as a builder of synergy among its various SBUs. Although such allocation of capital ought to produce some tendency toward superior financial performance, it may not yield as large a payoff as synergy building. Further, we need to explore possible reasons for our divergence with Kessides (1987).

In summary, it appears that Rumelt's basic proposition, namely that the variance within industries is greater than variance across industries, is strongly supported in our research results; and, the combined corporate effect and SBU effect account for far more of the variance than any other source, including error (see Tables 3 and 4). These results augur well for strategic management models.

REFERENCES

Andrews, K. (1971). *The Concept of Corporate Strategy*. Dow Jones-Irwin, Homewood, IL.

Barney, J. B. (1991). 'Firm resources and sustained competitive advantage', *Journal of Management*, **17**(1), pp. 99–120.

Bartlett, C. A. and S. Ghoshal (1991). 'Global strategic management: Impact on the new frontiers of strategy research', *Strategic Management Journal*, Summer Special Issue, **12**, pp. 5–16.

Bass, F. N., P. J. Cattin and D. R. Wittink (1977). 'Market structure and industry influence on profitability'. In H. B. Thorelli (ed.), *Strategy + Structure = Performance: The Strategic Planning Imperative*. Indiana University Press, Bloomington, IN, pp. 181–197.

Collis, D. J. (1991). 'A resource-based analysis of global competition: The case of the bearings industry', *Strategic Management Journal*, Summer Special Issue, **12**, pp. 49–68.

Conner, K. R. (1991). 'A historical comparison of resource-based theory and five schools of thought within industrial organization economics: Do we have a new theory of the firm?', *Journal of Management*, **17**(1), pp. 121–154.

Kessides, I. N. (1987). 'Do firms differ much: Some additional evidence', working paper, Department of Economics, University of Maryland.

Learned, E. P., C. R. Christensen, K. R. Andrews and W. D. Guth (1969). *Business Policy: Texts and Cases*. Irwin, Homewood, IL.

Lenz, R. T. (1981). 'Determinants of organizational performance: An interdisciplinary review', *Strategic Management Journal*, **2**(2), pp. 131–154.
Lippman, S. A. and R. P. Rumelt (1982). 'Uncertain imitability: An analysis of interfirm differences in efficiency under competition', *Bell Journal of Economics*, **13**, pp. 418–438.
Mason, E. S. (1939). 'Price and production policies of large scale enterprise', *American Economic Review*, **29**, pp. 61–74.
Montgomery, C. A. and M. E. Porter (1991). *Strategy: Seeking and Securing Competitive Advantage*. Harvard Business School Publishing, Boston, MA.
Nelson, R. R. (1991). 'Why do firms differ and how does it matter?', *Strategic Management Journal*, Winter Special Issue, **12**, pp. 61–74.
Nourse, E. G. and H. B. Drury (1938). *Industrial Price Policies and Economic Progress*. The Brookings Institution, Washington, DC.
Phillips, A. (1976). 'A critique of empirical studies of relations between market structure and profitability', *Journal of Industrial Economics*, **24**, pp. 241–249.
Porter, M. E. (1981). 'The contributions of industrial organization to strategic management', *Academy of Management Review*, **6**(4), pp. 609–620.
Porter, M. E. (1991). 'Towards a dynamic theory of strategy', *Strategic Management Journal*, Winter Special Issue, **12**, pp. 95–117.
Rumelt, R. P. (1974). '*Strategy, Structure, and Economic Performance*. Harvard University Press, Boston, MA.
Rumelt, R. P. (1984). 'Towards a strategic theory of the firm'. In R. B. Lamb (ed.), *Competitive Strategic Management*. Prentice-Hall, Englewood Cliffs, NJ, pp. 557–570.
Rumelt, R. P. (1991). 'How much does industry matter?', *Strategic Management Journal*, **12**(3), pp. 167–185.
Rumelt, R.P., D. E. Schendel, and D. J., Teece, (1994). *Fundamental Issues in Strategy*. Harvard University Press, Boston, MA.
Schmalensee, R. (1985). 'Do markets differ much?', *American Economic Review*, **75**(3), pp. 341–351.
Searle, S. R., G. Casella and C. E. McCulloch (1992). *Variance Components*. Wiley, New York.
Swamy, P. A. V. B. (1970). 'Efficient inference in a random coefficient regression model', *Econometrica*, **38**, pp. 311–323.
Teece, D.J. (1990). 'Contributions and impediments of economic analysis to the study of strategic management'. In J. W. Fredrickson (ed.), *Perspectives on Strategic Management*. Harper & Row, New York, pp. 39–80.
Weiss, L. (1971). 'Quantitative studies of industrial organization'. In M. D. Intriligator (ed.), *Frontiers of Quantitative Economics*. North-Holland, Amsterdam, pp. 361–403.
White, R. E. and R. G. Hammermesh (1981). 'Toward a model of business unit performance: An integrative approach', *Academy of Management Review*, **6**(2), pp. 213–223.
Winer, B. J. (1971). *Statistical Principles in Experimental Design* (2nd ed.). McGraw Hill, New York.

APPENDIX 1: VARIANCE COMPONENTS ANALYSIS (VARCOMP)

Variance component models are used extensively in the biological and life sciences for the analysis of experimental data. In these situations, there are often repeated observations taken on a single biological unit (typically a person or animal). The model postulates a unique latent 'effect' associated with each unit; such an effect is called a 'random effect' because it is assumed to be selected randomly from a process or population. Repeated measures on each unit are assumed to differ randomly from the unique effect. The term 'variance components' refers to the variability of latent unit effects in the respective population.

What makes variance components models so useful is that, unlike ordinary regression models, the variance of the response can be uniquely represented as a sum of variances due to multiple predictor variables. This in turn implies that a unique percentage of the response variable's variance is explained by predictor variable 1, by predictor variable 2, etc., and by random error. A limitation is that the predictor variables must be categorical; other assumptions also apply (Searle *et al.*, 1992).

Use of variance component models in business applications has been largely confined to the analysis of repeated-measures experimental data, as performed in sociological research (e.g., Winer, 1971). However, Swamy's (1970) 'random coefficients regression model' has been used for the analysis of econometric data with cross-sectional and time-varying characteristics. This model is similar to the experimental random-effects model in that individual units within a cross-section are assumed to behave according to unique latent time-series regression models, with the parameters of the regression models being the random effects.

APPENDIX 2: COMPARISON OF THE TWO METHODS OF CALCULATING AVERAGES

We define Rumelt's variance as

$$s_{TS}^2 = s^2(\bar{r}_{i..})$$

Assuming that the incidence pattern n_{ikt} is stable over time so that $n_{ikt} \equiv n_{ik}$, we have, using Rumelt's (1991: 180) calculations;

$$E(s_{TS}^2) = \sigma_\alpha^2 + (1/T)\sigma_\delta^2 + \sigma_\phi^2/I \sum_{i=1}^{I}\sum_{k=1}^{K}(n_{ik}/n_{i.})^2 + (1/T)\sigma_\epsilon^2/I\sum_{i=1}^{I}\sum_{k=1}^{K}(n_{ik}/n_{i.})^2$$

Extending Schmalensee's analyses to multiple years, we consider the *within-year cross-sectional industry variance, averaged over all years,* defined as

$$s_{CS}^2 = 1/T\sum_{t=1}^{T}s_t^2(\bar{r}_{i.t})$$

where $s_t^2(\bar{r}_{i.t})$ is the variance of the average industry return within a year. Algebraic manipulations similar to Rumelt's (1991: 180) yield

$$E(s_{CS}^2) = \sigma_\alpha^2 + \sigma_\delta^2 + \sigma_\phi^2/I \sum_{i=1}^{I}\sum_{k=1}^{K}(n_{ik}/n_{i.})^2 + \sigma_\epsilon^2/I\sum_{i=1}^{I}\sum_{k=1}^{K}(n_{ik}/n_{i.})^2$$

Thus, as with Rumelt's measure, the proportion of variance that can be attributed to the persistent industry effects can be measured as the ratio $\hat{\sigma}_\alpha^2/s_{CS}^2$. Note also that the total effects of industry (persistent and varying) are naturally defined as $(\hat{\sigma}_\alpha^2 + \hat{\sigma}_\delta^2)/s_{CS}^2$ with this measure.

Using the variance decompositions above, and assuming that the incidence pattern n_{ikt} is relatively stable in Rumelt's 4-year ($T=4$) study, Table A1 indicates how the variance of $\hat{\sigma}_\alpha^2/s_{CS}^2$ would have been partitioned in Rumelt's Table 5, p. 181. Although there are different values for industry and industry by year interactions, the total percentage of variance is stable using either definition: $39.3+9.3 = 48.6$ percent, vs. $25.5+24.1 = 49.6$ percent. Nevertheless, the latter percentage is the relevant percentage for the comparison with Schmalensee's figure of 75 percent, and as both Rumelt (1991) and Schmalensee (1985) pointed out, suggests unusual features with Schmalensee's selected year (1975).

Our third difference caused some concern due to the sensitivity of the variance components analysis to differing numbers of cases when analyzing industry averages. To make this clear, note that with a single year's data, Rumelts' second equation (1991: 180) reduces to

$$E(s_R^2) = \sigma_{\alpha'}^2 + \sigma_{\epsilon'}^2/m_h$$

where $m_h = I/\Sigma_i(1/n_i)$, which is the *harmonic mean* of the number of SBUs observed per industry in the working data base. Recall $\sigma_{\alpha'}^2$ and $\sigma_{\epsilon'}^2$ refer to interindustry and intraindustry variances, considering a single year only.

Proportion of variance in industry averages explained by industry effects is given by

$$\frac{\sigma_{\alpha'}^2}{\sigma_{\alpha'}^2+\sigma_{\epsilon'}^2/m_h}$$

or more simply as

$$\frac{1}{1+1/(\rho m_h)}$$

where $\rho = \sigma_{\alpha'}^2/\sigma_{\epsilon'}^2$. Using Table 4 of Rumelt (1991), we estimate ρ to be $16.12/83.08 = 0.194$ with Rumelt's data, and $19.46/80.54 = 0.242$ with Schmalensee's data. Adopting a conservative estimate of 75 percent variance explained, and solving for m_h, Schmalensee's data provide the harmonic mean of $m_h = 12.4$ SBUs per industry. The corresponding term in Rumelt's analysis, given in Equation 11 (1991: 175), is $1/0.195 = 5.12$, which would be the harmonic mean of SBUs per industry if the SBU incidence pattern were consistent over time. Note that

$$1/\{1+1/(5.12\times 0.194)\} = 0.498$$

agreeing with Rumelt's table.

Table A1. Variance partitions using data (sample A) from Table 5 of Rumelt (1991)

	Variance			
	s_{TS}^2		s_{CS}^2	
Source	Component	Percent	Component	Percent
Industry	23.3	39.3	23.3	25.5
Industry × Year	5.5	9.3	22.0	24.1
Business unit	25.3	42.7	25.3	27.7
Error	5.2	8.7	20.8	22.8
Total	59.27	100.0	91.4	100.0