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HOW MUCH DOES INDUSTRY MATTER, REALLY?

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In this paper, we examine the importance of year, industry, corporate-parent, and business-specific effects on the profitability of U.S. public corporations within specific 4-digit SIC categories. Our results indicate that year, industry, corporate-parent, and business-specific effects account for 2 percent, 19 percent, 4 percent, and 32 percent, respectively, of the aggregate variance in profitability. We also find that the importance of the effects differs substantially across broad economic sectors. Industry effects account for a smaller portion of profit variance in manufacturing but a larger portion in lodging/entertainment, services, wholesale/retail trade, and transportation. Across all sectors we find a negative covariance between corporate-parent and industry effects. A detailed analysis suggests that industry, corporate-parent, and business-specific effects are related in complex ways. © 1997 by John Wiley & Sons, Ltd.

Debate in strategy has long focused on the sources of performance differences among firms. In the research growing out of the industrial-organization tradition, industry structure is a central determinant of firm performance, and firm differences are considered against an industry background.[1] More recently, a line of thought sometimes called the resource-based view argues that firm performance is most influenced by unique organizational processes.[2] Under this view, industry structure is less important than idiosyncratic historical factors giving rise to firm differences.

Despite the importance of these questions, the relative influence of firm and industry effects on performance has received scant empirical study, reflecting both the unavailability of data and challenging statistical difficulties. Rumelt (1991) is perhaps the most influential study. Rumelt's research followed methods introduced by Schmalensee (1985) for disaggregating business-unit profits into components associated with industry effects, corporate-parent effects, and market-share effects. Neither Rumelt (1991) nor Schmalensee (1985) made claims about the economic or organizational processes underlying their results; both papers were descriptive rather than normative. Nevertheless some have interpreted Rumelt's finding of low stable industry effects to support the resource-based view.[3]

In this paper, we revisit the influence of industry, business-specific, and corporate-parent influences on profitability using comprehensive data and enhanced statistical methods. We examine the relative effects of these influences on profitability for the economy as a whole as well as in broad economic sectors. Finally, we begin to

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[1] Porter (1980) and Oster (1990) are in the industrial-organization tradition.

[2] For discussion of the resource-based view, see Conner (1991), Dierickx and Cool (1989a, 1989b), and Barney (1986, 1989).

[3] For example, see Levinthal (1995: 20).

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explore how the effects interact. Industry proves to have a powerful direct and indirect influence on profitability.

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Schmalensee (1985) examined the accounting profits of American manufacturing firms that were covered in the Federal Trade Commission's Line of Business Report for a single year, 1975. He found that industry effects accounted for about 20 percent of variation in business-unit profits (and nearly 100% of total variance explained), and that corporate-parent effects (or 'firm effects', in his terminology) had no impact on variation. Schmalensee's only measure of heterogeneity among participants in the same industry was market share. He reported that share positively affected business-unit profits, but only by a negligible amount.

Rumelt (1991) extended Schmalensee's approach by including data from the FTC Reports on manufacturing firms for all available years—1974 through 1977. With data on more than one year, Rumelt generalized Schmalensee's measure of intraindustry heterogeneity to all business-unit effects rather than just market-share effects. He reported that business-unit effects explain 44–46 percent of variation (about 73% of the explained variation), stable and transient industry effects account for a total of 9–16 percent of variation, and corporate-parent effects explain 1–2 percent of variation. It is these results—the relatively low proportion attributed to industry effects compared with business-unit effects—that have been interpreted to support the resource-based perspective.[4]

Our analysis differs from prior work in several ways. First, we use recently compiled data from the Compustat Business Segment Reports for 1981 through 1994. This dataset covers activity in all sectors of the American economy (except the financial sector), whereas the prior studies cover only manufacturing. The breadth of coverage provides not only a representative sample on the economy but also allows examination of profit influences across sectors. The average time series on each economic unit in our dataset is 5.7 years, which compares favorably with the 4-year series on each business unit in Rumelt's data. Because our dataset covers a 14-year period, our results reflect several phases of the business cycle.

Second, we show how the results are affected by a more robust statistical approach to intertemporal persistence. Rumelt's specification allows for transient industry effects, but does not similarly allow for transient year, corporate-parent, or business-unit effects. Our specification allows for transience in all effects, and we report the effect of the difference in method.

Third, our unit of analysis differs. The Compustat Reports contain information on firm profit by SIC code (i.e., by business *segment*), not by business *unit*. Schmalensee and Rumelt examined the business-*unit* returns given in the FTC data. We believe that the average business segment covers the activity of several business units. All else equal, the diversity of business-unit activity attributed to a single 4-digit SIC code may artificially reduce the measured influence of industry relative to Schmalensee and Rumelt. Moreover, our need to rely on the SIC system for industry classification further diminishes the measured estimates of industry influence because SIC industries err primarily in being overly broad. In our discussion, we suggest that the influence of industry might be even stronger if data of finer grain were available.

Like Rumelt, our specification includes a number of potential sources of variation in accounting returns: yearly macroeconomic fluctuations, industry factors, corporate-parent effects, and segment-specific effects. This last category, segment-specific effects, encompasses all business-segment

[4] Rumelt's report of low corporate-parent influence is not consistent with a resource-based view of diversification, and has stimulated additional research. In a study of diversified firms from the Compustat Business Segment Reports, Roquebert, Andrisani, and Phillips (1996) challenge Rumelt's result on corporate-parent effects. The authors find that corporate-parent effects are significantly more important than indicated by Rumelt (1991). The Roquebert *et al*. study is not directly comparable to Rumelt's (1991) or to ours because Roquebert *et al*. exclude single-business firms from their analysis. This exclusion means that estimates of industry effects are constructed from the performance of only diversified firms. In our Compustat Business Segment data, single-business firms account for half of all assets. When we exclude single-business firms from our data set, the estimated influence of industry decreases substantially. Low estimates of industry influence under the Roquebert *et al*. approach may distort estimates of corporate-parent influence because of negative covariance between industry and corporate-parent effects. This tendency may compound an upward bias in the estimated corporate-parent influence that arises from the exclusion of all single-business firms.

differences, including diversity in market share, differentiation, heterogeneity in fixed assets, differences in organizational processes, differences in organizational effectiveness, heterogeneity in activity configurations, anomalies in accounting practices, and differences in managerial competence. Our objective is to understand the relative significance of industry, corporate-parent, and segment-specific differences in explaining profit variation when industries are defined by the SIC system.

METHODS

Our analysis relies on the following model, which draws on the models used by Schmalensee and Rumelt:

$$r_{i,k,t} = \mu + \gamma_t + \alpha_i + \beta_k + \phi_{i,k} + \epsilon_{i,k,t} \qquad (1)$$

In this equation, $r_{i,k,t}$ is the accounting profit in year t of corporate-parent k's business in industry i. Profit is measured as the ratio of operating income to identifiable assets in percent. The first right-hand-side term is μ, which is the average profit over the entire period for all business segments. The second term is γ_t, which represents the difference between μ and the average profit of all business segments in year t. The next three terms represent industry, corporate-parent, and segment-specific effects. The term α_i is the increment to profit associated with participation in industry i; β_k is the increment to profit conferred by membership in a diversified corporate-parent k; and $\phi_{i,k}$ is the increment to profit associated with the specific situation of business segment i,k given the other effects. We assume that a corporate-parent effect arises only if a business segment is a member of a diversified firm. The final term, $\epsilon_{i,k,t}$, is the residual. Any of the increments to profit may be positive or negative. The model is estimated using dummy variables to represent industry, corporate-parent, and segment-specific effects.

Our study is limited by shortcomings in accounting measures of profit. Because accounting conventions exclude intangible assets from the balance sheet, measured assets may be too low for some segments. The use of operating income excludes the effects of differences in financing. Measurement error and accounting conventions may influence all four types of effects on profitability (i.e., year, industry, corporate-parent, and segment-specific).[5] Because we have no *a priori* hypothesis about the nature and direction of these biases, and because the Compustat Business Segment Reports are the best source of available data on profitability, we proceed with the analysis but interpret the results with caution.[6]

Our specification differs from Schmalensee's (1985) in several ways. Because Schmalensee had only one year of data, his analysis excluded both the year effect (γ_t) and the segment-specific effect ($\phi_{i,k}$). The segment-specific effect can only be identified when multiple years of data are available on each segment because only multiple years identify when a segment's performance differs systematically from the mean given the simultaneity of year, industry, and corporate-parent effects. Instead, Schmalensee included measures of market share that had been developed by David Ravenscraft for an earlier study on the FTC data (Ravenscraft, 1983).

Our model also differs from Rumelt's (1991), which is reproduced as Equation 2:

$$r_{i,k,t} = \mu + \gamma_t + \alpha_i + \beta_k + \delta_{it} + \phi_{i,k} + \epsilon_{i,k,t} \quad (2)$$

Rumelt's model includes an additional term to represent industry–year interactions, δ_{it}. By including both α_i and δ_{it}, he distinguishes 'stable' industry effects from 'transient' industry effects. Transient industry effects occur when all members of an industry have high or low profits in year t.

Rumelt proceeds by assuming that the error in Equation 2 is drawn independently. In making this assumption, he suppresses the possibility that a shock to the year, corporate-parent or business-specific effect at time $t-1$ influences the year, corporate parent or business-specific effect at time t. Suppose, for example, that a specific segment has an unusually good year at time $t-1$. Rumelt's specification does not account for the possibility

[5] For example, consider the ethical-pharmaceutical industry, which is relatively research-intensive. The industry effect for ethical pharmaceuticals reflects idiosyncratic conventions in accounting for research that similarly affect all members of the industry.

[6] Powell (1996) uses executives' perceptions instead of accounting profit to assess the influence of industry. He finds that industry accounts for about 20 percent of performance variation among the 54 single-business firms in his survey.

of a spillover effect on the segment in year t. By including industry–year interaction dummies, however, his model does capture spillovers that affect *all* the members of an industry. Now suppose that the business cycle generates unusually high year effects in successive years. Rumelt's industry–year interaction term may partly capture the influence of the business cycle, which would be attributed to persistence in the year effect in a complete model. Rumelt justified his approach by reporting no autocorrelation in residuals from his estimation. Nonetheless, this justification does not address the possibility that industry–year interaction effects may proxy for persistence in year, corporate-parent, and business-specific effects in his specification. This possibility is salient given that Rumelt's data cover the period immediately subsequent to the 1973 oil shock and to the removal of wage and price controls under the Nixon administration.

Although we appreciate the benefits of modeling transient industry effects, we exclude them because the model would be overspecified if we equally represented transient year effects, transient corporate-parent effects, and transient business-specific effects. This point is important to the differences in our econometric model compared with Rumelt's. In Rumelt's view, an asymmetry in treatment of industry effects is justified when the data cover a relatively short period because corporate-parent and business-specific effects will not change much (i.e., when shocks are small so that the persistence of shocks between years is not important). However, transience may arise at any level, and it is at least plausible that industry effects will change slower than business-specific or corporate-parent effects. Indeed, in another paper (McGahan and Porter, 1997) based on the same data set but somewhat different methods, we show that shocks to business-specific and corporate-parent effects may be larger than industry shocks.

To deal with the possibility that a shock in year $t-1$ might influence profits in year t, we allow for serial correlation on the errors in Equation 1 according to the following process:

$$\epsilon_{i,k,t} = \rho\, \epsilon_{i,k,t-1} + \omega_{i,k,t} \tag{3}$$

The parameter ρ captures the intertemporal persistence of effects *regardless* of source: macroeconomic fluctuations, industry, corporate-parent, or segment-specific. The error, $\omega_{i,k,t}$, for which we assume independence, is the portion of the transient shock that is not influenced by the shock in the prior year. This specification accommodates both new shocks and spillovers from the prior year, although it cannot capture differences in the rate at which shocks resound across years (Rumelt's model can capture differences in the rate of persistence in industry shocks). We acknowledge this deficiency, but argue that changes in the rate of persistence are important in the second order whereas the simple presence of persistence in year, corporate-parent and segment-specific shocks is important in the first order. As a result of this difference in specification, our principal estimates are comparable only with the stable effects in Rumelt's work.

It is important to note that α_i, β_k, and $\phi_{i,k}$ describe how a business segment is affected in *all* years by its industry, corporate parent, and segment-specific situation. The rate of persistence, ρ, reflects the influence of a shock in any single year on the performance in just the subsequent year. To isolate the portions of effects that are stable, we subtract from (1) the rate of persistence, ρ, multiplied by the lagged value of $r_{i,k,t}$:

$$\begin{aligned} r_{i,k,t} = {} & \rho r_{i,k,t-1} + (1-\rho)\mu + \gamma_t - \rho\gamma_{t-1} \\ & + (1-\rho)\alpha_i + (1-\rho)\beta_k + (1-\rho)\phi_{i,k} \\ & + \omega_{i,k,t} \end{aligned} \tag{4}$$

The left-hand side of this equation is the same as in (1): it is the profit to business segment i,k at time t in percent. The first term on the right-hand side is the rate of persistence multiplied by the profit to the same business segment at time $t-1$. In calculating lagged variables, we lose data for the first year for which we have information on each segment. The other terms on the right-hand side include the year, industry, corporate parent, and segment-specific effects.

We analyze this model in two ways, following Schmalensee and Rumelt. First, we conduct a components-of-variance (COV) estimation under the assumption that random processes generate each of the effects in Equation 1.[7] Consider, for

[7] This assumption is completely separate from our prior discussion of stable and transient effects. Here, we are describing the technical assumptions by which we estimate the model in Equation 4 *given* that the model includes only stable effects, year effects, and the error. At this point, we are interested in

example, the industry effect. The random-effects assumption stipulates that each observed industry effect is drawn randomly at some early date from an underlying population of possible industry effects. Once the effect is established, it remains fixed for the period under study. The population of possible industry effects cannot be observed, but is of primary interest because it determines the importance of industry. Because the observed industry effects are randomly drawn from this population, they may not perfectly represent the population (we expand on this point below).[8]

We also assume that the random processes that generate one type of effect are not correlated with the processes that generate other types of effects, with one exception. Following Schmalensee and Rumelt, we allow for covariance between corporate-parent and industry effects. A positive covariance would arise if attractive industries generated more opportunities for positive influence by corporate parents, or if corporate parents skilled at exploiting relationships between business units were also effective at selecting attractive industries in which to compete. A negative covariance would arise if the opportunities for positive influence by corporate parents were particularly great in unattractive industries.

We then decompose the variance of business-segment returns using Equation 5:

$$\sigma_R^2 = (1+\rho^2)\sigma_\gamma^2 + (1-\rho)^2(\sigma_\alpha^2 + \sigma_\beta^2 + \sigma_\phi^2) + 2(1-\rho)^2 C_{\alpha\beta} + \sigma_\omega^2 \quad (5)$$

The dependent variable in this equation, σ_R^2, is the variance of $R_{i,k,t}$, which is defined by $R_{i,k,t} = r_{i,k,t} - \rho r_{i,k,t-1}$ as the portion of the return to business segment i,k at time t that is not influenced by the shock in the prior year.[9] Equation 4 expresses the variance of this portion of return as a function of the rate of persistence, ρ; and of the population variances in year (σ_γ^2), industry (σ_α^2), corporate-parent (σ_β^2), and segment-specific effects (σ_ϕ^2); and of the population covariance between industry and corporate-parent effects ($2C_{\alpha\beta}$). Note that $\sigma_\omega^2 = [(1-\rho^2)\sigma_\epsilon^2]$. We use this expression to state our results in terms of σ_r^2, the total variance in $r_{i,k,t}$. Rumelt decomposed σ_r^2 by estimating the following equation:

$$\sigma_r^2 = \sigma_\gamma^2 + \sigma_\alpha^2 + \sigma_\beta^2 + \sigma_\delta^2 + \sigma_\phi^2 + 2C_{\alpha\beta} + \sigma_\epsilon^2 \quad (6)$$

In Equation 6, the term σ_δ^2 represents the population variance of the distribution of industry–year interaction effects.

The COV method is sufficiently unusual to merit further discussion.[10] The main idea is that each effect is treated as though it were generated by an independent, random draw from an underlying population of the class of effects. Once drawn, each effect is considered as fixed. The assumption of random effects does not stipulate that the Compustat data represent a random sample of business segments in the economy.[11] The assumption merely means that the represented effects are generated by random processes.

To estimate Equation 5, we exploit relationships in the sample variation among year, industry, segment-specific and corporate-parent effects. For example, the sample variation among industry effects is the sum of an unbiased estimate of industry variation plus a small portion of the underlying variation in the year effects plus a small portion of the underlying variation in the corporate-parent effects plus a portion of the underlying variation in the segment-specific effects. This equation may be expressed analyti-

the processes that make the stable effects differ across business segments. Searle (1971), chapter 9, provides a detailed discussion and several helpful examples of components-of-variance analysis. Also see Chamberlain (1984: 1254–1270; Chow (1984), Griliches (1984), and Rumelt (1991).

[8] Note that the assumption of random effects is somewhat different than an assumption of random sampling. Random samples arise when observations are independently drawn from a population. Random effects occur when observations are generated through draws from an underlying and unobservable probability distribution.

[9] We obtain Equation 5 from $R_{i,k,t} = (1-\rho)\mu + \gamma_t - \rho\gamma_{t-1} + (1-\rho)\alpha_i + (1-\rho)\beta_k + (1-\rho)\phi_{i,k} + \omega_{i,k,t}$. This expression gives $\sigma_R^2 = \mathrm{Var}[\gamma_t - \rho\gamma_{t-1} + (1-\rho)\alpha_i + (1-\rho)\beta_k + (1-\rho)\phi_{i,k} + \omega_{i,k,t}]$. Using our assumptions about the independence of random effects, we reduce the equation to $\sigma_R^2 = \sigma_\gamma^2 + \rho^2\sigma_\gamma^2 + (1-\rho)^2\mathrm{Var}(\alpha_i + \beta_k) + (1-\rho)^2\sigma_\phi^2 + \sigma_\omega^2$. Note that $\mathrm{Var}(\alpha_i + \beta_k) = \sigma_\alpha^2 + \sigma_\beta^2 + 2\mathrm{Cov}(\alpha_i,\beta_k)$. We therefore have $\sigma_R^2 = (1+\rho^2)\sigma_\gamma^2 + (1-\rho)^2(\sigma_\alpha^2 + \sigma_\beta^2 + \sigma_\phi^2) + 2(1-\rho)^2 C_{\alpha\beta} + \sigma_\omega^2$.

[10] Searle (1971) provides a comprehensive discussion of the approach. Rumelt (1991) provides an excellent discussion of how the method applies to a simple equation akin to the one here. He also describes the random-effects assumption in intuitive terms (pp. 172–173) and develops an example of the COV approach (pp. 174–176). Abowd *et al.* (1995) develop a model of covariance among persistence rates that accounts for the endogeneity of exit decisions.

[11] There has been some criticism of Schmalensee's and Rumelt's approach on the grounds that the FTC data do not represent a random sample of the population. We believe that this criticism is based on a misconception.

cally along with corresponding equations in which the dependent variable is the sample variation in each of year, corporate-parent, and segment-specific effects, and the right-hand side is a linear combination of the underlying population variances of the effects.[12] The result is a system of equations in unknowns that represent the unbiased estimates of population variances. By estimating the parameters in each equation (i.e., the 'portions' described above) and solving the system of equations, we estimate the portion of the variance attributable to each type of effect.

In our second approach to estimation, we analyze the variance of profits under the standard assumptions of ordinary least squares. Dummy variables represent year, industry, corporate-parent and segment-specific effects. Instead of examining each of the coefficients on the dummy variables, we examine the percent of variance explained by the models (R^2 and adjusted R^2) and evaluate F-tests to assess the importance of groups of effects. In theory, Equation 4 is estimable through simultaneous analysis of variance (ANOVA) methods. In practice, however, computational complexity prevented us from obtaining a simultaneous estimate of all types of effects.

Following Rumelt, we therefore estimate the model using nested ANOVA techniques.[13] The nested ANOVA allows us to evaluate whether each group of effects (i.e., year, industry, segment-specific or corporate-parent) is significant by introducing them in order. Under the approach, we first evaluate the full model in Equation 4 to obtain an estimate of ρ. We then obtain a null model by restricting all of the year, industry, corporate-parent, and segment-specific effects to zero. The null model stipulates that profits are entirely determined by shocks that persist at the rate, ρ, and the economic mean. The next step is to obtain year effects by regressing the residuals from the null model on the year dummies. An F-test provides an assessment of the importance of year effects by comparing the R^2 implied by ρ, the economic mean, and the year effects with the R^2 from the null model and by accounting for the number of year dummies that were introduced to achieve the additional explanatory power.

After we show that year effects are important, we obtain industry effects by regressing the residuals from the model (of year effects with the economic mean and accounting for persistence at the rate p) on the industry dummies. The industry effects are used to obtain an R^2 in a model that also includes the year effects, the economic mean, and the persistence in shocks at rate ρ. We conduct an F-test to evaluate whether the industry dummies add significant explanatory power. The procedure is then repeated for corporate-parent and segment-specific effects. After we complete the procedure, we repeat it under a different ordering to verify that the significance of each group of effects is not sensitive to the order of introduction.

There is controversy in the literature about the suitability of the COV and ANOVA approaches for this type of model. Schmalensee suggests that ANOVA results establish whether each set of effects is significant, and that COV results are preferable for evaluating the relative importance of each type of effect. He seems to prefer the COV over the ANOVA results (perhaps because he finds the random-effects assumption more natural than the fixed-effects assumption). The COV approach does not generate any test of significance, however, whereas the ANOVA approach generates F-statistics. The COV approach also incorporates a controversial assumption of independence in the random processes that generate the effects. The assumption of independence does not allow for the endogeneity of relationships between the levels of effects and subsequent entry or exit, for example. These issues apparently motivated Schmalensee to include the ANOVA estimates along with his COV analysis.

Rumelt (1991) makes a different assessment of the two approaches. He argues that an ANOVA

[12] For example, the equation that represents the relationship between the expected variance in the observed industry effects, Es_i^2, and the population variances is:

$$Es_i^2 = \sigma_\alpha^2 + a_\gamma\sigma_\gamma^2 + a_\beta\sigma_\beta^2 + a_\delta\sigma_\delta^2 + a_\phi\sigma_\phi^2 + a_C(2C_{\alpha\beta}) + a_e\sigma_e^2$$

where a_γ, a_β, a_δ, a_ϕ, a_C and a_e each represent complex ratios that account for number of draws on each type of effect. The intuition is based on the idea that the observed industry effects are calculated from data that include noise associated with the draws of year effects, corporate-parent effects, segment-specific effects, covariance effects, and errors. The amount of the 'noise' from each source is related to the number of draws from each distribution. Rumelt (1991: 174–176) provides a detailed example and shows how each of these ratios is obtained.

[13] See Searle (1987: chapter 3), for a detailed discussion of nested ANOVA.

test for significance is not a prerequisite to COV estimation. By Rumelt's logic, a COV analysis is a simple statistical description of the data, and he offers it as his flagship approach. Rumelt includes an ANOVA estimation because it has independent merit as a method for estimating the importance of effects. He suggests that further research on assumptions would be warranted if the two methods generate results that are very different.

We subscribe to Rumelt's logic, but add two additional words of caution. First, the nested ANOVA analysis is inherently imprecise because it largely attributes covariance between types of effects to the first effect introduced. In contrast, the COV approach is based on the assumption that effects are independently generated; for example, an incidence of exit by a segment is assumed to be unrelated to the industry effect for the segment. Although the COV approach is limited for this reason, we have no *a priori* hypothesis that the COV analysis is biased, and hence we also offer it as our flagship approach. We also concur with Rumelt's suggestion that qualitatively important differences in results should motivate further research on the appropriateness of the assumptions in each model.

DATA

The Compustat Business Segment Reports include information on companies with equity that is publicly traded in American markets. For each corporate parent, the Compustat Reports identify up to 10 lines of business because SEC guidelines require the reporting of information on segments that comprise 10 percent or more of the parent's business. Each line is identified by a segment number, which allows tracking of performance between years even if the name or primary SIC of the segment changed. For each business segment, the data set contains a primary 4-digit SIC code, operating income, sales, and identifiable assets. We used Compustat's conventions for dealing with the SIC revisions in 1981, 1987, and 1992.

We screened the Compustat data base in several ways. Before screening, the data set contained 151,929 records, each of which described a single business segment in a particular year between 1981 and 1994. From this dataset, we drop 2743 records that do not contain a primary SIC designation. A total of 22,041 segments are excluded because they are in SICs identified as 'not elsewhere classified,' 'nonclassifiable establishments,' or 'government, excluding finance.' We also drop segments designated as 'depository institutions' (15,689 financial business segments with SICs in the 6000s) because returns are not comparable with those in other industries. We exclude 2529 segments that are the only organizations covered by Compustat in their primary SIC classifications in specific years (analogous to monopolies) because we cannot distinguish their industry effects from their segment-specific effects. Another 1433 observations are excluded because they are associated with segments that are in Compustat for only one year. We then exclude 29,077 very small segments with sales less than \$10 million and an additional 5675 segments with assets less than \$10 million. Single-year appearances and small segments are often anomalous because they are created for the disposition of assets prior to exit, for example. The exclusion of small segments is comparable with Schmalensee's (1985) exclusion of units that account for less than 1 percent market share in his FTC Line of Business data set.

Our screened data set includes 72,742 observations, or an average of 5196 business segments per year. This figure is substantially larger than in previous studies. Schmalensee's dataset included 1775 observations. Rumelt ran his analysis on two datasets, which he labeled Sample A and Sample B. Sample A excluded the small business units that Schmalensee had excluded, and Sample B did not. Rumelt had 6932 observations in Sample A and 10,866 observations in Sample B. Because his results for the two datasets were similar, we focus our comparison with his Sample A to accommodate a simultaneous comparison with Schmalensee.

The raw Compustat Business Segment data (after screening only for missing observations and for financial firms) account for about two-thirds of the corporate sales and 45 percent of the corporate assets reported to the Internal Revenue Service for nonfinancial sectors from 1985 to 1992, the last year for which data are available. After the application of our screens, the data cover slightly more than half of corporate sales and slightly more than a quarter of corporate assets in nonfinancial sectors. Schmalensee reports that the FTC data in his study accounted for about half of manufacturing sales and two-thirds of manufacturing assets in 1975. Thus, our analysis covers a comparable percentage of competitive activity but over a much broader range of economic sectors.

In our analyses, we require that each observation include information on lagged performance. Thus, the first observation on each business segment is excluded. Our COV and nested ANOVA results are therefore based on 58,132 remaining observations. The screened dataset represents the activities of 12,296 distinct business segments in a total of 628 different industries, which are represented by their 4-digit SIC codes. The average business segment posts 5.7 years of data (including lagged information for the first observation). Each industry includes the activities of 7.7 business segments in the average year and 21.3 business segments on average over the entire period. Our analysis covers 7003 corporations, of which 1791 participate in more than one industry in at least one year for which we have data. Slightly less than half our observations are associated with diversified corporate parents. Table 1 describes the business segments in the screened data base by year and by economic sector. The mean profit is 9.3 percent with a variance of 248 percent.

There are several potent advantages to the Compustat data. First, the 5.7-year time series on each segment allows us to identify those effects that are stable over a somewhat longer period than the Rumelt study. Any measure of stability is integrally related to the number of years of data on each economic unit. A longer time series inherently leads to lower estimates of stability in effects. We believe that the 5.7-year average provides a useful benchmark.

A second advantage of the Compustat data is that it covers a longer period of time: 14 years vs. 4 years for the FTC dataset. The longer period allows us to measure the influence of various effects over several phases of the business cycle.[14] Although Rumelt's year effects surely capture part of the impact of these macroeconomic conditions, he does not have the latitude to examine whether the unusual conditions influenced industries, corporate parents, and business units in varying degrees. Our results are less vulnerable to anomalies because the entire period of our study is longer.

A third advantage of the Compustat data is that it captures a large portion of activity in all sectors of the American economy. Whereas Schmalensee's and Rumelt's studies focused on the manufacturing sector, our study covers the retail sector, wholesale services, mining and agriculture, food and textiles production, chemical businesses, transportation services, lodging and other services, entertainment, and all other industries except those in the financial and government sectors. This difference also means that we have many more observations than previous authors. In our final report of results, we exploit the variety in the Compustat data to show how results differ by economic sector.

There is evidence that the business segments in our data set are considerably larger than operating business units. The average segment in our screened data base has assets of $903 million, and diversified corporate parents post information on 2.6 segments on average. Montgomery (1994: 164) indicates that the *Fortune* 500 participated in 10.65, 10.85, and 10.90 different SICs on average in 1985, 1989, and 1992, respectively. Thus, it is likely that a typical Compustat segment, which is characterized by a 4-digit SIC code, actually reflects operating activity in several related 4-digit SIC codes.[15] As a consequence, the operations posted to each SIC in the Compustat data are probably more diverse than the actual operations in each SIC.

There are also some disadvantages to the Compustat data. The broadening of industry definition beyond the actual 4-digit level probably tends to dampen industry and corporate-parent effects, and potentially to distort segment-specific effects. These problems are exacerbated because the SIC system does not map closely to strategically distinct industries in some cases. As a result of these limitations, our results must be interpreted with caution. A finding of high segment-specific effects with low industry and low corporate-parent effects may reflect aggregation in Compustat

[14] The FTC dataset covers an unusual period in economic history immediately subsequent to the first oil shock and Nixon's wage and price controls.

[15] Seven out of our 628 industries are 2-digit, and 50 are 3-digit. The 2-digit industries account for 1.9 percent of assets in the dataset, and the 3-digit industries account for another 4.7 percent of assets.

Table 1. Screened Compustat Business-segment Data

(A) By year

	No.	Avg. assets ($mil)	Avg. profit[a]	Median profit		No.	Avg. assets ($mil)	Avg. profit[a]	Median profit
1982	5200	528	11.3	10.9	1989	5030	948	9.8	9.4
1983	5285	556	11.4	10.8	1990	5029	1028	9.5	9.0
1984	5205	598	11.9	11.6	1991	5114	1040	8.4	8.4
1985	5195	660	10.3	10.3	1992	5232	1051	9.0	8.7
1986	5249	699	9.2	10.0	1993	5396	1127	9.1	8.7
1987	5319	772	10.0	9.8	1994	5733	1161	9.1	9.0
1988	5112	865	10.4	9.9					

(B) By sector

First digit of SIC	Brief description of sector	No. of represented SICs	No. of represented segments	Avg. assets per segment ($mil)	Avg. profit per segment[a]
0,1,2	Agriculture, Mining	203	3661	966	11.2
3	Manufacturing	219	4068	677	8.1
4	Transportation	39	1651	2006	8.9
5	Wholesale & Retail Trade	91	1768	450	10.4
7	Lodging & Entertainment	53	987	315	9.2
8	Services	23	492	279	10.3

[a]Average ratio in percent of operating income to identifiable assets.

rather than real economic differences. This problem is related to the general question of appropriate industry definition.

EMPIRICAL RESULTS

In this section, we present our estimates of Equation 5 through COV methods and of Equation 4 through nested ANOVA methods. Table 2 shows the COV estimation of Equation 5. Results are expressed as a percent of σ_r^2, the total variance in business-segment profits. To transform our COV decomposition from σ_R^2 to σ_r^2, we use an estimate of ρ equal to 0.3777. This estimate is obtained from the nested ANOVA analysis and is described in detail below.

The results in Table 2 indicate that 51.60 percent of the total variance in business-segment profits is explained by the model. The error, which equals 48.40 percent of the total variance, arises because business-segment profits are sub-

Table 2. COV results developed from estimates of Equation 5[a]

	Percent of total variance
Year (σ_γ^2)	2.39
Industry (σ_α^2)	18.68
Corporate parent (σ_β^2)	4.33
Segment specific (σ_ϕ^2)	31.71
Corp.-par.–industry covariance ($2C_{\alpha\beta}$)	−5.51
Model	51.60
Error	48.40
Total (σ_r^2)	100.00

[a]Results are expressed as a percent of total variance, σ_r^2, rather than of σ_R^2 using an estimate of ρ equal to 0.3777.

ject to shocks, a portion of which may carry from one year to the next.

About 2 percent of the variance in profits is associated with *year effects*. By definition, these effects are macroeconomic fluctuations that affect all business segments to the same degree in a particular year.

Nearly 19 percent of variance is attributable to stable *industry effects*. This result provides strong support for the idea that industry membership has an important influence on profitability. The estimate is much higher than Rumelt's stable industry effect (8.32%) and is comparable with Schmalensee's result (19.59%).

Stable *effects of corporate-parent* membership account for nearly 4 percent of the variance in business segment profit. Although this estimate is absolutely low, it is higher than in prior research and suggests that the effects of corporate parents may have been greater during the 1980s and early 1990s than in previous decades. The negative covariance between corporate-parent and industry effects is consistent with the idea that corporate parents have a greater positive influence when they participate in unattractive industries.

Stable *segment-specific effects* account for nearly 32 percent of the variance in business-segment profitability. Our estimate of stable segment-specific influence is lower as a percent of total variance and of explained variance than Rumelt's business-unit effects, perhaps because of differences in method, in the unit of analysis, and in the average length of the series on each segment. A comparison with Schmalensee's model indicates that market share is a poor proxy for the segment-specific effect.

It is apparent that differences both in data and in method account for the differences between our results and those of previous authors. To obtain some insight into the relative importance of these two causes, we analyzed Rumelt's model on our manufacturing data and on our entire screened Compustat dataset. Table 3 compares Schmalensee's and Rumelt's reported results with our estimates.

The first column of Table 3 is a reproduction of Schmalensee's results. Because Schmalensee analyzed one year of data, the question of transient effects is not relevant, and his results are directly comparable to ours. His principal findings are that industry effects account for about 20 percent of variation in business-unit return; that market-share effects are small but significant; and that corporate-parent effects are not significant.

Rumelt's results for his Sample A are reproduced in the second column. They indicate that business-unit effects account for 46.37 percent of total variance, and that stable industry effects account for only 8.32 percent of variance. An additional 7.84 percent is explained by industry–year interaction (also called 'transient industry effects'). Rumelt originally estimated the variance in year effects as a small negative number, and the industry–corporate-parent covariance as a small positive number. As he notes, the negative estimate of the variance of year effects may be evidence of specification error; however, the absolute value of the estimate is so close to zero that it may be safely ignored. The impact of both the year variance and the industry–corporate-parent covariance are held to zero in the estimates reported in Rumelt's Table 3 and reproduced here.

The third column of Table 3 is our estimate of Rumelt's model, Equation 6, on the segments in our screened Compustat data classified as manufacturing. Stable and transient industry effects in the Compustat manufacturing data are modestly lower than in Rumelt's study, the influence of corporate-parent effects is higher, and a negative corporate-parent–industry covariance arises. The most striking difference between columns (2) and (3) is the 33.79 percent of variance attributable to segment-specific effects in the Compustat manufacturing data vs. the 46.37 percent of variance attributed to business-unit effects in Rumelt's study.

Because Rumelt's study covers only manufacturing firms, differences between columns (2) and (3) arise from the unit of analysis, the average length of the series, and the period from which the data are drawn. Problems in the SIC system for manufacturing probably lower the influence of industry effects in column (3). The difference between the results in columns (2) and (3) also may be affected by anomalies in the FTC dataset because of the 1973 oil shock and the removal of price and wage controls from the Nixon administration. Conditions in the macroeconomic environment may have exacerbated differences in business-unit positions to a greater extent than differences between industries. The unusual macroeconomic conditions also may have generated an unusually large variance in the industry–year interaction effects.

Table 3. Comparison of COV results (percent of total variance attributed to various effects)

	(1) Schmalensee[b] (as reported)	(2) Rumelt[c] (as reported)	(3) Rumelt model on McGahan and Porter manufacturing data	(4) Rumelt model on all McGahan and Porter data	(5) McGahan and Porter[a]
No. of observations	1775	6932	18,298	58,132	58,132
Year (σ^2_γ)					
Industry (σ^2_α)	N/A	N/A	0.40	0.37	2.39
Corporate parent (σ^2_β)	19.59	8.32	7.20	17.32	18.68
Segment specific (σ^2_ϕ)	N/A	0.80	2.05	6.96	4.33
Business unit (σ^2_ϕ)	N/A	N/A	N/A	N/A	31.71
Corp.-par.–ind.	N/A	46.37	33.79*	29.57*	N/A
covariance ($2C_{\alpha\beta}$)	–0.62	N/A	–1.42	–5.37	–5.51
Market share	0.62	N/A	N/A	N/A	N/A
Industry–year	N/A	7.84	4.44	4.39	N/A
MODEL	19.59	63.33	46.46	54.23	51.60
Error	80.41	36.87[d]	53.54	46.77	48.40
TOTAL (σ^2_r)	100.00	100.00	100.00	100.00	100.00

*Based on business segments rather than business units.
[a]Results in column (5) are reproduced from Table 2.
[b]Results in this column are reproduced from Schmalensee's Table 1 (1985: 348). Schmalensee's model is a variant of Equation 6 with an additional term for market share.
[c]These results apply to Rumelt's data set A and are based on his Table 3 (Rumelt, 1991: 178); Rumelt's Sample A excludes the same small business units that Schmalensee had excluded in his analysis of the FTC data.
[d]We calculate that this number, which is reproduced directly from Rumelt's Table 3, should be 36.67 given Rumelt's reports of the actual values of his estimates.

The fourth column of Table 3 shows our estimate of Rumelt's model, Equation 6, on our entire screened Compustat dataset. If we had used Rumelt's model, we would have found that stable industry effects account for 17.32 percent of variance and that transient industry effects account for 4.39 percent of variance. Although we would have attributed a greater portion of variance to corporate-parent effects (6.96%) than in Rumelt's study (0.80%), our attribution of variance to segment-specific effects (29.57%) would have been significantly lower than Rumelt's attribution to business-unit effects (46.37%).

A comparison of columns (3) and (4) provides support for the idea that differences in sectoral coverage influence the results. The Compustat dataset covers activity in all sectors of the economy, whereas the FTC data set used in Rumelt's study covers only manufacturers. The greater diversity of industries covered in the Compustat data generates higher industry effects. This tendency is probably offset in part by differences in the unit of analysis. If we had been able to disaggregate the Compustat data to the business *unit* level, it is likely that the figures for stable industry effects in columns (4) and (5) would be even greater than 17.32 percent and 18.68 percent.

Before conducting the estimation, we were concerned that our unit of analysis would suppress corporate-parent effects because of aggregation across business units. The results in columns (3), (4), and (5) indicate a greater influence of corporate parents than in previous studies. This outcome might reflect general changes in the climate for diversification. During the 1970s, unrelated conglomerates were probably more prevalent than during the 1980s and early 1990s.[16]

A comparison of the results in columns (4) and (5), which differ only in the employed model, is also instructive. The percent of variance explained by stable industry effects in column (5) is not much greater than the stable industry

[16] See Wernerfelt and Montgomery (1988) for a study of corporate-parent effects that accounts for relatedness.

effects in column (4). Also note that the portion of variance attributed to the corporate-parent effect is lower in column (5), but that the portion attributed to segment-specific effects is larger. The suppression of persistence in segment-specific and corporate-parent effects in Rumelt's model also results in a smaller error in column (4).

These comparisons suggest that the difference in method affects the results in an important way. When industry–year interaction is excluded from the decomposition, the variance attributed to year effects and to segment-specific effects increases. This supports the possibility that the interaction term in Rumelt's model may indeed proxy for persistence in other types of effects. The exclusion of the industry–year interaction is also associated with a lower attribution of variance to corporate-parent effects. This change indicates the possibility of strong covariance between the *persistence* of industry and corporate-parent effects, which is consistent with the strong covariance in the stable effects reported in the table. We cannot test for these relationships in this study, however, without overspecifying the model.

Table 4 shows the COV analysis by broad economic sector. The first section of the table, panel (A), provides information on the data. The greatest number of observations are present in the first two sectors: agriculture and mining,[17] and manufacturing. Over 200 different 4-digit industries fall within these two sectors. About half as many observations are associated with the transportation and wholesale/retail sectors, and somewhat fewer are associated with the lodging/entertainment and services sectors. Separate rates of persistence in shocks are obtained for each sector through nested ANOVAs by type of effect for each sector. Persistence is greatest in the manufacturing and lodging/entertainment sectors, with wholesale/retail trade, agriculture/mining, and transportation showing moderate persistence rates. Persistence is lowest in the service sector.

Panel (B) of Table 4 shows the results. The analysis generated three negative estimates of variance: for the year effect in the lodging/entertainment sector (–0.43%); for the corporate-parent effect in the manufacturing sector (–1.98%); and for the corporate-parent effect in the services sector (–2.66%). Negative variance estimates may be evidence of specification error, or they may reflect unimportant anomalies in the data. Concerns about data made us least confident about COV results for the service sector because the Compustat data excludes the many service-sector firms that are privately owned and not traded on major financial exchanges. Following Rumelt, we constrain the negative estimates of variance to zero and report results in Table 4 under the assumption that the negative estimates are too low to be significant.

There are several striking patterns in panel B of Table 4. The first is a remarkable variation in the importance of industry effects. In wholesale/retail, lodging/entertainment, and services, industry accounts for over 40 percent of the variance in profitability. In agriculture/mining and transportation, industry accounts for 39.50 percent and 29.35 percent, respectively, of variance. Manufacturing is the outlier, with industry accounting for just 10.81 percent of variance in profitability (and 23.3% of explained variance). In addition, manufacturing is characterized by the lowest total explained variance of the sectors.

Second, corporate-parent effects also vary markedly in impact. For manufacturing and service segments, corporate parents have no direct influence on variance in profitability. In wholesale/retail, however, variance in corporate-parent effects contributes more to the model than variance from any other source. This may reflect more pervasive opportunities for cross-unit relationships in wholesale/retail than in the more variegated manufacturing and service sectors. Corporate-parent effects are also large in transportation and agriculture/mining, perhaps for similar reasons.

Third, variance in segment-specific effects is more important in manufacturing than in any other sector. On average, manufacturing may offer richer possibilities for sustainable positioning than other sectors, a possibility also supported by the results of the previous studies. The only other sector in which segment-specific effects are comparable in importance is services. In the agriculture/mining, wholesale/retail and transportation sectors, variance in segment-specific effects contributes relatively little to total variance in profitability. In agriculture/mining and transportation, commoditization and regulatory influences may dampen interfirm differences.

[17] We pooled the agricultural and mining sectors in the analysis because there is apparent overlap in the SIC system between the sectors.

Table 4. COV by economic sector

	All	Agriculture, mining	Mfrs.	Transp.	W'sale, retail trade	Lodging and ent.	Services
(A) Characteristics of the data							
SIC designation		0,1,2	3	4	5	7	8
No. observations	58,132	16,829	18,298	9221	7937	4016	1831
No. industries	628	203	219	39	91	53	23
No. segments	12,296	3,661	4,068	1651	1768	987	492
No. diversified corp.'s	1,791	920	836	428	432	225	122
Total corporations	7,003	2,131	2,432	1164	1383	827	400
No. years/segment	5.7	5.6	5.5	6.6	5.5	5.1	4.7
Average profit[a]	9.3%	11.2	8.1	8.9	10.4	9.2	10.3
Est. persistence[b]	37.77%	29.91	40.52	26.90	34.31	44.20	14.03
(B) COV analysis developed from estimates of Equation 5[c]							
Year (σ_γ^2)							
Industry (σ_α^2)	2.39	2.25	2.34	3.25	2.64	N/A	4.17
Corporate parent (σ_β^2)	18.68	29.35	10.81	39.50	41.79	64.30	47.37
Segment specific (σ_ϕ^2)	4.33	22.35	N/A	28.33	44.06	14.71	N/A
Corp.-par.–industry	31.71	5.02	35.45	9.72	2.04	19.41	33.46
covariance ($2C_{\alpha\beta}$)	–5.51	–9.45	–2.27	–16.49	–20.24	–29.80	–23.98
MODEL	51.60	49.52	46.33	64.31	70.29	68.63	61.02
Error	48.40	50.48	53.67	35.69	29.71	31.37	38.98
TOTAL (σ_r^2)	100.00	100.00	100.00	100.00	100.00	100.00	100.00

[a]Average ratio in percent of operating income to identifiable assets.
[b]Obtained through a nested ANOVA on segments in the economic sector.
[c]Results are expressed as a percent of total variance, σ_r^2, in the profitability of segments in the sector.

Finally, the negative corporate-parent–industry covariance is remarkably robust. Again, manufacturing is an outlier, with an influence of covariance at –2.27%. In services, the negative corporate-parent–industry covariance is large even though corporate-parent effects do not contribute directly to the total variance. This result suggests that diversification in the service sector may be more affected by industry selection than by relationships between business segments.

Table 5 shows the sequential ANOVA analysis. Panel A shows the results when the industry effects are introduced before corporate-parent effects. In panel B, corporate-parent effects are introduced first. In each panel, the column labeled 'd.f.' shows the number of degrees of freedom associated with the introduction of each type of effect. The next column shows the increment to R^2 when each class of effect is introduced. Recall, however, that the ANOVA results are not reliable measures of the sizes of effects. The column labeled 'F-value' shows the F-statistic associated with the null hypothesis that the class of effects has no explanatory power. In all cases, F-values are significant at the 0.001 level, indicating that all types of effects are significant. The F-tests are flawed, however, because the estimates do not account for covariance. The final two columns show the minimum and maximum values of the effects implied by the estimates. In each case, the value is in the same terms as the expression in parentheses in the first column (marked 'source').

The estimate of ρ indicates that shocks in year $t-1$ persist in year t at the rate of 37.77 percent.[18] This persistence generates an R^2 of about 13 percent in the null model, which accounts for lagged effects and the grand mean. It is in this null model that we capture the intertemporal persistence of shocks between years, regardless of

[18] McGahan and Porter (1997) study this persistence in detail and show that it differs for high and low performers. For all classes of effects, the rate of persistence is significantly greater than zero.

Table 5. Results of nested ANOVA on Equation 4

Source	d.f.	Incr. R^2	F-value	Min. est.[a]	Max. est.[b]
(A) Ordering of effects: year, industry, corporate-parent, segment-specific					
Null model ($\rho r_{i,k,t-1} + (1-\rho)\mu$)*	2	0.129	8613.64**	−164.02	174.06
Year ($\gamma_t - \rho\gamma_{t-1}$)	12	0.003	18.26**	−1.40	1.75
Industry ($(1-\rho)\alpha_i$)	616	0.094	10.14**	−30.21	44.71
Corporate-parent ($(1-\rho)\beta_k$)	1,791	0.091	3.65**	−77.36	46.73
Segment-specific ($(1-\rho)\phi_{i,k}$)	9,877	0.351	2.39**	−113.34	171.39
MODEL	12,298	0.668			
Error	45,834	0.332			
TOTAL	58,132				
(B) Ordering of effects: year, corporate-parent, industry, segment-specific					
Null model ($\rho r_{i,k,t-1} + (1-\rho)\mu$)*	2	0.129	8613.64**	−164.02	174.06
Year ($\gamma_t - \rho\gamma_{t-1}$)	12	0.003	18.26**	−1.40	1.75
Corporate-parent ($(1-\rho)\beta_k$)	1,791	0.119	4.32**	−80.42	47.68
Industry ($(1-\rho)\alpha_i$)	616	0.068	8.21**	−34.49	36.80
Segment-specific ($(1-\rho)\phi_{i,k}$)	9,877	0.349	2.39**	−112.84	171.91
MODEL	12,298	0.668			
Error	45,834	0.332			
TOTAL	58,132				

*Estimate of ρ: 0.3777.
**Significant at the 0.0001 level.
[a]Minimum value of expression in parentheses implied by estimated coefficients.
[b]Maximum value of expression in parentheses implied by estimated coefficients.

source. Intertemporal persistence is introduced first in the sequence because in theory it is determined by activity in the prior year. The percent of variation that is not explained by the model, 33.2 percent, reflects transient shocks that do not persist between years.

The marginal R^2 for industry effects is 7–9 percent, for corporate-parent effects is 10–13 percent, and for segment-specific effects is 35 percent. The increment to R^2 for all three types of effects is smaller than estimated by Rumelt (as reported in his Table 2), perhaps because of a greater diversity of sectoral coverage and the longer time series in the Compustat data.

In the sequential ANOVA, the percentage of variation explained by industry effects is smaller than in the COV estimation, and the percentage of variation explained by corporate-parent effects is larger than in the COV estimation. The sequential ANOVA generates an incremental R^2 for segment-specific effects that is comparable to the percent of variance for segment-specific effects in the COV estimation. These differences may arise from relationships in the data between types of effects.[19] The negative covariance between industry and corporate-parent effects in the COV estimation has an impact of the same order as the variance of corporate-parent effects.[20] The sequential ANOVA tends to attribute this covariance to the first effect in the pair that is intro-

[19] Results from James (1996) suggest that corporate-parent effects and perhaps segment-specific effects might partially arise from managerial choice of generic strategy and from organizational learning. (James cannot identify segment-specific effects through dummy-variable techniques because she has a single observation on each business. Thus, her analysis focuses on the disaggregation of corporate-parent effects.) James's results are based on survey data from only 99 Compustat firms in 14 industries; each corporation participates in at least three different 4-digit SIC categories.

[20] Brush and Bromiley (1998) argue against this style of analysis because variance decomposition does not account for the details of relationships between corporate-parent and business-specific effects. For example, they note that the approach may attribute the effect of a corporate parent to one of its segments if the corporate parent improves only the performance of the one segment. Although we share the concerns expressed by Brush and Bromiley, we argue that a variance decomposition generates insights about aggregate performance that are important to establish the context for detailed analysis of specific relationships.

duced to the model, and thus the industry influence may be significantly lower than in a simultaneous ANOVA.[21]

As Rumelt originally suggested, the differences in the results from the COV analysis and ANOVA warrant research on the relationships between the processes through which year, industry, corporate-parent, and segment-specific effects arise. A close examination of these relationships is critical for verifying and perhaps revising the estimation approaches.

CONCLUSIONS

In this study, we revisit fundamental questions in strategy and economics about the relative importance of year, industry, corporate-parent, and segment-specific effects on business-segment profits using comprehensive data covering most broad economic sectors drawn from Compustat's Business Segment Reports for 1981 through 1994. The results indicate that variation in year effects, stable industry effects, stable corporate-parent effects, and stable segment-specific effects account for 2 percent, 19 percent, 4 percent, and 32 percent, respectively, of the aggregate variance in business-segment profits. We find a negative covariance between stable industry and stable corporate-parent effects that dampens the variance in business-segment profits by about 6 percent. These results support Schmalensee's (1985) principal conclusion that industry effects contribute importantly to variation in business-specific profitability, and call into question Rumelt's finding that stable industry effects have low influence.

Our results differ from those of previous studies for two reasons. First and most important, our data represent all economic sectors (except finance), and cover a longer period encompassing several phases of the business cycle. Second, our method treats transient effects differently. Through first-order differencing, we accommodate the possibility of persistence in shocks to year, industry, corporate-parent and segment-specific effects. As a result, we report results for only the stable portions of effects. These differences more than offset the reduction in the estimated influence of industry that results from the use of data aggregated to the Compustat business segment rather than to the FTC business unit.[22]

We also estimate the results by broad economic sector, and find large and interesting differences in the attribution of variance. In manufacturing, industry and corporate-parent effects account for a relatively lower portion of variance, while segment-specific effects account for a relatively high portion of variance (although less of total variance is explained). When we apply Rumelt's model to our manufacturing data, we obtain results quite similar to those reported in his 1991 study (which covered the manufacturing firms in the FTC Line-of-Business survey). Our analysis indicates that manufacturing, which has been the focus of previous studies, is an outlier: generalizations about the economy as a whole that are based on the results for manufacturing understate the importance of industry and corporate-parent effects, and overstate the importance of segment-specific effects.

Our analyses provide strong support that industry really matters in three important ways. First, industry directly accounts for 19 percent of aggregate variation in business-specific profits, and 36 percent of explained variation. Second, industry influences the effect of the corporate parent on business-specific profitability. Third, the absolute and relative influence of industry, corporate-parent, and business-specific effects differs substantially across broad economic sectors in ways which suggest characteristic differences in their industry structural context. To these three findings, we add a fourth from a related study. We find that industry effects are more persistent over time than business-specific or corporate-parent effects, which is consistent with the view that

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[21] A simultaneous ANOVA would generate estimates of coefficients which could be examined for covariance. We are prevented from this analysis by limitations in computing capacity. Even among the coefficients as estimated by the nested ANOVA, we have evidence of complex relationships among types of effects, however. The simple correlation between estimates of industry and segment-specific coefficients is –0.0203 in panel (A) and 0.0111 in panel (B) of Table 5. The simple correlation between estimates of corporate-parent and segment-specific coefficients is –0.0101 in panel (A) and 0.0343 in panel (B) of Table 5.

[22] The difference in our unit of analysis affects results in subtle ways. Although business segments nominally represent a corporation's activity by 4-digit SIC code, we have evidence that aggregation occurs in reporting. Aggregation probably dampens industry effects and may obscure interesting differences in business-unit performance. The longer average series in our data set—5.7 years vs. 4 years in Rumelt's study—also tends to diminish the portion of effects that are stable.

industry structure changes relatively slowly (McGahan and Porter, 1997). These results do not support the assertion that rapid change in the economy has diminished the influence of industry. While the organizational differences emphasized by the resource-based view are surely meaningful (and would be included in our estimates of segment-specific differences), it would be misguided to disconnect the influence of organization from the industry and competitive contexts in which firms operate.

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