

BUSINESS SEGMENT PERFORMANCE REDUX: A MULTILEVEL APPROACH

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Over the last 20 years, strategy scholars have explored the relative influence of industry and corporate effects on business segment performance. The present research acknowledges the inherent multilevel, cross-classified nature of the data and demonstrates that results are not robust to statistical method. Using 1995–99 data from ‘operating segments,’ the multilevel analysis presented in this article found that (1) business segment effects explain twice as much variance in business segment performance as do corporate effects, (2) corporate effects explain almost four times more variance in business segment performance than industry effects, and (3) segments explain almost eight times more variation than industry effects. Methodologically, multilevel analysis offers statistical advantages over variance components analysis, nested ANOVA, and two-stage least squares. More importantly, the method provides a means for modeling relationships between the industry, corporation, and business segments, thereby moving beyond the descriptive nature of explained variance. Copyright © 2006 John Wiley & Sons, Ltd.

When an industry with a reputation for bad economics meets a manager with a reputation for excellence, it's usually the industry that leaves with its reputation intact. (Warren Buffet)

Buffet's quote captures one of the fundamental strategy conversations of the last 20 years: the extent to which industry and corporate parentage influence business segment performance (Brush, Bromiley, and Hendrickx, 1999; McGahan and Porter, 1997; Roquebert, Phillips, and Westfall, 1996; Rumelt, 1991; Schmalensee, 1985; Wernerfelt and Montgomery, 1988). Results indicate that industry factors explain from 10 percent (Roquebert *et al.*, 1996) to 20

percent (Schmalensee, 1985; Wernerfelt and Montgomery, 1988) of segment performance, while corporate-level factors explain from less than 1 percent (Rumelt, 1991; Schmalensee, 1985) to almost 18 percent (Roquebert *et al.*, 1996). Four studies showed that industry effects were greater than corporate-level effects (McGahan and Porter, 1997; Rumelt, 1991; Schmalensee, 1985; Wernerfelt and Montgomery, 1988). In sharp contrast, Brush *et al.* (1999) and Roquebert *et al.* (1996) found that corporate effects were greater than industry effects by an R^2 ratio of 1.7 to 1.

Several explanations have been offered for these conflicting results. First, corporate effects are dampened by the inclusion of single-business corporations, which effectively constrains the corporate effects to zero for a portion of the sample (Brush *et al.*, 1999). Second, the two different data sources, FTC line-of-business and Compustat, combine corporate divisions in slightly different ways, which influences the magnitude

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of corporate effects (Bowman and Helfat, 2001). In addition, the FTC data covered the time period 1974–77 when corporate diversification was not as prevalent or as strategically important as during the 1980s. Thus, corporate effects using FTC datasets may be smaller than corporate effects observed in Compustat datasets from time periods when diversification was more widespread. Third, studies have used datasets ranging from 1 to 14 years. Although longitudinal data helps distinguish stable from transient effects through examination of year crossed with industry, corporate, or segment effects, the stable portion of industry and corporate effects are dampened as the length of the time series increases (Mauri and Michaels, 1998; McGahan and Porter, 1997). Fourth, many studies used variance components analysis (VCA), which may produce unreliable variance estimates or estimates that underrepresent the true importance of the effect (Brush and Bromiley, 1997). Also, VCA can produce negative variance estimates (Rumelt, 1991). With one exception (i.e., Ruefli and Wiggins, 2003),¹ the remaining studies employed analysis of variance (ANOVA) techniques, which provide equivocal results due to order of entry differences (Kennedy, 1998) and the collinearity of corporate and business segment dummy variables (Bowman and Helfat, 2001).

The separation of single- vs. multi-segment businesses and the use of more recent longitudinal data have been incorporated into this line of inquiry by earlier research. However, methodological problems with VCA and nested ANOVA remain. Brush *et al.* (1999) propose the use of two-stage least squares (2SLS) as a solution. One advantage of 2SLS is the ability to use continuous variables, such as industry or corporate profitability, in the examination of business unit profitability, thus requiring fewer degrees of freedom than required by dummy variable approaches such as nested ANOVA. 2SLS also provides more power than VCA to detect smaller, but significant, effects (Brush *et al.*, 1999). Yet, simultaneous equations approaches, such as 2SLS, require that models be

limited to corporations with a specified number of business segments (e.g., Brush *et al.*, 1999, examined three-segment corporations and four-segment corporations in separate models). These restricted models may not be representative of estimates that would be observed in models with a different number of segments or in models with varying numbers of segments per corporation. Furthermore, 2SLS creates an artificial segment ‘position’ classification; that is, separate equations are estimated for business segment 1, 2, 3, etc., thus generating separate R^2 values based on an arbitrary ordering of the segments. To estimate the overall variance explained by corporation or industry, the various segments must be averaged or otherwise aggregated (see Table 6 in Brush *et al.*, 1999). Furthermore, much like ANOVA techniques, the estimation of segment effects in 2SLS requires the use of dummy variables.

This paper provides an alternative technique that addresses the shortcomings of traditional VCA, nested ANOVA, and 2SLS by exploiting the inherent multilevel nature of business segment performance. This approach, which is appropriate for many strategy problems, but rarely used, offers a means for moving beyond simple models of variance decomposition toward complex models that examine explanatory variables at multiple levels of a data hierarchy. The next section uses a simple example to provide a general overview of multilevel analysis. The remainder of the paper applies multilevel analysis to the problem of estimating industry, corporate, and business segment effects. For comparison purposes, the multilevel results are compared to results from VCA, nested ANOVA, and 2SLS using the same dataset. Additionally, the results are compared to results from several previous studies.

APPLYING MULTILEVEL ANALYSIS

Organizations are hierarchically ordered systems. That is, employees belong to departments, departments are nested within divisions, and divisions make up corporations. The divisions, or business segments, are also nested within industries. This double nesting of business segments within corporations and within industries is a special case of hierarchical systems called cross-classification. The use of multilevel analysis to examine such hierarchically ordered systems avoids statistical

¹ Ruefli and Wiggins (2003) used a non-parametric, ordinal variable approach that measures the percentage of segments correctly classified as superior, modal, or inferior performers. Thus, their approach is not comparable to approaches such as VCA, nested ANOVA, 2SLS, or multilevel analysis that can be used to decompose the percentage of business segment performance variance into its component parts.

concerns (Hofmann, Griffin, and Gavin, 2000) such as lack of independence and aggregation to higher levels. Lack of independence between observations occurs when multiple observations are included from the same higher-level unit, for example, using observations from multiple business segments from the same corporation in a study examining the relationship between business segment profitability and corporate climate. Aggregation to higher levels of analysis creates a loss of information, for example, aggregating international sales from multiple business segments to the corporate level in a study of corporate strategy and international activity.

By explicitly modeling each level of the hierarchy, multilevel models acknowledge that individuals within a group (or business units within a corporation) are more similar to one another than individuals from different groups. Practically speaking, multilevel modeling allows for regression-like modeling of relationships at the lowest level of analysis alongside regression-like models that describe how the within-unit relationships vary between units. Thus, random influences on the outcome variable can be modeled for each level of the data hierarchy (e.g., performance differences among business segments within a corporation, performance differences among business segments within the same industry, and the residual influences between years for a given segment). In effect, multilevel analysis provides the benefits of 2SLS (i.e., the use of continuous predictor variables and fewer degrees of freedom than dummy variable approaches), without the drawbacks (i.e., multilevel analysis does not require a pre-specified number of business segments, does not create an artificial segment 'position' that requires averaging across position to arrive at summary statistics for the corporation, and does not necessitate the use of dummy variables to estimate industry, corporate, or segment effects).

Consider the influence of business-level effects on business-level returns. Strategy, structure, climate, control systems, management characteristics, and international activity are just a few of the business-level factors that have been related to business-level profitability. For example, we might hypothesize that innovation, as indicated by R&D intensity, has a positive effect on business-level returns. The simple ordinary least squares (OLS) regression equation at the business unit level of analysis is shown in Equation 1. The errors, e_i ,

are assumed to be independent and normally distributed with constant variance.

$$\text{Return on assets}_i = \beta_0 + \beta_1 \text{R&D intensity} + e_i \quad (1)$$

However, this equation disregards the industry context of the business segment, thereby ignoring the fact that average returns differ from industry to industry even after accounting for the effects of R&D intensity. To account for industry effects, dummy variables could be added to the OLS regression equation, thereby changing the intercept for each industry. Extending this simple example to examine three different industries, e.g., pharmaceuticals, consumer products, and retail, we could use two dummy variables as follows:

$$\begin{aligned} \text{Return on assets}_i = & \beta_0 + \beta_1 \text{R&D intensity} \\ & + \beta_2 \text{Consumer products} + \beta_3 \text{Retail} + e_i \end{aligned} \quad (2)$$

In essence, Equation 2 estimates three separate parallel lines representing the three industry contexts, thereby indicating that some industries perform better, after accounting for R&D intensity, than others. This acknowledges that the relationship between R&D intensity and ROA is, in some ways, similar between industries (i.e., common slope of β_1) and in some ways the relationship differs between industries (i.e., varying intercepts of β_0 for pharmaceuticals, $\beta_0 + \beta_2$ for consumer products, and $\beta_0 + \beta_3$ for retail). Models taking on the form of Equation 2 are commonly known as *analysis of covariance* (ANCOVA) models. Deleting the R&D intensity covariate, the model takes the form of a traditional one-way *analysis of variance* (ANOVA) for ROA across the pharmaceutical, consumer products, and retail industries.

By modeling ROA as a function of R&D intensity plus the cross-products of the industry dummy variables and R&D intensity (i.e., adding cross-products to Equation 1), we estimate three separate equations that have the same intercept but different slopes. Steeper slopes indicate that the relationship between R&D intensity and ROA is stronger for that particular industry. On the other hand, if we add these cross-product terms to Equation 2, we estimate three separate lines with different intercepts and different slopes for the three different industry contexts. Such an analysis acknowledges the uniqueness of the industry contexts and does not assume common intercepts or slopes.

In Equations 1 and 2, the coefficients (e.g., β_0 , β_1 , β_2 , β_3) are known as *fixed effects coefficients*. One limitation of fixed effects analyses such as ANCOVA or ANOVA is the inability to estimate the relative importance of various groups of effects (e.g., industry effects vs. corporate effects). To escape this problem, researchers have compared R^2 values for nested models (e.g., Brush *et al.*, 1999; McGahan and Porter, 1997; Rumelt, 1991; Schmalensee, 1985; Wernerfelt and Montgomery, 1988; cf. Kmenta, 1971). However, this approach produces equivocal results dependent on the order of variable entry. Another problem arises when we are interested in a group that is defined by a large number of members, e.g., industries defined by 4-digit SIC code or all diversified corporations. When groups have a large number of members, dummy variable approaches use many degrees of freedom and therefore limit statistical power when compared to approaches that are more parsimonious (e.g., approaches such as 2SLS, which estimate fewer parameters by using continuous predictors; Brush *et al.*, 1999: Appendix 2).

Instead of estimating $j - 1$ fixed industry effects (where j is the number of industries), we may want to make inferences about the population of industries. In this case, we can estimate the industry parameter as a *random effect* that consists of random (and perhaps fixed) components where the random component is assumed to be distributed as a probability function (Kreft and de Leeuw, 1998). Conceptually, fixed effects models estimate parameters for a given and generally small set of contexts that are of particular interest to the researcher, e.g., the three industries considered in the example above. Random effects models, on the other hand, use information provided in the sample to estimate parameters that describe how the population of contexts differs from the overall average. This is the same argument used by Rumelt (1991) to support use of VCA, which is a random effects technique. ‘The real substance of the random-effects assumption is that the differences among effects, whatever their sources, are ‘natural’, not having been controlled or contrived by the research design’ (Rumelt, 1991: 172).

Thus, if we want to model the differences across industries as a random intercept and a fixed slope (cf. OLS Equation 2, which estimated different fixed intercepts for three specific industries and a common fixed slope), we use industry subscripts to model business segment ROA as a function of

industry (Equation 3a). In addition, we add level 2 equations that model the variance of the industry intercepts (Equation 3b) and that model a fixed industry slope (Equation 3c). Thus, Equation 3a represents the business unit level of analysis, referred to as level 1, while Equations 3b and 3c represent the industry level intercepts and slopes, referred to as level 2. It is important to note that we can now examine a much broader range of industries than the three industries selected earlier without losing degrees of freedom as would be the case in traditional fixed effect OLS approaches. Furthermore, the three equations demonstrate why multilevel analysis is described as a system of regression equations with more than one error term (in this example, e_{ij} and u_{0j}).

$$\text{Return on assets}_{ij} = \beta_{0j} + \beta_1 \text{R\&D intensity} \\ + e_{ij} \quad (3a)$$

$$\beta_{0j} = \gamma_{00} + u_{0j} \quad (3b)$$

$$\beta_1 = \gamma_{10} \quad (3c)$$

Substituting Equations 3b and 3c into 3a yields Equation 3d, where γ_{00} and γ_{10} are the fixed effects and u_{0j} and e_{ij} are the random effects. This model is referred to as the *random intercepts model*. Such models are similar to the traditional ANCOVA models discussed above (see Equation 2) except the group effects, u_{0j} , are treated as random effects rather than fixed effects. In essence, ROA is modeled as the mean of the intercepts across industries, γ_{00} ; plus a pooled within-industry regression coefficient of ROA on R&D intensity; γ_{10} , plus industry-dependent deviations from the intercept; u_{0j} , plus a residual after adjusting for R&D intensity, e_{ij} . The total variance of ROA after controlling for R&D intensity is the variance of e_{ij} plus the variance of u_{0j} .

$$\text{Return on assets}_{ij} = (\gamma_{00} + u_{0j}) \\ + \gamma_{10} \text{R\&D intensity} + e_{ij} \\ = \gamma_{00} + \gamma_{10} \text{R\&D intensity} \\ + u_{0j} + e_{ij} \quad (3d)$$

If the model does not depend on predictor variables at any level (i.e., deleting R&D intensity from Equation 3a and thus Equation 3d), the model is referred to as *fully unconditional* (Raudenbush and Bryk, 2002) or *null* (Kreft and de

(Leeuw, 1998). The fully unconditional model is equivalent to a variance components model with one important caveat—the method of estimation. Rumelt (1991), McGahan and Porter (1997), and Brush and Bromiley (1997) used sum of squares estimation techniques in their variance components models, which can produce negative variances. Multilevel analysis, on the other hand, uses iterative estimation procedures that do not produce negative variances.² Furthermore, multilevel analysis can be extended to include predictors at any level of analysis, whereas VCA only estimates the variance components.

We can extend the random intercepts model of Equation 3d to allow for variation in the industry slopes by adding a random effect to the level 2 equation for the slope (Equation 3c). After substitution we obtain the *random-coefficients regression* model given in Equation 4. Note that the term u_{1j} R&D intensity allows for heteroscedasticity, meaning that the error variance among industry slopes depends on R&D intensity, a condition that violates the assumptions of ordinary least squares regression.

$$\text{Return on assets}_{ij} = \gamma_{00} + \gamma_{10} \text{R&D intensity} \\ + e_{ij} + u_{0j} \\ + u_{1j} \text{R&D intensity} \quad (4)$$

where γ_{00} = mean intercept across industries, γ_{10} = mean slope across industries, $\text{var}(e_{ij})$ = within-business segment residual variance, $\text{var}(u_{0j})$ = variance among industry intercepts, and $\text{var}(u_{1j})$ = variance among industry slopes.

Equations 2, 3d, and 4 are represented graphically in Figure 1(a, b, c) (cf. Kreft and de Leeuw, 1998). The traditional fixed-effects ANCOVA represented by Figure 1(a) (see Equation 2) provides three separate parallel lines representing three specific industry contexts, indicating that some industries perform better than others after accounting for R&D intensity. The random intercepts model shown in Figure 1(b) (see Equation 3d) shows an average line with equidistant dashed lines on either

² Due to the presence of multiple random effects, estimation of the multilevel model is accomplished using iterative procedures such as maximum likelihood or restricted maximum likelihood, which alternate between estimation of the fixed and random coefficients until the solution converges. Chapter 2 in Goldstein (1995) and Chapters 3 and 14 in Raudenbush and Bryk (2002) provide mathematical details for estimation.

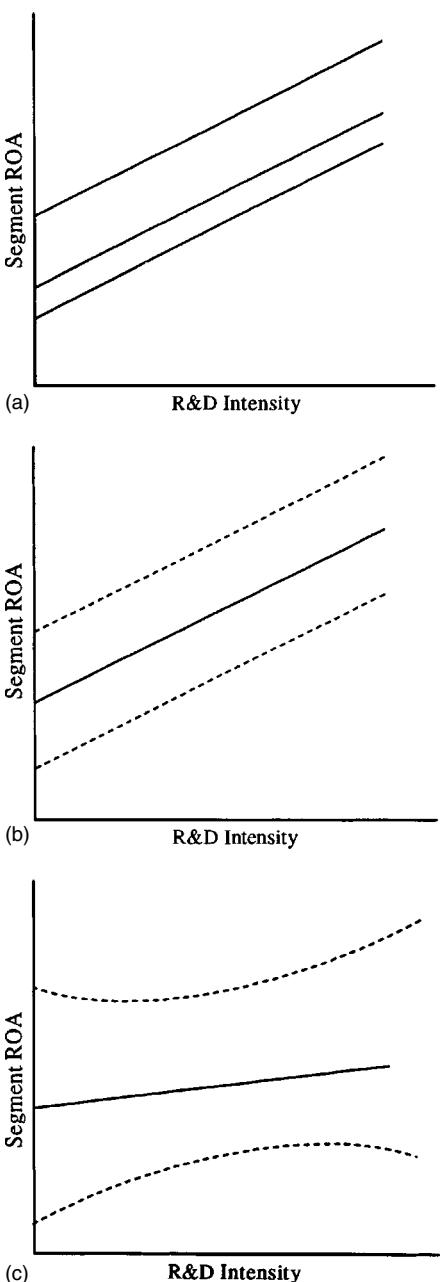


Figure 1. Graphical representation of R&D intensity vs. segment ROA for (a) ANCOVA, (b) random intercepts model, and (c) random coefficients regression

side, which indicate a constant slope. The dashed lines represent the random variation in intercepts across industries, which is equal for all values of R&D intensity. Figure 1(c) (see Equation 4) represents the random coefficients regression where the pattern of variation around the solid line represents variance in the slopes, variance in the intercepts,

and the covariance between the slopes and intercepts. The irregular space between the dashed lines in Figure 1(c) illustrates that the variance of the slopes and the covariance between the slopes and intercepts is dependent on the value of R&D intensity.

Two-level models, such as those just discussed, can be extended to encompass additional levels and may include multiple predictors at each level. For example, the change in business segment ROA over time can be modeled with a three-level model where level 1 is time, level 2 is the business segment, level 3 is the industry, and the dependent variable is the business segment ROA for a specific year. Furthermore, R&D intensity could be included as a level 1 predictor, business segment size could be included as a level 2 predictor, and industry growth rate could be included as a level 3 predictor.

Adding the corporate level to our analysis requires acknowledging that the relationship between business segments, corporations, and industries is not strictly hierarchical. Instead, business segments are nested within corporations *and* within industries. For example, NBC is an operating segment of General Electric (GE) that competes in the broadcasting industry. However, GE competes in many other industries as well. So, NBC is nested within GE *and* within the broadcasting industry. Multilevel analysis permits the direct estimation of such cross-classified models (Goldstein, 1995) and correctly partitions the shared variance between business segments, corporations, and industries.³

In summary, multilevel analysis offers several advantages over traditional VCA (e.g., McGahan and Porter, 1997; Rumelt, 1991), nested ANOVA (e.g., McGahan and Porter, 2002), and 2SLS

³ For example, in two-level data structures that are strictly hierarchical, the covariance matrix of y has a block-diagonal structure where the blocks are defined by the level 2 units. With a cross-classified structure, we add another set of level 2 units, which requires modification of the covariance matrix to a non-block diagonal form. Thus, where business segments are cross-classified within corporations and within industries, the variance of y is the variance in industries plus the variance in corporations plus the random error. The covariance between two segments is (1) the variance of the corporation, when the segments are from the same corporation but different industries, (2) the variance of the industry, for two segments from the same industry but different corporations, (3) the variance of the corporation plus the variance of the industry, when the segments are from the same corporation and the same industry, and (4) zero, when the two segments are from different corporations and different industries. For additional detail, see Rasbash and Goldstein (1994) and Chapter 8 in Goldstein (1995).

(e.g., Brush *et al.*, 1999) when examining business segment performance. First, multilevel analysis addresses dependence between levels of analysis by permitting complex error structures at each level of the analysis. In contrast, nested ANOVA techniques model a single independent error term even though inherently nested data structures (such as segments within corporations) violate the assumption of independence. Although VCA partitions variance into different effects, sum of squares estimation techniques may produce negative values. Multilevel analysis, however, uses iterative estimation to simultaneously estimate all variance components and produce feasible, i.e., non-negative, estimates. Second, random effects approaches, such as multilevel analysis, provide increased statistical power over fixed effect, dummy variable approaches such as ANOVA. Although VCA also estimates random effects, Monte Carlo studies show that VCA using sum of squares estimation techniques lacks the power to find 'smaller but substantial' effects (Brush *et al.*, 1999: 519). Multilevel analysis, on the other hand, uses more powerful estimation techniques. Third, multilevel cross-classification procedures resolve the problem of collinearity between corporations and industries encountered when using 2SLS (Brush *et al.*, 1999) and ANOVA (Bowman and Helfat, 2001; Kennedy, 1998; Rumelt, 1991), which often impute shared variance to the first term entered in the analysis. Furthermore, unlike 2SLS, multilevel cross-classification allows any number of segments to be associated with a corporation (including situations where the number of segments for a corporation varies across years) and therefore does not require the artificial classification and estimation of segment position 1, segment position 2, etc.⁴ Most importantly, multilevel analysis provides a framework for moving beyond the descriptive nature of variance partitioning. By modeling relationships at each level of analysis and identifying cross-level relationships, multilevel analysis allows for examination of causal relationships.

The following assumptions of two-level, multilevel models can be extended to models with any number of levels: (1) level 1 residuals are independent and normally distributed with a mean of zero and variance σ^2 ; (2) level 1 predictors are

⁴ See earlier discussion on the advantages and disadvantages of 2SLS for more on artificial classification of segments.

independent of level 1 residuals; (3) level 2 random errors are independent and multivariate normal with a mean of zero, some variance, and some covariance among the random elements; (4) level 2 predictors are independent of level 2 residuals; and (5) level 1 and level 2 errors are independent (Raudenbush and Bryk, 2002). Assumptions 2, 4, and 5 address model specification, i.e., the adequacy of the predictor variables, while assumptions 1 and 3 refer to the error structure. The next section uses cross-classified, multilevel analysis to estimate industry, corporate, and business segment effects and compares these results to those obtained using VCA, nested ANOVA, and 2SLS.

METHODS

Business segment data were collected from Compustat's Research Insight for the years 1995–99. This is the most recent 5-year time period that exhibits relative stability in gross domestic product (GDP), the producer price index (PPI), and the industrial price index (IPI).⁵ Consistent with earlier studies, performance was measured using business segment return on assets. Diversified (i.e., multiple operating segments in a given year) and non-diversified (i.e., single segment firms) firms were included with diversification explicitly considered in the model to avoid the problem of constraining corporate effects to zero (Brush *et al.*, 1999). Observations were deleted if no primary or line of business SIC was listed, if the primary or line of business SIC was listed as not elsewhere classified, or if the primary or line of business SIC indicated that the firm or business segment was a depository institution (i.e., SICs in the 6000s), in which case performance is not comparable to corporations or segments in other industries (McGahan and Porter, 1997). Segments with only 1 or 2 years of data,⁶ instances where only one segment operated in a given 4-digit SIC in

a given year, and segments with assets or sales less than \$10 million (see McGahan and Porter, 1997) were also excluded. The screening process yielded 19,405 segment-year observations nested within 5,092 business segments that are cross-classified within 4,035 corporations and 625 industries (as defined by 4-digit SIC).

A change in accounting standards for segment reporting represents an important difference between this dataset and those in earlier studies. Statement of Financial Accounting Standards (SFAS) 131, which became effective for fiscal years after December 15, 1997, changed the basis for defining the reportable segments of an enterprise. As noted by McGahan and Porter (1997), the earlier standard (i.e., SFAS 14) called for segments based on industry lines, which often resulted in segments that represented multiple business units. In response to concerns that this method of segment reporting was inconsistent with internal management reports, the new standard specifies that a 'management approach' should be used for determining reportable segments. 'The management approach is based on the way that management organizes the segments within the enterprise for making operating decisions and assessing performance. Consequently, the segments are evident from the structure of the enterprise's internal organization' (FASB, 1997:¶4). Accounting studies indicate that the majority of firms redefined their segments under the standard and that the new reporting structure has increased consistency with information in the Management Discussion and Analysis and other annual report disclosures (Herrmann and Thomas, 2000; Street, Nichols, and Gray, 2000). For example, whereas Wal-Mart reported only one segment under SFAS 14, they began reporting four segments under SFAS 131: Wal-Mart Stores, Sam's Club, International, and Other.

Thus, while SFAS 14 resulted in 'industry' or 'line of business' reporting, SFAS 131 requires reporting based on 'operating segments.' Although the new standard still allows for aggregation of business units, the conditions are more restrictive, i.e., the segments must be similar in terms of: economic characteristics, the nature of products and services, the nature of the production processes, the type or class of customer for their products and services, the methods used to distribute their products or provide their services, and, if applicable, the nature of the regulatory environment (FASB, 1997: ¶17). Furthermore, firms are generally required to

⁵ The yearly percentage changes in GDP between 1995 and 1999 were 2.7, 3.6, 4.4, 4.3, and 4.1 percent; PPI changes were 1.9, 2.7, 0.4, -0.8, and 1.8 percent; IPI changes were 2.9, 6.1, 7.0, 2.7, and 5.7 percent.

⁶ Observations with only 1 or 2 years of data are excluded to avoid late-stage or early-stage operations that may skew the results (McGahan and Porter, 1997). The exclusion of these units leaves an unbalanced panel (i.e., segments may have 3, 4, or 5 years of data); however, multilevel modeling provides efficient estimates for unbalanced data (Raudenbush and Bryk, 2002).

restate information for earlier periods if there is a change in the composition of reportable segments (FASB, 1997: ¶34–35). Thus, the 1995–99 dataset used in this study contains information for *operating* segments while datasets covering earlier time periods contain *line of business* or *industry* information that confounded industry and business segments.

The analysis of this dataset should not be viewed as a population analysis. Rather, random effects are used to make inferences to the population based on a sample. While extractions from Compustat databases produce large datasets, the data do not represent the overall population of firms or industries. First, Compustat segment data covers only those firms traded on U.S. exchanges thereby excluding many non-U.S. firms as well as all privately held firms. Many of these firms play a major role in their respective industries and are therefore of interest when making inferences about the components of variation related to business segment performance. Second, by following the screening precedents of McGahan and Porter, segments with less than \$10 million in sales and/or assets have been excluded from the analysis. More importantly, the screens exclude all segments with primary SICs that are ‘not elsewhere classified’; thus there are many industries that are excluded simply because the 4-digit SIC system does not contain an appropriate descriptor.

Business segment performance can be conceptualized as a three-level model with years (level 1) nested within business segments (level 2) nested within the cross-classification of corporations and industries (level 3). Thus, the unconditional model, which models segment ROA as a grand mean (γ_{0000}) with random effects for: industry k (u_{000k}), corporation j (u_{000j}), business segment i (r_{0ijk}), and year t (e_{tijk}) can be written as

$$\text{SegROA}_{tijk} = \gamma_{0000} + u_{000j} + u_{000k} + r_{0ijk} + e_{tijk} \quad (5)$$

Following the three-level notation of Raudenbush and Bryk (2002) and extending the unconditional model to a linear growth, random coefficients regression yields the following set of equations:

$$\text{SegROA}_{tijk} = \pi_{0ijk} + \pi_{1ijk} \text{Year}_{tijk} + e_{tijk}$$

where Year_{tijk} is defined as the number of years since the first year of the analysis for business segment i ; e.g., $\text{Year}_{tijk} = 0$ for 1995 data, $\text{Year}_{tijk} =$

1 for 1996 data, etc.

$$\begin{aligned} \pi_{0ijk} &= \beta_{00jk} + r_{0ijk} \\ \pi_{1ijk} &= \beta_{10jk} + r_{1ijk} \\ \beta_{00jk} &= \gamma_{0000} + u_{000j} + u_{000k} \\ \beta_{10jk} &= \gamma_{1000} \end{aligned}$$

or by substitution:

$$\begin{aligned} \text{SegROA}_{tijk} &= \gamma_{0000} + \gamma_{1000} \text{Year}_{tijk} + \text{Year}_{tijk} r_{1ijk} \\ &\quad + u_{000j} + u_{000k} + r_{0ijk} + e_{tijk} \end{aligned} \quad (6)$$

The model was extended once again to include diversification as a corporate-level, dummy variable predictor by adding the term ‘ γ_{2000} Diversification_{tijk}’ to Equation 6. A value of zero indicated that the corporation was not diversified during that particular year and a value of one indicated that the corporation was diversified. Seventy-seven percent of the corporations in the dataset were not diversified.

Finally, based on earlier studies suggesting that the importance of effects for manufacturing sectors differs from the importance of effects for other sectors (McGahan and Porter, 1997, 2002), analyses were conducted for the entire dataset as well as for the manufacturing sector and for non-manufacturing sectors. Consistent with McGahan and Porter (1997), the manufacturing sector was defined as segments with a primary SIC of 3000–3999. The non-manufacturing sector was defined as all other SICs.

The next section presents detailed results in the following order: multilevel analysis, VCA using two types of estimation, nested ANOVA, 2SLS, and results from manufacturing and non-manufacturing samples.

RESULTS

Table 1 shows the results for the unconditional multilevel model (Equation 5), the linear growth model (Equation 6), and a linear growth model with a fixed effect for corporate diversification. Results indicate that all variances are statistically significant where industry explains 5.3 percent, corporations explain 20.2 percent, and business segments explain 40.1 percent of business segment

Table 1. Multilevel analysis of business segment ROA

Unconditional model (Equation 5)			
Fixed effects	Coefficient	S.E.	
Intercept	8.49	0.41	
Random effects	Variance	S.E.	% Var. explained
Industry	20.92	3.03	5.3
Corporate	79.44	8.75	20.2
Business segment	157.99	8.34	40.1
Error	135.78	1.63	34.5
Linear growth model (Equation 6)			
Fixed effects	Coefficient	S.E.	
Intercept	10.05	0.43	
Year	-0.77	0.09	
Random effects	Variance	S.E.	
Industry	20.33	3.01	
Corporate	58.91	16.48	
Business segment intercept	170.43	16.19	
Business segment slope	15.00	0.88	
Cov. (year, segment)	-11.41	1.88	
Error	107.79	1.65	
Linear growth with diversification			
Fixed effects	Coefficient	S.E.	
Intercept	7.70	0.44	
Year	-0.78	0.09	
Diversification	5.38	0.48	
Random effects	Variance	S.E.	
Industry	16.20	2.62	
Corporate	48.08	13.84	
Business segment intercept	176.81	14.18	
Business segment slope	14.98	0.87	
Cov. (year, segment)	-11.86	1.87	
Error	107.79	1.64	

n = 19,405; industries = 625; corporations = 4,035; segments = 5,092; years = 5

ROA.⁷ When year is added only as a fixed effect at level 1, the proportional reduction in residual

⁷A model based on a dataset that included segments with 2, 3, 4, and 5 years of data (*n* = 23,879) produced smaller stable corporate effects (4.7% as compared to 20.2%) and larger stable segment effects (60.7% vs. 40.1%). This pattern would be expected given the longer time series of this dataset. Future research should explore the effects of late-stage, early-stage, or other transitory segment operations.

variance is less than 1 percent.⁸ Adding diversification as only a level 1 fixed effect provides less than a 1 percent reduction in proportional residual variance.⁹ Following Brush *et al.* (1999) and using proportional *R*s rather than *R*², the results of this study indicate that corporate effects are smaller than segment effects by 0.71 to 1,¹⁰ corporate effects are greater than industry effects by a ratio of 1.95 to 1, and segment effects are greater than industry effects by a ratio of 2.75 to 1.

Variance components analysis using MIVQUE0 estimation¹¹ of the current sample indicates that industry effects explain 5.8 percent of the total variance in business segment ROA, corporate effects explain 11.2 percent, business segments explain 33.5 percent, year plus year by industry effects explain 2.8 percent of the total variance in business segment ROA, and 46.6 percent of the variance is unexplained. While the results for industry and year effects are similar to those obtained with multilevel analysis, VCA provided smaller estimates for corporate and segment effects (11.2 vs. 20.2 and 33.5 vs. 40.1 respectively), which supports Brush and Bromiley's (1997) claim that VCA estimates are unreliable and lack the power to detect corporate effects even when they clearly exist. In addition, improper estimates (i.e., negative variance estimates) were obtained using Rumelt's (1991) sum of squares quadratic forms. Table 2 compares the results from multilevel analysis to the results obtained using MIVQUE0 sum of squares VCA and sum of squares quadratic forms VCA (see Rumelt, 1991).¹²

⁸The level 1 variance for a fixed year effect is 135.08; the level 1 variance with year and diversification as fixed effects is 135.13. See Snijders and Bosker (1999) for a discussion of explained variance in multilevel models.

⁹A model of non-diversified firms only (*n* = 11,456; 3,120 firms) indicates that industry explains 5.8 percent of the variance, business segments (single business corporations in this case) explain 62.0 percent of the variance, and a fixed effect for year explains an additional 1 percent. The level 1 error is 32.1 percent.

¹⁰Ratio = square root(variance of corporate effects/variance of segment effects) = sqrt(20.2/40.1) = 0.71.

¹¹MIVQUE0 estimation is based on Hartley *et al.* (1978) and is the default estimation technique in SAS.

¹²Consistency of implementation with earlier studies was verified by rescreening Compustat data and replicating the results outlined in Table 5 of McGahan and Porter (2002), Tables 3 and 4 of McGahan and Porter (1997), and Table 6 of Brush *et al.* (1999).

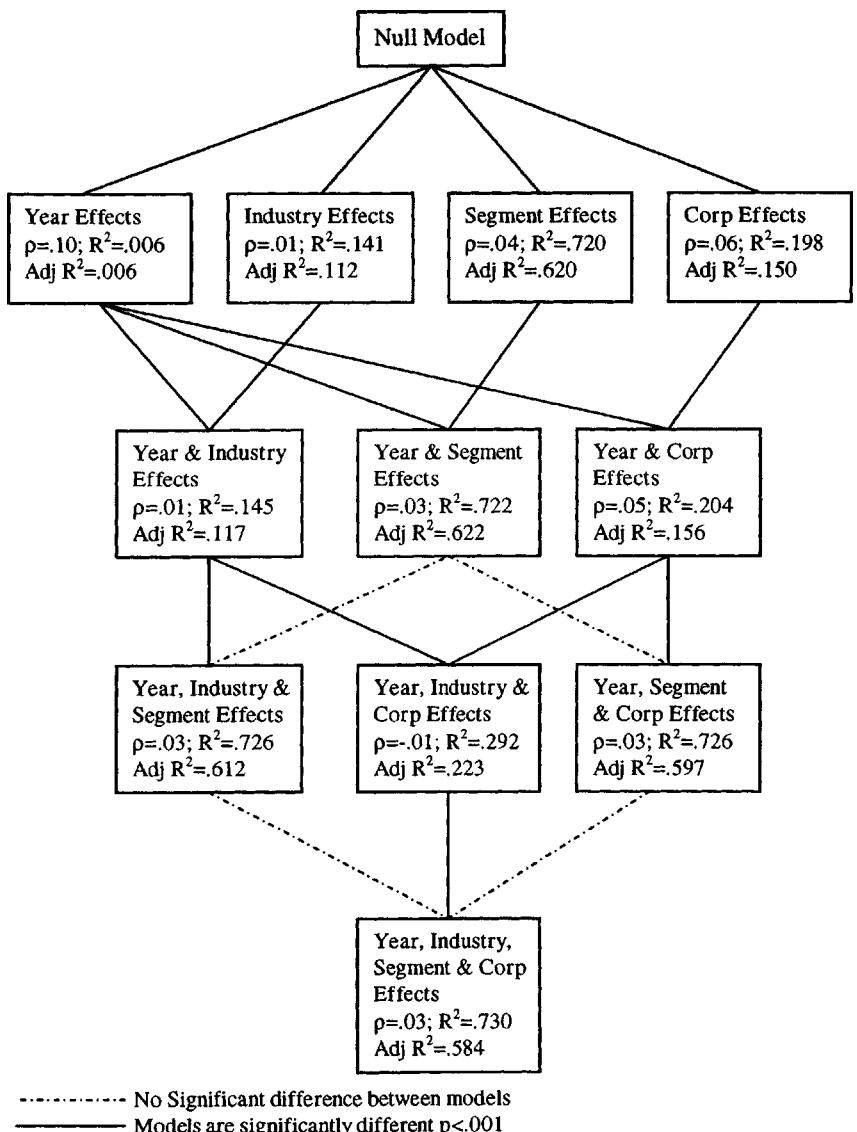


Figure 2. Nested analysis of variance (ANOVA) for business segment ROA

Figure 2 provides results using nested ANOVA. The lines indicate nested models that were examined for significant changes in R^2 . For example, beginning at the bottom and moving up, a model with year, industry, segment, and corporate effects was compared to a model with year, industry, and corporate effects. The significant change in R^2 indicates that the full model has significantly more explanatory power than a model that does not include segment effects. However, the full model does not have significantly more explanatory power than a model with year, segment, and corporate parent effects.

Following McGahan and Porter (2002) the increment to explanatory power was reported in Table 2 by introducing year, industry, corporate, and business effects, in that order. Year effects explain less than 1 percent of the total variance in business segment ROA. Comparing a model with year and industry effects to a model with year effects only suggests that industry adds 13.9 percent (11.1% adjusted R^2). Adding corporate effects to the model with year and industry effects suggests that corporations add 14.7 percent (10.6% adjusted R^2). Finally, business segment effects explain an additional 43.8 percent (36.1% adjusted R^2).

Table 2. Comparison of percent variance explained in studies of business segment return on assets across all economic sectors*

Method	Multilevel	Current study	Current study	Current study	Current study	McGahan and Porter (1997)	McGahan and Porter (2002)	McGahan and Porter (2002)	Brush et al. (1999)
		VCA using SAS Varcomp MIVQUE0	VCA using SS approach uncorrected	Nested ANOVA uncorrected for serial correlation	2SLS 3seg-4seg	VCA using SS approach uncorrected	VCA using SS approach uncorrected for serial correlation	Nested ANOVA standard 3seg-4seg correction	Nested ANOVA 2SLS 3seg-4seg
Time frame	1995–99	1995–99	1995–99	1995–99	1995–99	1981–94	1981–94	1981–94	1986–95
Sample size	19,405	19,405	19,405	19,405	449–123	58,132	72,742	72,742	535–173
Industry	5.3	5.8	13.5	13.9 ^a	14.0 ^b	17.3	18.7	9.6	7.3–13.5
Corporate	20.2	11.2	Neg.	14.7 ^c	14.9 ^d	7.0	4.3	12.0	8.9–14.4 ^e
Segment	40.1	33.5	52.1	43.8 ^c	43.7–55.2 ^f	29.6	31.7	37.7	66.6–53.7 ^f
Year	<1.0	<1.0	<1.0	<1.0 ^d	N/A	<1.0	2.4	<1.0	N/A
Ind.-year	N/A	2.2	Neg.	N/A	N/A	4.4	N/A	N/A	N/A
Corp.-ind. cov.	N/A	N/A	–2.5	N/A	N/A	–5.4	–5.5	N/A	N/A
Error	34.5	46.6	36.3	27.0	27.1	28.5–24.0	46.8	48.4	39.4
Sqrt(corp/seg.)	0.71	0.58	N/A	0.58	0.58	0.22–0.33	0.49	0.37	0.55
Sqrt(corp/ind.)	1.95	1.39	N/A	1.03	1.03	0.29–0.64	0.64	0.48	1.12
Sqrt(seg./ind.)	2.75	2.40	1.96	1.78	1.76	1.31–1.94	1.31	1.30	1.98
								2.07	3.02–1.99

* Except financial sector (SIC 6000s) and SICs indicating 'not elsewhere classified.'

^a Increment in model of year and industry effects over model of year effects.^b Increment in model of year, industry, and corporate effects over model of year and industry effects.^c Increment in full model over model of year, industry, and corporate effects.^d Increment in model of year effects over null model.^e Increment in model of industry and corporate effects over model of industry effects.^f Increment in model of industry, corporate and segment effects over model of industry and corporate effects.

N/A, not applicable; Neg., estimate for variance component is negative.

However, if the effects are examined in the order of year, corporate, segment, and finally industry, year explains less than 1 percent; corporate effects explain 19.8 percent (15.0% adjusted R^2); segment effects explain 52.2 percent (44.1% adjusted R^2); and industry does not explain a significant portion of the variance in segment ROA. This clearly demonstrates the order of entry problem in nested ANOVA (see Bowman and Helfat, 2001; Kennedy, 1998). Thus, depending on the order of entry (assuming year is always entered first and using adjusted R^2), industry effects range from 0 percent to 11.1 percent, corporate effects range from 10.6 percent to 15.0 percent, and segment effects range from 36.1 percent to 44.1 percent. Regardless of the sample being examined, such differences in interpretation make the results of nested ANOVA difficult to compare with other methods.

The data were also examined using the 2SLS approach described by Brush *et al.* (1999). A model for firms with exactly three business segments ($n = 449$ segment-years) indicates that industry explains 25.6 percent of the variance in segment ROA, while a model with four business segments ($n = 123$ segment-years) indicates that industry explains 14.7 percent of the variance. Corporate effects account for 2.2 percent of segment ROA for three-segment firms and 6.1 percent for four-segment firms. Adding dummy variables for business segments indicates that segment effects account for 43.7 percent of the variance in segment ROA beyond industry and corporate effects for three-segment firms. In four-segment firms, segments account for 55.2 percent of the variance. Similar to nested ANOVA, using 2SLS to estimate industry, corporate, and segment effects produces equivocal results based on the order in which the incremental effects are considered. In addition, the limited number of three- and four-segment businesses severely restricts the number of industries considered (i.e., in this study, the three-segment, non-manufacturing businesses operated in only 110 SICs out of the 412 covered by the full non-manufacturing sample; three-segment, manufacturing firms operated in only 64 out of 211 manufacturing SICs; the number of industries covered by four-segment businesses fell even further). The small sample compromises statistical power and makes comparison to Brush *et al.*'s (1999) sample meaningless. Furthermore, Brush *et al.* (1999) deleted observations for ROA

greater than 0.4 or less than -0.3, which could have a notable effect on samples of three- and four-segment businesses, whereas this study did not screen on the dependent variable.

Table 3 compares the results from multilevel analysis to the results obtained using MIVQUE0 VCA, sum of squares quadratic forms VCA, nested ANOVA, 2SLS, and the results of earlier studies where the sample represents manufacturing or non-manufacturing sectors. Comparing results from the manufacturing sector to the non-manufacturing sector, corporate effects are larger for firms participating in the manufacturing sector, while industry and segment effects are typically very similar between sectors (with the exception of smaller segment effects in the manufacturing sector for multilevel analysis). Even though the sample size calls into question the results of 2SLS, corporate effects are greater in manufacturing for three-segment firms. Examination of proportional R_s for MIVQUE0 VCA and nested ANOVA analyses shows similar ratios regardless of sector coverage. In particular, corporate to segment ratios are 0.52:1 and 0.70:1 using MIVQUE0 VCA (for non-manufacturing and manufacturing respectively) and 0.60:1 and 0.60:1 for nested ANOVA; corporate to industry ratios are 1.26:1 and 1.85:1 using MIVQUE0 VCA and 1.04:1 and 1.12:1 for nested ANOVA; segment to industry ratios are 2.44:1 and 2.64:1 using MIVQUE0 VCA and 1.72:1 and 1.87:1 for nested ANOVA. Yet, the multilevel analysis demonstrates clear differences based on sector coverage. That is, for non-manufacturers the ratio of corporate to segment effects is 0.62:1 for non-manufacturers and 0.99:1 for manufacturers. The ratio of corporate to industry effects is 1.80:1 and for manufacturers it is 2.51:1. In addition, multilevel analysis shows larger ratios than other methods for corporate to industry ratios and segment to industry ratios. Overall, we conclude that corporate effects are more important in the manufacturing sector than in the non-manufacturing sector.

It should be acknowledged that the multilevel analysis did not account for potential serial correlation between errors at level 1. However, results for uncorrected and corrected nested ANOVA (Table 2) indicated that serial correlation had no significant effect in this sample. This is consistent with research by McGahan and Porter (2002), which concluded that serial correlation has a minimal effect even with reported autocorrelations of

Table 3. Comparison of percent variance explained in studies of business segment return on assets for non-manufacturing and manufacturing sectors

Method	Current study	Current study	Current study	Nested ANOVA uncorrected	2SLS 3seg-4seg	Multilevel	VCA using SAS Varcomp	VCA using sum of squares approach	1995-99	1995-99	VCA using SAS Varcomp	VCA using sum of squares approach	Nested ANOVA uncorrected
Time frame	1995-99	1995-99	1995-99	1995-99	1995-99	1995-99	1995-99	1995-99	1995-99	1995-99	1995-99	1995-99	1995-99
	Non-manuf.	Non-manuf.	Non-manuf.	Non-manuf.	Non-manuf.	Non-manuf.	Manuf.	Manuf.	Manuf.	Manuf.	Manuf.	Manuf.	Manuf.
Sector	13,221	13,221	13,221	13,221	13,221	292-90	6184	6184	6184	6184	6184	6184	6184
	5.3	5.7	13.7	14.4 ^a	27.3-11.0	4.7	4.7	4.7	15.0	15.0	12.5 ^a	12.5 ^a	12.5 ^a
Sample size	17.1	9.1	Neg.	15.5 ^b	1.9-10.7 ^e	29.6	16.1	16.1	Neg.	Neg.	15.6 ^b	15.6 ^b	15.6 ^b
	43.8	33.9	52.4	42.8 ^c	42.2-58.1 ^f	30.0	32.7	32.7	52.6	52.6	43.8 ^c	43.8 ^c	43.8 ^c
Industry	<1.0	<1.0	<1.0	<1.0 ^d	N/A	<1.0	N/A	N/A	1.0	1.0	1.0 ^d	1.0 ^d	1.0 ^d
	N/A	2.1	Neg.	N/A	N/A	N/A	N/A	N/A	2.6	2.6	N/A	N/A	N/A
Year	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
	33.9	48.7	35.6	26.8	28.6-20.3	35.7	42.8	42.8	-4.3	-4.3	35.6	35.6	35.6
Segment	0.62	0.52	N/A	0.60	0.21-0.43	0.99	0.70	0.70	N/A	N/A	0.60	0.60	0.60
	1.80	1.26	N/A	1.04	0.26-0.99	2.51	1.85	1.85	N/A	N/A	1.12	1.12	1.12
Sqrt(corp/seg.)	2.87	2.44	1.96	1.72	1.24-2.30	2.53	2.64	2.64	1.87	1.87	1.87	1.87	1.87

(continued overleaf)

Table 3. (Continued)

Method	2SLS 3seg-4seg	VCA	VCA using sum square approach	Nested ANOVA uncorrected	VCA	VCA $\rho = 0.41$	Nested ANOVA uncorrected	McGahan and Porter (2002)	McGahan and Porter (1997)	Roquebert et al. (1996)	Rumelt (1991) Sample A	Schmalensee (1985)	Current study	
Time frame	1995–99	1975 Manuf. (FTC)	1974–77 Manuf. (FTC)	1974–77 Manuf. (FTC)	1985–91 Manuf. (FTC)	1981–94 Manuf. (FTC)	1981–94 Manuf.	(3000–3999)	(3000–3999)	(3000–3999)	(3000–3999)	(3000–3999)	1985–91 Manuf.	
Sector	Manuf. (3000–3999)	118–13	1775	6932	16,596	18,298	18,298							11,233
Sample size		11.5–62.8	19.6	8.3	17.9	10.2	10.8							8.2
Industry		12.7–9.1 ^c	N/A	0.8	14.8	17.9	N/A							13.7
Corporate		47.2–18.5 ^d	0.6	46.4	33.9	37.1	35.5							44.3
Segment		N/A	N/A	IF	<1.0	<1.0	2.3							0.2
Year		N/A	N/A	7.8	9.8	2.3	N/A							N/A
Ind.–year		N/A	N/A	–0.6	N/A	N/A	N/A							N/A
Ind.–m. shr. cov.		N/A	N/A	IF	N/A	N/A	N/A							N/A
Corp.–ind. cov.		N/A	N/A	80.4	36.9	23.5	53.7							N/A
Error		24.4–9.6	0.52–0.70	N/A	0.13	0.66	0.69	N/A						33.6
Sqrt(corp./seg.)		0.90–0.38	N/A	0.31	0.91	1.32	N/A							0.56
Sqrt(corp/ind)		1.73–0.54	0.17	2.36	1.38	1.91	1.81							1.29
Sqrt(seg./ind.)														2.32

^a Increment in model of year and industry effects over model of year effects.^b Increment in model of year, industry, and corporate effects over model of year and industry effects.^c Increment in full model over model of year, industry, and corporate effects.^d Increment in model of year effects over null model.^e Increment in model of industry and corporate effects over model of industry effects.^f Increment in model of industry, corporate and segment effects over model of industry and corporate effects.

N/A, not applicable; IF, insignificant in first model and therefore not included in final model; Neg., estimate for variance component is negative.

0.34 for year effects alone and autocorrelations of 0.10 for a full model. Further, the relative economic stability of the 1995–99 time frame used in this study produced even smaller serial correlations than those reported by McGahan and Porter (see Figure 2, $\rho = 0.10$ for year effects only and $\rho = 0.03$ for the full model). There is no statistical reason that autocorrelation and cross-classified data structures can not be modeled together. The limitation is software related. As new versions of multilevel software incorporate this capability, researchers should more carefully examine the effects of serial correlation.

CONCLUSION

Although nested ANOVA analysis provides variance estimates while allowing for covariance between parameter estimates (such as between corporate and industry parameter estimates), these methods do not unambiguously partition variance in cross-classified, hierarchical data structures such as business segments nested within corporations and segments nested within industries. Furthermore, nested ANOVA allows only a single error term. VCA with sum of squares estimation also allows for parameter covariance but decidedly partitions the variance between segments, corporations and industries. However, VCA produces unreliable, and potentially negative, estimates. Furthermore, fixed effects techniques such as ANOVA provide inference only to the sampled units rather than to the general population. Although random effects techniques overcome some of these limitations, techniques such as simple VCA do not provide a means for moving beyond the examination of variance explained.

Multilevel analysis, on the other hand, allows modeling of the idiosyncratic relationships between levels of the data structure using continuous variables, categorical predictors, and/or complex error structures. This provides a tool that avoids the problems of aggregation and disaggregation of data, inherently accounts for the nesting of segments within corporations and within industries through the use of cross-classification,¹³ allows inference to the population rather than the sampled

fixed effects, and provides a powerful means for modeling and testing theory.

With respect to business segment performance, multilevel analysis indicates that (1) corporate effects explain half as much variation as segment effects, while previous research reported that corporate effects explained only one quarter to one third as much as business segments, (2) corporate effects explain almost four times more variance in business segment performance than industry effects (20.2% vs. 5.3%), which is at least three times greater than previously reported (McGahan and Porter, 2002), and (3) segments explain almost eight times more variation than industry, which is twice the rate reported by most earlier research (see Table 2). In manufacturing sectors, the strength of corporate effects compared to industry and segment effects is even more pronounced and the relationship between segment effects and industry effects is only slightly smaller in the manufacturing sample than in comprehensive samples. The difference between methods clearly demonstrates the importance of appropriately partitioning the within- and between-group variance and accounting for the cross-classified nature of the data. This argues for the use of techniques such as multilevel analysis in this line of research—as well as other areas of research that depend on analysis of hierarchical data.

Multilevel modeling has been prevalent in educational and sociological research for a number of years (see a discussion of historical developments in Raudenbush and Bryk, 2002). Yet organization scientists have only recently begun to adopt this methodology despite earlier recognition of the ‘level of analysis’ problem (e.g., James, 1982; Rousseau, 1985). This is evidenced by the publication of a special issue of the *Journal of Management* in 1997 on hierarchical linear modeling, Academy workshops on multilevel methods, the publication of Klein and Kozlowski’s (2000) book on multilevel theory and methods, and the emergence of published studies using such methodology (e.g., Hofmann and Stetzer, 1998; Vancouver *et al.*, 1994; Whitener, 2001).

¹³ Multilevel modeling can be implemented using a variety of widely available software packages (e.g., SAS’s Proc Mixed, the multilevel option in LISREL, HLM by Scientific Software,

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Yet, a search of the *Strategic Management Journal* revealed only one study using multilevel methods of analysis (Hough and White, 2003). Perhaps strategy researchers have been slow to adopt this methodology because of the problem of cross-classification. Thus, this study serves three purposes: (1) it re-examines the relative influence of industry and corporate effects highlighting major differences with regard to earlier studies; (2) it highlights a method for answering McGahan and Porter's (2002: 849) call to identify cross-sectional relationships between industry, corporation, and business segments rather than continuing to focus only on the descriptive nature of explained variance; and (3) it provides an example of how cross-classified structures can be practically applied when modeling the inherently complex structure of strategy problems and issues. In doing so, this study calls our attention to the need for re-examination of results in any area of strategy research based upon hierarchical data structures that has not explicitly modeled the inherent nesting of the data. Furthermore, any research using business segment data that was conducted before 1998 when SFAS 131 took effect should be reconsidered.

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