*Strategic Management Journal*
*Strat. Mgmt. J.*, **20**: 519–547 (1999)

# THE RELATIVE INFLUENCE OF INDUSTRY AND CORPORATION ON BUSINESS SEGMENT PERFORMANCE: AN ALTERNATIVE ESTIMATE

THOMAS H. BRUSH[1]*, PHILIP BROMILEY[2] AND MARGARETHA HENDRICKX[1]
[1]*Krannert Graduate School of Management, Purdue University, West Lafayette, Indiana, U.S.A.*
[2]*Carlson School of Management, University of Minnesota, Minneapolis, Minnesota, U.S.A.*

*Rumelt's (1991) widely cited paper presents estimates of the relative influence of industry, corporate, business unit, and other influences on business unit profitability. He finds corporations explain almost none of the variability in business unit profitability. Using a simultaneous equation model, we provide alternative estimates of the influence of industry and corporation on business unit performance. We find that both corporations and industries influence business unit profitability but corporations have the larger influence.* 

Rumelt's (1991) widely cited paper uses variance components analysis (VCA) to estimate the influence of corporations, business unit, industry, and time on business unit profitability. Surprisingly, he finds that the corporate influence accounts for only 1–2 percent of the variation of business unit performance. Some suggest these results demonstrate that the interest in corporate strategy is misplaced; corporate strategy just doesn't matter (Hoskisson, Hill, and Kim, 1993a; Ghemawat and Ricart I. Costa, 1993; Carroll, 1993).

A number of related studies have raised concerns about Rumelt's finding of no corporate effect. Roquebert, Phillips, and Westfall (1996) replicates Rumelt's study with more recent data and finds similar results except for a corporate effect that was substantially larger than the industry effect. On the other hand, McGahan and Porter (1997a) find a corporate effect that was substantially smaller than the industry effect. In addition, Brush and Bromiley (1997), based on a Monte Carlo study of VCA estimates, argue that VCA lacks the power to find smaller but substantial effects and must be interpreted based on a nonlinear transformation of the components rather than the components themselves (as Rumelt did). Thus an important surprise in Rumelt (1991), the lack of a corporate effect, remains in controversy. Our paper provides an alternative approach to estimation of the corporate effect using continuous variable techniques in a simultaneous equation model.

Rumelt and related studies rely on two techniques: analysis of variance (ANOVA) and VCA. Both techniques have problems when interpreted

Key words: business unit performance; diversification; methodology
* Correspondence to: Prof. T. Brush, Krannert Graduate School of Management, Purdue University, 1310 Krannert Building, West Lafayette, IN 47907-1310, U.S.A.

CCC 0143–2095/99/060579–29 $17.50

*Received 12 March 1997*
*Final revision received 25 August 1998*

as measuring the relative importance of the effects of industry, corporation, and business unit. Brush and Bromiley (1997) question the metric of importance inherent in VCA and note other metrics have been used in social science research. For example, researchers in other areas often discuss importance of a variable as the expected change in the dependent variable for a one standard deviation change in the independent variable (the standardized beta) rather than VCA's explained variance. Brush and Bromiley (1997) also argue VCA lacks the power to find effects, even when they are present. ANOVA presents difficulties because corporate effects must be entered into the model before business unit effects, giving perhaps an inappropriate estimate of their relative importance (Rumelt, 1991; see also Bowman and Helfat, 1997). Rumelt (1991) finds a substantial corporate effect when he enters corporation before business unit.

Given these methodological concerns, this paper takes a different methodological approach to estimating the relative influence of corporations and industries on business unit performance. We use a continuous-variable model estimated with two-stage least-squares on the COMPUSTAT industry segment data base. Whereas ANOVA and VCA approaches use a degree of freedom for each business unit, industry, corporation, and time period, the continuous variable approach uses far fewer degrees of freedom and so may provide better (lower variance) estimates. At the cost of making some alternative assumptions, continuous variable approaches also allow the model to impose fewer orthogonality assumptions between different effects.

## LITERATURE REVIEW

Let us briefly describe ANOVA and VCA. ANOVA basically estimates an ordinary linear regression model using dummy variables for different qualitative treatments and, sometimes, continuous variables. In the studies discussed here, such dummy variables would be included for industry and corporation and other effects (depending on the study). Researchers assess the importance of an effect by the amount of variance explained by a given set of dummy variables (e.g., the explained variance from all the industry dummies) (See Equation 7, Appendix 1 for more detail). VCA is also known as random effect ANOVA because the levels of the effects are assumed to be randomly selected from an infinite population (Searle, 1971). VCA estimates a model similar to ANOVA, but instead of actual estimates of each dummy variable's parameter, it reports the variance of a set of implicit dummy variables. This variance corresponds to the amount of variance in the dependent variable explained by that set of implicit dummy variables (see Equation 8, Appendix 1 for more detail).

Given this overview, let us now consider the literature. Within industrial economics, a debate exists between economists who emphasize a classical focus on industry and market power as a primary determinant of firm profitability, and the members of a revisionist school who emphasize firm efficiency (Demsetz, 1973). Schmalensee (1985) attempts to resolve this conflict by estimating an analysis of variance (ANOVA) model with corporate[1] (referred to as firm), industry, and market share effects (as a proxy for business-unit effects). In this model, corporate and business-unit effects jointly represent what Demsetz (1973) considered as firm efficiency. Schmalensee finds that corporate effects do not exist, important industry effects exist and explain 19 percent of variance in rates of return, and market share effects exist and explain little variance. Schmalensee (1985: 349) interprets these results to indicate that the absence of corporate effects 'merely means that knowing a firm's profitability in market A tells nothing about its likely profitability in a randomly selected market B.' The finding of important industry differences supports the classical focus on industry-level analysis, while it is agnostic concerning the structural explanation of those differences.

When Wernerfelt and Montgomery (1988) follow up on Schmalensee's research with Tobin's $q$ as the dependent variable and 'corporate focus'—a measure of similarity of business units in diversified firms, rather than corporate dummy

[1] Rumelt (1991) renames Schmalensee's firm effects as corporate effects because the norm in economics is to refer to an autonomous competitive unit within an industry as a firm. Thus in Rumelt's paper, corporate effects are meant to identify the effects of a common legal entity which contains several autonomous competitive units within different industries. For Rumelt, industries and corporations are two different ways of grouping business units. Recognizing that the data we use are at the 'business segment level' we parallel Rumelt's usage by adopting the terms corporate and segment effects.

variables—they also find strong industry effects. However, they find corporate focus effects that were roughly 13–21 percent of the size of industry effects, which is inconsistent with the Schmalensee results.

Rumelt (1991) respecifies Schmalensee's (1985) model by decomposing line of business profitability variance over time into corporate, business, industry, and other effects. Whereas Schmalensee (1985) uses market share as a proxy for business unit effects, Rumelt (1991) treats business units as he does corporations and industries by entering a separate variance component for them in the VCA analysis and separate effects for them in the ANOVA analysis. Rumelt estimates his model using both ANOVA and VCA but emphasizes the VCA results. While the ANOVA results find substantial corporate effects, the VCA results agree with those of Schmalensee (1985) in finding a very small corporate effect and modest industry effect. Rumelt finds a large business unit effect; much of this effect appears to be part of the error term in Schmalensee's model. Rumelt's business unit effect is much larger than the corporate and industry effects.

Rumelt (1991) discusses the small corporate effect, which he finds in common with Schmalensee (1985), as a conundrum. He finds it 'surprising to find vanishingly small corporate effects in these data' given the extent of the literature on corporate strategy, corporate culture, the number of corporate management consulting firms, and the focus on senior corporate leaders in the business world (Rumelt, 1991: 182). While Rumelt's conclusion rests formally on the relative size of the estimated corporate variance component, he suggests, and it has been interpreted by others, that the relatively small size of the corporate effect to that of other effects indicates that corporate strategy is relatively unimportant for explaining business unit performance.

Roquebert *et al.* (1996) replicate Rumelt (1991) using more recent data from the COMPUSTAT Industry Segment data base. Their results are consistent with Rumelt's except that they find a comparatively large corporate effect. This corporate effect accounts for 18 percent of the variance in business segment return on assets (segment ROA) while the industry effect accounts for 10 percent and the business unit effect accounts for 37 percent. The magnitude of the corporate effect declines as the number of business segments per corporation increases. They conclude that the corporate effect diminishes with diversification of the corporation.

McGahan and Porter (1997a) also use the COMPUSTAT business segment data but their model allows for a more complex set of time series effects. For example, they include a variety of lags in influence, control for prior profitability, and allow for serial correlation in the error term. They find a corporate parent effect that is about one quarter as large as the industry effect (in terms of estimated variance components). Based on ANOVA they find a substantial corporate effect although one that remains smaller than the industry effect.

Other researchers use survey data on large U.S. corporations to examine how different managerial or strategic factors (rather than membership in a given corporation) influence performance (e.g., Hansen and Wernerfelt, 1989; Powell, 1992; James, 1996). Hansen and Wernerfelt (1989) find that organizational factors appear more influential than economic factors. Powell (1992) uses the general approach of investigating explained variance in financial performance to examine the effects of organizational alignment and internal structure. James (1996) finds that an interaction between generic strategy and learning approach appeared to explain more of the variance in competitive advantage than industry effects.

Studies which estimate corporation or industry effects on business unit performance rely on ANOVA and VCA, but both techniques have serious problems. First, in ANOVA, business unit ROA is in essence the dependent variable and dummy variables (main effects) for each corporation, industry, business unit, etc., are independent variables. Because the sum of the business unit dummy variables for a given corporation equals the corporate dummy variable for that corporation, a model that entered both at the same time would be unidentified. To identify both corporate and business unit effects, the corporate effect must enter the model before the business unit effect. Both Schmalensee and Rumelt entered the corporate effect first. Rumelt found that doing this gave incremental $R^2$s for the corporation of 0.148, 0.109, 0.176, and 0.116 depending on the sample and which other variables entered before the corporation. But entering the corporate effect first assigns all shared variance between the business units and the corporation to the corporation (see Bowman and Helfat, 1997) for a discussion of this problem). Rumelt uses this argument in justifying his use of the VCA method.

But the VCA technique has problems also. Brush and Bromiley (1997) identified three such problems: interpretation, power, and model specification. Using a Monte Carlo simulation, they found that the estimated variance components appeared to vary with the square of what they called 'importance,' or the relative size of simulated distributions of corporate and business unit effects, and so gave an unreasonably small estimate for smaller effects. If one effect were 0.2 and the other 0.8, squaring gives 0.04 and 0.64 making the first appear unimportant. This problem in interpretation can be readily fixed by appropriate transformations of the results by examining the square roots of variance components rather the variance components directly.

The second problem, power of the analysis, does not have such an easy solution. Brush and Bromiley (1997) find that multiple runs of the same underlying model resulted in a wide variation in estimates which means the method is not reliable in any single application. In particular, the method lacks the power to find smaller effects even when they exist by construction. Table 4 in Roquebert *et al.* (1996) supports this claim. By random sampling without replacement, Roquebert *et al.* (1996) divide their sample of 16,000 observations into 10 samples with average size around 1600. Their estimates of the corporate effect range from 9 percent to 28 percent—a factor of three.

Finally, Brush and Bromiley (1997) question some of the structural assumptions of Rumelt's VCA model. For ordinary least-squares regression to be applicable, one must assume the error term has a zero correlation with the explanatory variables in order to identify the variance of the error term. Analogous (but different) assumptions are required to estimate VCA models. They raise concerns about these structural assumptions in the VCA and the implications for interpretation of results from these models.

We examined some of the literature on VCA with multiple components. When a VCA model includes more than one component, assumptions are required for identification (otherwise it would have the same identification problems as the ANOVA analysis). Most theoretical developments of multiple component VCA impose the assumption that the implicit dummy variable parameters will be uncorrelated across effects (i.e., that $\mu_n$ and $\gamma_m$ are uncorrelated (see Equation 8, Appendix 1) (Dielman, 1989; Fomby, Hill, and Johnson, 1988; Maddala, 1977; Matyas and Sevestre, 1996; Searle, 1971). In studies of the form of Rumelt (1991), the vector of implicit business unit effects will be uncorrelated with the vector of implicit corporate effects and the sum of such effects will be zero. Both of these are important structural assumptions that may strongly influence the results.

Since VCA has been widely used in the quantitative genetics literature, let us illustrate the problems with ANOVA and VCA in an analogous situation from the genetics literature. Suppose you want to understand the relations between height of children at ages 2, 4, and 6 years of age and the height of their parents. The ANOVA procedure takes each child age as an observation. The model contains dummy variables for age and for each pair of parents and for each child. If we tried to enter the children dummy variables at the same time as the parent dummy variables, the matrix of independent variables is not of full rank; the sum of the children dummy variables equals the parent dummy variable for each family. ANOVA estimates require that the parents enter the model first and the children enter second but this ascribes any joint variance between the parent and children to the parent.

VCA solves this identification problem by imposing the constraint that the children's implicit dummy variables ($\mu_n$ or $\gamma_m$ in Equation 8 in Appendix 1) will be uncorrelated with the parent implicit dummy variables and will sum to zero across the entire sample (Dielman, 1989; Fomby *et al.*, 1988; Maddala, 1977; Matyas and Sevestre, 1996). Whether this makes sense or not requires a very sophisticated understanding of the structural assumptions of the model.

In this example, an alternative approach can be seen. If we know the heights of the parents, we can use that information instead of just their identity to examine the influence of parents' height on children's heights. We can regress children's heights on parents' heights. As such we use more information and obtain a much more powerful (in an estimation sense) model. Whereas a dummy variable approach requires one parameter for each parental pair (which consumes a substantial number of degrees of freedom), a continuous variable approach uses only one parameter for parental heights (assuming linearity; a few more for a nonlinear model). The continuous variable model also has a somewhat easier interpretation than the dummy variable model. In the dummy variable model, one has to discuss importance in terms of variability of the implicit dummy variables ($\mu_n$ and $\gamma_m$ in Equation 8 for VCA in Appendix 1) or the total variance explained by the dummy variables (while taking into account the number of dummy variables). In the continuous variable model, we get a parameter which tells us the expected change in child's height for a 1-inch change in the parents' height. We can also examine the amount of variance in children's heights explained by parents' heights. On the other hand, the continuous model does impose the assumption that the relation between parental and children heights has a particular functional form which depends on parental height. We compare the continuous variable approach to the dummy variable approach in Appendix 2.

## MODEL DEVELOPMENT

In this paper we use a continuous variable model to examine the issue of corporate vs. industry influence on business unit profitability. We use data on corporate and industry profitability to estimate their influence on business unit profitability.

Paralleling the height example, we begin with an equation where business unit ROA is a linear function of Corporate ROA and Industry ROA. In this equation, idiosyncratic business unit effects will be incorporated in the error term (although a model presented later examines the sensitivity of the results to this assumption). But, unlike the height example, we cannot assume that corporate ROA influences business unit ROA and not vice versa. In fact, these two effects are simultaneously and jointly identified, i.e., they are endogenously determined. As a result, one needs exogenous variables to identify these effects; a single-equation model explaining business unit performance as a function of corporate performance would be misspecified. Consequently, the model has a second equation where corporate ROA is a function of business unit ROA and another corporate variable. The model structure resembles the classic example requiring simultaneous equations to estimate a Keynesian consumption function (Theil, 1971, Ch. 9). In both the Theil (1971) example and in this case, simultaneous equation techniques allow consistent estimation of the parameters in the model. In the consumption function example the simultaneous and jointly determined endogenous variables are consumption and income. In our case, business segment and corporate performance are simultaneously and jointly determined. We estimate the effect of corporate and industry performance on business unit performance while controlling for the endogenous, or simultaneous influence of business unit performance on corporate performance. The intuition for why a simultaneous equation is necessary in this case is that we identify the influence of Corporate ROA on a business segment ROA in one equation and simultaneously identify the influence of business segment ROA on Corporate ROA in another equation. The next section develops the model more explicitly.

Like Rumelt (1991) and Schmalensee (1985), we want to assess the relative importance of corporate and industry influences on business segment performance rather than test an explicit theory of such performance (see Schmalensee, 1985: 343). Thus, the model below attempts to reflect important relations among these variables without specifying the underlying process.

The model uses the following variables:

- *Corporate* $ROA_{J,T}$—operating return on assets (profits before interest, taxes, and depreciation) divided by total assets for corporation $J$ in year $T$.
- *Segment* $ROA_{I,J,K,T}$—operating return on assets for business segment $I$ of corporation $J$ in industry $K$ in year $T$.
- $w_{I,J,T}$—proportion of total corporate assets in the $I$th business segment of corporation $J$ in a given year $T$.
- *Industry* $ROA_{K,T}$—average operating return on assets for the business segment's industry $K$ in year $T$.
- *Debt/Total Assets*$_{J,T}$—total corporate debt divided by the sum of debt plus equity for corporation $J$ in year $T$

The business segment subscript represents the order of the segment within the corporation as it appeared in the original data.

We begin with equations for the determination of business segment performance. These equations include Corporate $ROA_{J,T}$ and Industry $ROA_{K,T}$ as independent variables.

Rumelt assumed that corporate identity should influence business unit ROA (and was surprised when his analysis did not support this assumption). Well-managed (profitable) corporations should positively influence the performance of their business segments. Such an influence might be by a number of mechanisms: (1) appropriate diversification (e.g., selection of synergistic businesses), (2) direct improvements in management (e.g., by the imposition of appropriate managerial techniques or selection of managers), (3) interdivisional improvements in management (e.g., by sharing learning), (4) wise allocation of capital across divisions, or (5) any of a number of other factors. Corporate performance should positively influence segment performance.

Following the industrial organization literature, industry structure should influence business segment performance. Much of the empirical tradition in industrial organization economics focuses on differences in average levels of profitability across industries with the assumption that profitability differences across industries reflect industry structures that facilitate collusive, anticompetitive conduct. In other words, industries differ in the features that enable firms to avoid competition. We use the industry's profitability as a proxy for these differences. Such usage has been widespread in strategy research (Christensen and Montgomery, 1981; Hansen and Wernerfelt, 1989; Bromiley, 1991). Some researchers have taken a related approach by normalizing firm profitability by subtracting the weighted average of industry ROA from firm profitability (Rumelt, 1982). Industry profitability should have a positive influence on business segment profitability.

Prior studies using annual data have included year or industry–year effects (Rumelt, 1991; Roquebert *et al.*, 1996). If macroeconomic factors influence profitability, they should influence different industries to different extents. Industry profitability in a given year provides a better representation for the influence of such factors on a particular industry than a single-year dummy variable and makes the inclusion of both year and an interaction between year and industry variables unnecessary.

The model in this paper does not contain dummy variables for business segments (although we present a model later in the paper that does). If we include a dummy variable for each business segment, it will pick up the mean performance for that business segment. Since the mean of such dummies for a given corporation does not need to equal zero, the business segment dummy variables could reflect any stable performance effects, including those associated with membership in a given corporation. This would leave only the variation over time in performance to the corporate performance variable that might substantially understate its importance. We discuss these issues further when we introduce our second model.

This leads to the following general business segment equation for our first model:

$$\text{Segment ROA}_{I,J,K,T} = \delta_1 + \beta_I \text{ Corporate ROA}_{J,T} + \gamma_I \text{ Industry ROA}_{K,T} + \epsilon_{I,J,K,T} \quad (1)$$

Equation 1 repeats for each business segment in a given corporation. Since the model requires one equation per business segment, it must be estimated on a sample of corporations with the same number of segments. Since the number of corporations available fell as the number of business segments increased, we estimate the model on corporations with three and four segments. We omitted corporations with one or two business segments because they may lack a corporate portfolio effect. Few firms have more than four business segments.[2] For a sample of firms with three business segments, the business segment equations will be

$$\text{Segment ROA}_{1,J,1,T} = \delta_1 + \beta_1 \text{ Corporate ROA}_{J,T} + \gamma_1 \text{ Industry ROA}_{K,T} + \epsilon_{1,J,1,T} \quad (1.1)$$

$$\text{Segment ROA}_{2,J,2,T} = \delta_2 + \beta_2 \text{ Corporate ROA}_{J,T} + \gamma_2 \text{ Industry ROA}_{K,T} + \epsilon_{2,J,2,T} \quad (1.2)$$

$$\text{Segment ROA}_{3,J,3,T} = \delta_3 + \beta_3 \text{ Corporate ROA}_{J,T} + \gamma_3 \text{ Industry ROA}_{K,T} + \epsilon_{3,J,3,T} \quad (1.3)$$

Equation 1.1 corresponds to business segment 1, 1.2 to business segment 2 and 1.3 to business

[2] Note that our sample differs from Roquebert *et al.* (1996). Their sample consists of corporations with two or more business segments thus pooling corporations with differing numbers of segments.

segment 3. Separate parameters are estimated for each business segment.

We examine the parameters' magnitude and magnitude relative to the variance of the related variable (the standardized beta) to evaluate the relative importance of corporate and industry effects on business segment performance. We also examine explained variance. A corporate effect which contributes to segment performance implies $\beta_1$, $\beta_2$, and $\beta_3$ should be positive. Our main hypothesis is

*Hypothesis 1: Corporate ROA has a positive influence on Business Segment ROA (coefficients $\beta_1$, $\beta_2$ and $\beta_3 > 0$) after controlling for the simultaneous contribution of Business Segment ROA on Corporate ROA.*

In addition, we expect the parameters, $\gamma_1$, $\gamma_2$, and $\gamma_3$, to be positive reflecting the contribution of the Industry ROA to Segment ROA. Industry ROA controls for the independent effect of a business segment's environment.

*Hypothesis 2: Industry ROA has a positive influence on Business Segment ROA ($\gamma_1$, $\gamma_2$, and $\gamma_3 > 0$).*

An equation for the influence of business segment performance on corporate performance completes the model. We first calculate $w_{I,J,T}$, which is the proportion of total corporate assets in the $I$th business segment in a given year. For a sample of firms with three business segments we thus have $I = 1,2,3$. The return on assets for the corporation should be a weighted sum of the return on assets of its business segments. However, the equation is not an accounting identity because some corporate activities influence corporate reported ROA without figuring into the Segment ROAs. Business segments with less than 10 percent of revenue, profits/losses, and assets may not be separately reported. Furthermore, corporate expenses, revenues earned at the corporate level, most interest expenses, and a variety of other items will be retained at the corporate level and not allocated to segments. Finally, corrections must be made in corporate figures for intersegment sales and assets shared by segments.

We include financial leverage as a measure of the absence of slack at the corporate level. The absence of slack limits the company from taking corporate-level strategic actions. Several studies suggest that financial leverage influences operating earnings (Bromiley, 1991; Balakrishnan, and Fox, 1993). For example, highly leveraged firms may find their investment options limited to those that can be offered as collateral to lenders. Such a constraint reduces the corporations' ability to seek good investments, resulting in lower operating returns for firms with leverage. Although a number of different proxies have been used for such costs, we follow Hoskisson *et al.* (1993b) and Lubatkin and Chatterjee (1991) in using debt to total assets as a proxy for financial leverage. The resultant equation is

$$\begin{aligned}\text{Corporate ROA}_{J,T} &= \phi_1 \\ &+ \alpha_1\, w_{1,J,T}\,\text{Segment ROA}_{1,J,K,T} \\ &+ \alpha_2\, w_{2,J,T}\,\text{Segment ROA}_{2,J,K,T} \\ &+ \alpha_3\, w_{3,J,T}\,\text{Segment ROA}_{3,J,K,T} \\ &+ \alpha_4\,\text{Debt/Total Assets}_{J,T} + u_{J,T} \qquad (2)\end{aligned}$$

In Equation 2, we expect the parameters $\alpha_1$, $\alpha_2$, and $\alpha_3$ to be positive and of roughly the same magnitude. The parameter on debt to assets, $\alpha_4$, should be negative indicating higher leverage should lower reported corporate returns. Our full model for corporations with three segments includes Equations 1.1, 1.2, 1.3, and 2. For corporations with four segments, Equation 1 repeats an additional time to add Equation 1.4.

### Complex null hypothesis

If corporate activities do not influence business segment performance, the corporate parameters in the business segment equations ($\beta$s) should be statistically insignificant. On the other hand, we wish to consider Herbert Simon's criticism of simply testing hypotheses by whether coefficients are different from zero or the 'extreme null' hypothesis (Ijiri and Simon, 1977; Savage, 1954). Most statistical work uses zero for the null hypothesis—it tests whether the parameter of interest has the right sign and differs from zero. But what if two plausible theories make the same prediction for the sign of the parameter? In this case, simply testing against a null hypothesis of zero does not help reject the alternative explanation. One can differentiate among such alternative models if they make different predictions for the magnitudes of parameters and this is what we do by developing a complex null hypothesis.

In our model, a particularly obvious alternative explanation exists. Assuming Rumelt's (1991) findings are correct, corporations should have no influence on business segment performance. In this case, if we did not control for the simultaneity of the equation system, we would find an association between corporate and business segment performance in the business segment equations, but the model would have the wrong causal direction. Rather than Corporate ROA influencing Segment ROA as our model has specified it, a positive association between the two could reflect the influence of segment ROA on Corporate ROA (which is created by aggregating business segment returns). In other words, changes in Segment ROA would appear to be caused by changes in corporate ROA when in fact the causal mechanism was the reverse; the Business Segment ROA changes actually drive the changes in Corporate ROA.

If corporate performance does not influence business segment performance but is constructed by aggregating business segment performance, simple OLS estimates of the business segment equation would provide positive coefficients on corporate performance due to accounting relationships. While both this alternative model and the original model imply positive coefficients, they imply different specific magnitudes for these parameters. In this section, we develop alternative hypotheses based on the assumption that corporations do not influence business segments but corporate performance reflects an aggregation of business segment performances. We examine this complex null hypothesis for corporations with three business segments since the larger number of observations allows us the most accurate parameter estimates.

Assume that by accounting construction the following Equation 2 holds for a corporation with three business segments (subscripts, *J*,*K*, and *T* omitted):

$$\begin{aligned}\text{Corporate ROA} = {} & \phi_1 \\ & +\alpha_1\, w_1 \text{ Segment ROA}_1 \\ & +\alpha_2\, w_2 \text{ Segment ROA}_2 \\ & +\alpha_3\, w_3 \text{ Segment ROA}_3, \\ & +\alpha_4 \text{ Debt/Total Assets} + u \qquad (2)\end{aligned}$$

Since the weights ($w$s) already incorporate the different sizes of the business segments, the accounting model implies the coefficients ($\alpha$s) are equal in magnitude. Let us show this formally. Assume a corporation consists of three divisions with incomes and assets of $(a,b)$, $(c,d)$, and $(e,f)$ for divisions 1, 2, and 3 respectively. Corporate return on assets equals the total income $(a+c+e)$ over the total assets $(b+d+f)$. Return on assets for each division is $a/b$, $c/d$, and $e/f$ for divisions 1, 2, and 3 respectively. Since total assets equals $b+d+f$, the weights ($w_1$, $w_2$, and $w_3$ in Equation 2) are $b/(b+d+f)$, $d/(b+d+f)$, and $f/(b+d+f)$. If we write out Equation 2a and abbreviate CROA for Corporate ROA we see

$$\begin{aligned}\text{CROA} = {} & \phi_1 + \alpha_1\, w_1 \text{ Segment ROA}_1 \\ & + \alpha_2\, w_2 \text{ Segment ROA}_2 \\ & + \alpha_3\, w_3 \text{ Segment ROA}_3 \\ & + \alpha_4 \text{ Debt/Total Assets} + u \\ = {} & \phi_1 + \alpha_1 \{b/(b+d+f)\}\{a/b\} \\ & + \alpha_2 \{d/(b+d+f)\}\{c/d\} \\ & + \alpha_3 \{f/(b+d+f)\}\{e/f\} \\ & + \alpha_4 \text{ Debt/Total Assets} + u \\ = {} & \phi_1 + \alpha_1 \{a/(b+d+f)\} + \alpha_2 \{c/(b+d+f)\} \\ & + \alpha_3 \{e/(b+d+f)\} \\ & + \alpha_4 \text{ Debt/Total Assets} + u \\ = {} & \phi_1 + \{(\alpha_1 a + \alpha_2 c + \alpha_3 e)/(b+d+f)\} \\ & + \alpha_4 \text{ Dept/Total Assets} + u \qquad (2a)\end{aligned}$$

But we know that $\text{CROA} = (a+c+e)/(b+d+f)$. If all the $\alpha$s equal one we get

$$\begin{aligned}\text{CROA} = {} & \phi_1 + \{(a+c+e)/(b+d+f)\} \\ & + \alpha_4 \text{ Debt/Total Assets} + u\end{aligned}$$

Our first complex null hypothesis is therefore

> *Hypothesis 3:* $\alpha_1 = \alpha_2 = \alpha_3 = 1$ *[complex null hypothesis].*

If there is no corporate effect, then we should have no causal connection between Corporate ROA and Business Segment ROA. But if we estimate the business segment Equation 1 without controlling for simultaneity, we would find positive coefficients. Consider the business segment equation for business segment 1:

$$\text{Segment ROA}_1 = \delta_1 + \beta_1 \text{ Corporate ROA} + \gamma_1 \text{ Industry ROA} + \epsilon \quad (1.1)$$

If we substitute the value of Corporate ROA from Equation 2 into Equation 1.1, we obtain

$$\begin{aligned}\text{Segment ROA}_1 &= \delta_1 \\ &+ \beta_1[\alpha_1\, w_1 \text{ Segment ROA}_1 \\ &+ \alpha_2\, w_2 \text{ Segment ROA}_2 \\ &+ \alpha_3\, w_3 \text{ Segment ROA}_3 \\ &+ \alpha_4 \text{ Debt/Total Assets}_t + u] \\ &+ \gamma_1 \text{ Industry ROA} + \epsilon \quad (1.2)\end{aligned}$$

We can readily derive an appropriate value for $\beta_1$. Consider what happens if ROA for business segment 1 increases by one unit. The left-hand side of the equation increases by one unit. On the right-hand side, we have a one-unit increase in segment $ROA_1$ but for the equation to remain in balance the product of $\beta_1\ \alpha_1\ w_1$ segment $ROA_1$ must equal one. This implies $\beta_1 = \alpha_1\ w_1 = 1$. But as we demonstrate above, $\alpha_1 = 1$, so $\beta_1\ w_1 = 1$ and consequently $\beta_1 = 1/w_1$. By exactly the same logic, $\beta_2 = 1/w_2$, and $\beta_3 = 1/w_3$ (which could be derived by inserting the value for Corporate ROA in Equation 2 into Equations 1.2 and 1.3).

Since the data in COMPUSTAT generally report the largest business segments first, the average values for $w_1$, $w_2$, and $w_3$ are 0.51, 0.29, and 0.20. Thus, under the accounting model, we would expect that in Equation 3.1 $\beta_1 \times w_1 = 1$ or $\beta_1 = 1/w_1 = 1.954$ for the first business segment. Likewise, in Equation 3.2, $\beta_2 \times w_2 = 1$ or $\beta_2 = 1/w_2 = 3.464$ and in Equation 3.3, $\beta_3 = 1/w_3 = 5.010$. In other words, in any given business segment equation, the size of the parameter on Corporate ROA should equal the ratio of one over the relative asset size of that business segment in the corporation. Since we know the $1/w_1$, $1/w_2$, and $1/w_3$ (above) our second complex null hypothesis is that these ratios will equal the parameter as well as a joint test of whether all of these tests are true.

*Hypothesis 4a:* $\beta_1 \times w_1 = 1$ *or* $\beta_1 = 1/w_1 = 1.954$ *[complex null hypothesis].*

*Hypothesis 4b:* $\beta_2 \times w_2 = 1$ *or* $\beta_2 = 1/w_2 = 3.464$ *[complex null hypothesis].*

*Hypothesis 4c:* $\beta_3 \times w_3 = 1$ *or* $\beta_3 = 1/w_3 = 5.010$ *[complex null hypothesis].*

Hypothesis 4d is the joint hypothesis that Hypothesis 4a, 4b, and 4c are true:

*Hypothesis 4d:* $\beta_1 \times w_1 = 1$ *and* $\beta_2 \times w_2 = 1$ *and* $\beta_3 \times w_3 = 1$ *or* $\beta_1 = 1/w_1 = 1.954$ *and* $\beta_2 = 1/w_2 = 3.464$ *and* $\beta_3 = 1/w_3 = 5.010$ *[complex null hypothesis]*

Note that Hypotheses 3 and 4 are complex null hypotheses. If not rejected, they suggest that associations between corporate and business segment performance derive from accounting relations whereas Hypotheses 1 and 2 reflect a causal model where corporate behavior influences business segment performance.

## DATA AND METHODS

The model requires data on business segment profitability, corporate profitability, and industry profitability. Two sources provide such data: the FTC Line of Business data base (where the business level is referred to as a business unit) which Rumelt (1991) uses and the COMPUSTAT industry segment data base from 10Ks which Roquefort *et al.* (1996) and McGahan and Porter (1997a) uses (Federal Trade Commission, 1985; Standard and Poor's Compustat, 1994). The two sources have different advantages and disadvantages (Roquefort *et al.*, 1996). The FTC data base contains more detailed information, but covers a smaller sample of larger manufacturing firms and the data only cover 1975–77. The 10K reports, on the other hand, cover a much larger number of corporations and more recent time periods. Although the FTC data may have been collected more carefully and report separately on smaller business activities, business units in that data have been defined as all sales in a given industry. In contrast, COMPUSTAT allows segments which do not simply follow industry. For example, while General Motor's Chevrolet and Cadillac divisions both sell in the same SIC code, they operate as separate business units in GM and appear as separate segments in the COMPU-

STAT data. Following McGahan and Porter (1997a) and Roquebert *et al.* (1996) we use the business segment data from the COMPUSTAT tapes.

The calculations of the measures are straightforward and include observations from both the Annual COMPUSTAT data tape and the Industry Segment COMPUSTAT data tape. Corporate ROA equals operating income before depreciation (COMPUSTAT entry 13, Net Income plus taxes, interest and depreciation) divided by total assets for the corporation. Following Roquebert *et al.* Business Segment ROA is measured by the business segment operating income divided by business segment assets. To remove any possibility of simultaneity between Business Segment ROA and Industry ROA, we calculate the Industry ROA to be used for a given corporation's business segment by removing that segment from the relevant industry operating income and industry total assets. That is, if there are $K$ firms in the industry, the Industry ROA used for business unit $m$ equals $1/(K-1)\ \Sigma_{k \neq m}$ Firm $\mathrm{ROA}_k$. Corporate Debt to Total Assets equaled Long-Term Debt/(Long-Term Debt + Common Equity) [COMPUSTAT entry 12/ (entry 60 + entry 12)].

The estimation of the model requires some additional consideration. Let us begin by presenting the model as a system of equations:

$$\text{Segment ROA}_{1J,1,T} = \delta_1 + \beta_1 \text{ Corporate ROA}_{J,T} + \gamma_1 \text{ Industry ROA}_{K,T} + \epsilon_{1,J,1,T} \tag{4.1}$$

$$\text{Segment ROA}_{2,J,2,T} = \delta_2 + \beta_2 \text{ Corporate ROA}_{J,T} + \gamma_2 \text{ Industry ROA}_{K,T} + \epsilon_{2,J,1,T} \tag{4.2}$$

$$\text{Segment ROA}_{3,J,3,T} = \delta_3 + \beta_3 \text{ Corporate ROA}_{J,T} + \gamma_3 \text{ Industry ROA}_{K,T} + \epsilon_{3,J,1,T} \tag{4.3}$$

$$\begin{aligned}\text{Corporate ROA}_{J,T} = {} & \phi_1 \\ & + \alpha_1\, w_{1,J,T} \text{ Segment ROA}_{1,J,K,T} \\ & + \alpha_2\, w_{2,J,T} \text{ Segment ROA}_{2,J,K,T} \\ & + \alpha_3\, w_{3,J,T} \text{ Segment ROA}_{3,J,K,T} \\ & + \alpha_4 \text{ Debt/Total Assets}_{J,T} + u_{J,T}\end{aligned} \tag{5}$$

The model is a standard simultaneous equation system with four endogenous variables (the Segment ROAs and Corporate ROA) and four exogenous variables (the Industry ROAs and Debt/Total Assets). The Industry ROAs for each segment act as separate exogenous variables: the Industry ROAs for the list of segment ones is quite different from the segment ROAs for the list of segment twos or threes.

If Corporate ROA equaled the weighted sum of the business unit ROAs, then Equation 5 would be replaced by an identity:

$$\begin{aligned}\text{Corporate ROA}_{J,T} = {} & \phi_1 \\ & + \alpha_1\, w_{1,J,T} \text{ Segment ROA}_{1,J,K,T} \\ & + \alpha_2\, w_{2,J,T} \text{ Segment ROA}_{2,J,K,T} \\ & + \alpha_3\, w_{3,J,T} \text{ Segment ROA}_{3,J,K,T}\end{aligned} \tag{6}$$

where the parameter values would be $\phi_1 = 0$ and $\alpha_1 = \alpha_2 = \alpha_3 = 1$. Consistent estimates of the parameters can be obtained by a variety of techniques. These techniques require that Equation 6 hold in the data: that corporate ROA actually equals the weighted sum of the business unit ROAs. In business segment accounting according to FASB (1988) and Jarnagin (1994), this identity does not need to hold. Even for assets, sales, and income taken separately, the reported corporate total does not equal the sum of the business unit figures. The financial standard covering segment reporting (FASB, 1988) includes a variety of factors that can create this lack of equality including: (i) corporate expenses and interest expense should not be allocated to segments, (ii) sales between segments with a corporation can appear as sales within the segment data but must be adjusted out in corporate data, and (iii) some small lines of business activity may not pass the requirements for being reported as a separate segment. In short, the underlying accounting standard is absolutely clear that the sum of the segment reports *does not generally equal the consolidated corporate figures*.

Given that Equation 6 does not hold, we have the equation system of Equations 4.1–4.3 and 5. This is a very standard simultaneous equation system where the dependent variables in each equation appear on the right-hand side of other equations. Ordinary least-squares estimation of these equations will provide biased and inconsistent estimates of the parameters (Judge *et al.* 1985; Kennedy, 1985).

A variety of techniques can give consistent estimates of such a system including two-stage least-squares, three-stage least-squares, iterated three-stage least-squares, and full-information maximum likelihood. We chose two-stage least-squares for its simplicity and the fact that errors in one equation will not hurt the estimation in other equations (Kennedy, 1985). Two-stage least-squares provides consistent estimates of the parameters. We also used the Yule-Walker serial correlation correction with one lag.

We implemented the two-stage least-squares as follows. First we developed instruments for Corporate ROA, and the various Business Segment ROAs. To estimate the instrument, we used current values of exogenous variables, the lagged value of the variable for which the instrument was being developed, and additional lagged accounting data for the corporation.

The lagged accounting data for corporate instrument included the current ratio (current assets divided by current liabilities), the quick ratio (cash and short-term investments plus receivables divided by current liabilities), and percent change in sales. More specifically, we used 1- and 2-year lags on Corporate ROA, Business Segment ROA for segments 1, 2, and 3, current ratio, and quick ratio. We only included one lag for percent change in sales since this already includes information from a previous year. We also include exogenous variables with no lags: Debt/Total Assets, Industry $ROA_1$, Industry $ROA_2$, Industry $ROA_3$ (and Industry $ROA_4$ for corporations with four segments), the endogenous variables (Corporate ROA, Business Segment $ROA_1$, Business Segment $ROA_2$, Business Segment $ROA_3$ and for corporations with four segments Business Segment $ROA_4$) were regressed on the instrumental variables. Predicted values from these regressions formed the instrumental variables for the second state of the estimation procedure. Then the structural Equations (4.1–4.3 and 5) were estimated with the instruments (i.e., the predicted value of the appropriate endogenous variable) in place of the endogenous variables on the right-hand side of the equations. This removes the potential for simultaneity in the endogenous variables. If not removed, the presence of simultaneity would result in biased estimates of the parameters.

COMPUSTAT annual and business segment data were collected from 1986 to 1995. After eliminating observations with missing data, we ended up with a data set of 4114 business segment-year observations for two or more business segment corporations, 2359 for three, 988 for four, 355 for five, and 114 for six or more business segment corporations. In some cases, the order of the segments within a corporation changed from year to year (i.e., industry $X$ as segment one in year 1, $Y$ as segment two, followed by industry $Y$ as segment one in year 2 and $X$ as segment two). Where appropriate, we reordered segments to make sure they appeared to be consistent over time. We estimated the model separately for corporations active in exactly three segments, and exactly four segments.

Data were lost for a number of reasons. Calculating the lags removed 2 years of data as well as corporations that did not have at least three consecutive years of data. Some cases were dropped with extreme values of ROA in the Business Segment ROA variables (ROA greater than 0.4 or less than $-0.3$) and with negative sales or assets. We believe such extreme values reflect factors other than those of interest to this study. Further, we dropped influential observations based on a conservative cut-off of DFFITS $> 3$ or $<3$ on both instruments and final equations which resulted in a sample of 535 three-segment and 173 four-segment annual observations on corporations (Belsley, Kuh, and Welsch, 1980). Since each corporation had three or four segments, the data covered 1605 segment-years (in the three-segment set) and 692 segment-years (in the four-segment set).

Table 1 presents descriptive statistics for the different samples. While the samples do not appear to differ radically, the average segment size appears larger for corporations with four segments than for corporations with three segments. Likewise, segment sales appear higher. Interestingly, the returns on the last segment are the lowest in each sample, suggesting the last segment may differ in some way from the others. Average segment size ranges from \$1.05 billion in assets (for three-segment corporations) to \$1.96 billion in assets (for four-segment corporations).[3]

[3] To test for sample selection bias, we compared the industry ROA for the entire COMPUSTAT sample to the ROA for the segments in our sample. The segments in our sample have an ROA that is 0.235 percent higher than the other segments in their same industries. The difference between the two samples is statistically insignificant at the 0.23 $p$-value. We conclude that our sample is representative of the industries from which they are drawn.

Table 1. Descriptive statistics for different samples

| Variable | 3 segments | | | 4 segments | | |
|---|---|---|---|---|---|---|
| | N | Mean | S.D. | *N* | Mean | S.D. |
| Segment 1 ROA | 535 | 0.106 | 0.088 | 173 | 0.136 | 0.098 |
| Segment 2 ROA | 535 | 0.106 | 0.080 | 173 | 0.102 | 0.068 |
| Segment 3 ROA | 535 | 0.085 | 0.091 | 173 | 0.096 | 0.077 |
| Segment 4 ROA | | | | 173 | 0.077 | 0.098 |
| Segment 1 Assets | 535 | 1566 | 3138 | 173 | 2530 | 4,767 |
| Segment 2 Assets | 535 | 944 | 1831 | 173 | 1577 | 2,252 |
| Segment 3 Assets | 535 | 649 | 1623 | 173 | 2842 | 6,298 |
| Segment 4 Assets | | | | 173 | 876 | 1,116 |
| Segment 1 Sales | 535 | 1277 | 2963 | 173 | 1692 | 2,539 |
| Segment 2 Sales | 535 | 968 | 1786 | 173 | 1746 | 2,543 |
| Segment 3 Sales | 535 | 633 | 1559 | 173 | 4578 | 10,769 |
| Segment 4 Sales | | | | 173 | 760 | 1,193 |
| Corporate ROA | 535 | 0.126 | 0.047 | 173 | 0.132 | 0.041 |
| Corporate Debt/Assets | 535 | 0.387 | 0.185 | 173 | 0.373 | 0.203 |

## EMPIRICAL RESULTS

We discuss the parameter estimates for corporations with three segments first and then for four-segment corporations. Subsequent sections consider the complex null hypothesis, standardized coefficients, and explained variance. Table 2 presents the correlations among segment ROA, industry ROA, corporate ROA and Debt/Assets for each sample.

### *Results on corporations with three segments (Table 3)*

Consistent with Hypothesis 1, the parameter estimates on Corporate ROA in the equation explaining Business Segment ROA are positive and statistically significant in all three of the business segment equations. Business Segment 1, Business Segment 2 and Business Segment 3 have coefficients of 0.826, 0.516, and 0.561 respectively (See Table 3, all significant beyond 0.0001 probability). These parameters support the influence of corporate performance on business segment performance after removing simultaneous effects of business segment performance on corporate performance.

We also find positive significant coefficients on Industry ROA for all three business segments. These coefficients are 0.277, 0.243, and 0.176 for the first, second, and third business segments respectively (see Table 3). The positive and significant coefficients on Industry ROA in these three equations support Hypothesis 2 that industry profitability influences business segment profitability.

The Corporate ROA equation has positive and statistically significant coefficients on the Segment ROA variables and an insignificant negative coefficient on the ratio of debt to assets. The $R^2$ of 0.31 demonstrates both that the model explains a substantial portion of the variance in Corporate ROA but also that it is far from an accounting identity.

### *Results for corporations with four segments (Table 4)*

The results for firms with four business segments are consistent with those for three-segment corporations. Corporate ROA has positive and statistically significant coefficients in all four segments (all at $p < 0.001$). Industry ROA has positive, statistically significant coefficients in three equations but has a negative coefficient in one. The Corporate ROA equation has positive and statistically significant coefficients on all four-segment ROA variables. The control variable on corporate financial leverage, the ratio of debt to assets, has a negative coefficient, as expected, but it is marginally significant. For four-segment corporations, high levels of debt lower operating income. This is consistent with the argument that leveraged firms have their investment options

Table 2. Correlations: According to corporations with three and four segments

| | $SROA_1$ | $SROA_2$ | $SROA_3$ | $SROA_4$ | Ind. $ROA_1$ | Ind. $ROA_2$ | Ind. $ROA_3$ | Ind. $ROA_4$ | Corp. ROA | Corp. D/A |
|---|---|---|---|---|---|---|---|---|---|---|
| $SROA_1$ | 1.0 | | | | | | | | | |
| $SROA_2$ | 0.07 | 1.0 | | | | | | | | |
| $SROA_3$ | 0.19* | 0.09* | 1.0 | | | | | | | |
| Ind. $ROA_1$ | 0.34* | 0.09* | 0.21* | | 1.0 | | | | | |
| Ind. $ROA_2$ | 0.20* | 0.27* | 0.31* | | 0.22* | 1.0 | | | | |
| Ind. $ROA_3$ | 0.23* | −0.01 | 0.17* | | 0.26* | 0.16* | 1.0 | | | |
| Firm ROA | 0.51* | 0.29* | 0.32* | | 0.23* | 0.19* | 0.19* | | 1.0 | |
| Firm D/A | −0.32* | −0.15* | −0.21* | | −0.06 | −0.28* | −0.16* | | −0.22* | 1.0 |
| $SROA_1$ | 1.0 | | | | | | | | | |
| $SROA_2$ | 0.05 | 1.0 | | | | | | | | |
| $SROA_3$ | 0.09 | 0.23* | 1.0 | | | | | | | |
| $SROA_4$ | 0.08 | 0.27* | 0.27* | 1.0 | | | | | | |
| Ind. $ROA_1$ | 0.35* | 0.26* | 0.37* | 0.17 | 1.0 | | | | | |
| Ind. $ROA_2$ | 0.09 | 0.43* | 0.10 | 0.21* | 0.00 | 1.0 | | | | |
| Ind. $ROA_3$ | 0.25* | 0.13 | −0.06 | 0.27* | 0.00 | 0.19* | 1.0 | | | |
| Ind. $ROA_4$ | −0.06 | 0.21* | 0.17* | 0.44* | 0.04 | 0.26* | −0.02 | 1.0 | | |
| Corp. ROA | 0.37* | 0.43* | 0.48* | 0.33* | 0.42* | 0.17* | 0.30* | 0.14 | 1.0 | |
| Corp. D/A | −0.17* | −0.18* | −0.27* | −0.15* | −0.21 | 0.05 | −0.23* | 0.04 | −0.43* | 1.0 |
| Corp. ROA | −0.01 | 0.17 | 0.25 | 0.56* | −0.13 | −0.07 | 0.08 | 0.13 | 1.0 | |
| Corp. D/A | −0.13 | 0.17 | 0.17 | 0.02 | −0.29 | 0.61* | −0.07 | −0.17 | −0.31* | 1.0 |

$SROA_i$ = Segment ROA for Segment $i$; Ind. $ROA_i$ = Industry ROA for Segment $i$; Corp. ROA = Corporate ROA; Corp. D/A = Corporate Debt/Assets.
*|Probability| > 0.05

limited and so earn lower returns (Balakrishnan and Fox, 1993; Bromiley, 1991).[4] For three-segment corporations, we find a negative but statistically insignificant coefficient, which does not support the leverage argument. Given that the corporate equation and leverage were not central issues in this paper, we will not pursue these findings further.

### *Complex null hypothesis*

Let us turn now to the complex null hypothesis—do accounting relations explain these results? We investigate this possibility with Hypotheses 3 and 4. Given the much larger sample size and consequently more precise parameter estimates, we use the results on the corporations with three segments for these tests. Hypothesis 3 tests for the relative magnitude of the coefficients on Business Segment ROA for the three business segments in the Corporate ROA equation (Equation 5). Hypothesis 3 (the joint hypothesis that $\alpha_1 = \alpha_2 = \alpha_3 = 1$) is rejected beyond the 0.001 significance level (See Table 5). The coefficients estimated in the corporate equation are not consistent with the coefficients that one would expect from the alternative explanation.

The second alternative null hypothesis (Hypotheses 4a, 4b, 4c, and 4d) tests whether the magnitude of the coefficients on Corporate ROA for the three Business Segment ROA equations equals the inverse ratio of their weights—$w_1$, $w_2$, and $w_3$. We reject the alternative Hypotheses 4a, 4b, and 4c that $\beta_1 = 1/w_1$, $\beta_2 = 1/w_2$ and that $\beta_3 = 1/w_3$. We can also reject the joint hypothesis that all of these are true, i.e., that $\beta_1 = 1/w_1$, and $\beta_2 = 1/w_2$ and $\beta_3 = 1/w_3$. All can be rejected beyond the 0.001 level. Given strong rejection of all of these versions of the complex null hypothesis, we conclude that the analysis does not support the complex null hypothesis.

[4] As a test for possible misspecification of the model, we also added the logarithm of firm sales to all equations on the grounds that the continuous variable performance model may not include structural differences of industries or firms. Firm sales have significant negative coefficients in two segments of the four-segment sample and one positive significant coefficient in one segment of the three-segment sample. However, the parameters of interest associated with Corporate ROA and Industry ROA did not change. Thus we continued with the simpler model with Corporate ROA and Industry ROA.

Table 3. Estimates of simultaneous equation model for three business segments[a]

| | Business Segment 1 ROA (Eq. 4.1) | | Business Segment 2 ROA (Eq. 4.2) | | Business Segment 3 ROA (Eq. 4.3) | | Corporate ROA (Eq. 5) | |
|---|---|---|---|---|---|---|---|---|
| | OLS | 2SLS[b] | OLS | 2SLS | OLS | 2SLS | OLS | 2SLS |
| Intercept ($\delta,\phi$) | −0.039*** | −0.031 | 0.025* | 0.013 | −0.001 | −0.004 | 0.055*** | 0.078*** |
| | (−4.033) | (−2.432) | (2.491) | (1.098) | (−0.106) | (−0.309) | (9.624) | (9.786) |
| Corporate ROA ($\beta$) | 0.874*** | 0.000 | 0.425*** | 0.002 | 0.578** | 0.003 | | −0.002 |
| | (12.670) | 0.826*** | (6.036) | 0.516*** | (7.079) | 0.561*** | | |
| | 0.464 | (9.773) | 0.248 | (6.270) | 0.294 | (5.764) | | |
| | | 0.370 | | 0.254 | | 0.241 | | |
| Segment 1's Industry ROA ($\gamma_1$) | 0.338*** | 0.277*** | | | | | | |
| | (6.505) | (5.249) | | | | | | |
| | 0.238 | 0.196 | | | | | | |
| Segment 2's Industry ROA ($\gamma_2$) | | | 0.269*** | 0.243*** | | | | |
| | | | (5.455) | (4.839) | | | | |
| | | | 0.224 | 0.203 | | | | |
| Segment 3's Industry ROA ($\gamma_3$) | | | | | 0.143*** | 0.176* | | |
| | | | | | (2.740) | (3.110) | | |
| | | | | | 0.114 | 0.141 | | |
| Segment 1 ROA ($\alpha_1$) | | | | | | | 0.665*** | 0.495*** |
| | | | | | | | (18.824) | (9.853) |
| | | | | | | | 0.627 | 0.409 |
| Segemnt 2 ROA ($\alpha_2$) | | | | | | | 0.651*** | 0.527*** |
| | | | | | | | (14.370) | (7.717) |
| | | | | | | | 0.483 | 0.342 |
| Segment 3 ROA ($\alpha_3$) | | | | | | | 0.508*** | 0.426*** |
| | | | | | | | (9.605) | (5.326) |
| | | | | | | | 0.318 | 0.232 |
| Corporate Debt/Assets ($\alpha_4$) | | | | | | | 0.020* | 0.004 |
| | | | | | | | (2.229) | (−0.386) |
| | | | | | | | 0.077 | −0.016 |
| Rho | | −0.477*** | | −0.539*** | | −0.476*** | | −0.444*** |
| $R^2$ | 0.3217 | 0.2710 | 0.1313 | 0.1094 | 0.1123 | 0.1035 | 0.4925 | 0.3110 |
| Adjusted $R^2$ | 0.3192 | 0.2683 | 0.1280 | 0.1061 | 0.1089 | 0.1002 | 0.4887 | 0.3058 |
| $N$ | 535 | 535 | 535 | 535 | 535 | 535 | 535 | 535 |

[a]In numerical cells, the parameter estimate appears over $t$-statistic in parentheses and then the standardized coefficient.
[b]Two Stage Least Squares Estimator (2SLS) include the use of instrumental variables and serial correlation correction.
*** |Probability| > 0.001; ** |Probability| > 0.01; * |Probability| > 0.05; ^ |Probability| > 0.10

Table 4. Estimates of simultaneous equation model for four business segments[a]

| | Business Segment 1 ROA (Eq. 4.1) | | Business Segment 2 ROA (Eq. 4.2) | | Business Segment 3 ROA (Eq. 4.3) | | Business Segment 4 ROA (Eq. 4.4) | | Corporate ROA (Eq. 5) | |
|---|---|---|---|---|---|---|---|---|---|---|
| | OLS | 2SLS[b] | OLS | 2SLS | OLS | 2SLS | OLS | 2SLS | OLS | 2SLS |
| Intercept ($\delta,\phi$) | 0.024 | 0.013 | −0.016 | −0.036^ | −0.012 | −0.011 | −0.065** | −0.080** | 0.069*** | 0.086*** |
| | (1.137) | (0.470) | (−1.097) | (−1.957) | (−0.701) | (−0.504) | (−3.053) | (−3.155) | (7.915) | (7.143) |
| | | 0.002 | | 0.004 | | −0.001 | | −0.009 | | 0.000 |
| Corporate ROA ($\beta$) | 0.558*** | 0.685*** | 0.606*** | 0.733*** | 1.072*** | 1.074*** | 0.684*** | 0.945*** | | |
| | (3.361) | (3.215) | (5.914) | (6.025) | (8.625) | (7.034) | (4.509) | (5.444) | | |
| | 0.256 | 0.278 | 0.375 | 0.423 | 0.581 | 0.515 | 0.294 | 0.360 | | |
| Segment 1's Industry ROA ($\gamma_1$) | 0.367** | 0.298* | | | | | | | | |
| | (3.283) | (2.571) | | | | | | | | |
| | 0.250 | 0.203 | | | | | | | | |
| Segment 2's Industry ROA ($\gamma_2$) | | | 0.405*** | 0.361*** | | | | | | |
| | | | (6.106) | (5.047) | | | | | | |
| | | | 0.387 | 0.344 | | | | | | |
| Segment 3's Industry ROA ($\gamma_3$) | | | | | −0.383*** | −0.429*** | | | | |
| | | | | | (−4.030) | (−4.343) | | | | |
| | | | | | −0.271 | −0.304 | | | | |
| Segment 4's Industry ROA | | | | | | | 0.538*** | 0.275*** | | |
| | | | | | | | (6.352) | (3.503) | | |
| | | | | | | | 0.414 | 0.211 | | |
| Segment 1 ROA ($\alpha_1$) | | | | | | | | | 0.723*** | 0.521*** |
| | | | | | | | | | (9.758) | (5.487) |
| | | | | | | | | | 0.511 | 0.364 |
| Segment 2 ROA ($\alpha_2$) | | | | | | | | | 0.723*** | 0.741*** |
| | | | | | | | | | (9.858) | (7.000) |
| | | | | | | | | | 0.488 | 0.437 |
| Segment 3 ROA ($\alpha_3$) | | | | | | | | | 0.776*** | 0.459** |
| | | | | | | | | | (7.613) | (3.277) |
| | | | | | | | | | 0.405 | 0.218 |
| Segment 4 ROA ($\alpha_4$) | | | | | | | | | 0.632*** | 0.349* |
| | | | | | | | | | (5.762) | (2.531) |
| | | | | | | | | | 0.274 | 0.151 |
| Corporate Debt/Assets ($\alpha_5$) | | | | | | | | | −0.029* | −0.026^ |
| | | | | | | | | | (−2.606) | (−1.706) |
| | | | | | | | | | −0.139 | 0.126 |
| Rho | | −0.316*** | | −0.353*** | | −0.432*** | | −0.520*** | | −0.258*** |
| $R^2$ | 0.1814 | 0.1844 | 0.3343 | 0.3235 | 0.3094 | 0.3044 | 0.2941 | 0.3035 | 0.6486 | 0.4899 |
| Adjusted $R^2$ | 0.1718 | 0.1748 | 0.3265 | 0.3155 | 0.3013 | 0.2962 | 0.2858 | 0.2953 | 0.6381 | 0.4746 |
| $N$ | 173 | 173 | 173 | 173 | 173 | 173 | 173 | 173 | 173 | 173 |

[a]In numerical cells, the parameter estimate appears over $t$-statistic in parentheses and then the standardized coefficient. [b]Two Stage Least Squares Estimates (2SLS) include the use of instrumental variables and serial correlation correction. ***|Probability| > 0.001; *|Probability| > 0.01; *|Probability| > 0.05; ^|Probability| > 0.10

Table 5. Test of restrictions in alternative null hypothesis

| | | $F$-value | Probability $> F$ |
|---|---|---|---|
| *Within-equation tests* | | | |
| Joint test: H3 | $\alpha_1 = \alpha_2 = \alpha_3 = 1$ | 64.01*** | 0.000 |
| *Cross-equation tests* | | | |
| H4a | $\beta_1 = 1/w_1$ | 243.17*** | 0.001 |
| H4b | $\beta_2 = 1/w_2$ | 855.40*** | 0.001 |
| H4c | $\beta_3 = 1/w_3$ | 1341.10*** | 0.001 |
| Joint test: H4d | $\beta_1 = 1/w_1$ and $\beta_2 = 1/w_2$ and $\beta_3 = 1/w_3$ | 813.22*** | 0.001 |

***|Probability| > 0.001

### *Standardized coefficients*

We also calculate the standardized coefficients. The standardized coefficient is the parameter estimated which is then multiplied by the ratio of the standard deviation of the repressor to the standard deviation of the dependent variable. It reflects the expected change in the dependent variable for a one standard deviation change in the explanatory variable. The standardized coefficient allows comparison of the relative importance of different variables. The average standardized coefficient on Corporate ROA, or $\beta$ from Equations 4.1–4.3, is 0.288 (calculated from Table 3). The average standardized Industry ROA, or $\gamma$ from Equations 4.1–4.3, is 0.180 (calculated from Table 3). A one standard deviation change in corporate performance has one and two thirds times the impact on business segment performance as a one standard deviation change in industry performance (0.288/0.180 = 1.60). Using this metric for influence, corporations are substantially more influential than industries in determining business segment performance. For firms with four segments, the comparable ratio of the average standardized coefficients is 3.46 (0.394/0.114) (Table 4). Overall, based on standardized coefficients, corporations have around twice to three times the influence on business unit performance that industries do—the average effect for the two samples of the ratio of standardized coefficients is 2.53.

### *Explained variance*

Although one can compare standardized parameter estimates as indicators of the importance of different variables, prior research in this stream relied on explained variance. Consequently, we examine how much of the variance in business segment returns can be explained by corporate and industry performance.

To understand explained variance, we estimate the model with three different equations for each segment. The full model includes both Industry and Corporate ROA variables (Equations 4.1, 4.2, and 4.3 for corporations with three segments). The second includes just the corporate variable (i.e., Segment $\text{ROA}_{I,J,I,T} = \delta_1 + \beta_1$ Corporate $\text{ROA}_{J,T} + \epsilon_{I,J,I,T}$) and the third just the industry variable (Segment $\text{ROA}_{IJ,I,T} = \delta_1 + \gamma_1$ Industry $\text{ROA}_{I,T} + \epsilon_{I,J,I,T}$). The second and third equations provide estimates of the variance in Business Segment ROA explained by Corporate ROA and Industry ROA respectively (Hansen and Wernerfelt, 1989; Schmalensee, 1985). Table 6 summarizes the $R^2$ for these estimates for corporations with three and four segments.

Consider the first row containing the results of segment 1 in Table 6. For corporations with three segments, the segment 1 estimates indicate the Corporation-alone equation has an $R^2$ of 0.229 (column labeled 2, Corporate only) and Industry-alone equation has an $R^2$ of 0.117 (column labeled 3, Industry only); the corporate $R^2$ is about twice the size of industry. Similarly, for segment 2 we have 0.06 and 0.07 so corporation has about 0.9 times the effect of industry. For segment 3, we have 0.09 and 0.03 so corporation is about 3 times industry. If we compare $R$s rather than $R^2$, as Brush and Bromiley (1997) indicate we should, we get substantially smaller differences between the corporate and business segment

Table 6. Incremental $R^2$ analysis for three- and four-segment firms with 2SLS analysis

| Firms with three business segments | 1 Corp. and industry $R^2$ | 2 Corporate only $R^2$ | 3 Industry only $R^2$ | (1 − 3) Incremental corporate $R^2$ | (1 − 2) Incremental industry $R^2$ | (1 − 3)/3—$R^2/R^2$ Incremental corp./ind. effect ratio | (2/3)—$R^2/R^2$ Corp. effect/ind. effect ratio | Sqrt (1 − 3)/sqrt(3) $R/R$ | Sqrt(2)/sqrt(3) $R/R$ |
|---|---|---|---|---|---|---|---|---|---|
| Segment 1 | 0.2710 | 0.2293 | 0.1171 | 0.1539* | 0.0417* | 1.3143 | 1.9582 | 1.1464 | 1.3993 |
| Segment 2 | 0.1094 | 0.0642 | 0.0718 | 0.0376* | 0.0452* | 0.5237 | 0.8942 | 0.7237 | 0.9456 |
| Segment 3 | 0.1035 | 0.0952 | 0.0286 | 0.0749* | 0.0083* | 2.6189 | 3.3287 | 1.6183 | 1.8245 |
| Mean | 0.1613[a] | 0.1296[a] | 0.0725[a] | 0.0888[a] | 0.0317[a] | 1.2248[b] | 1.7871[b] | 1.1067[b] | 1.3368[b] |
| **Firms with four business segments** | $R^2$ | $R^2$ | $R^2$ | $R^2$ | $R^2$ | | | | |
| Segment 1 | 0.1844 | 0.1407 | 0.1270 | 0.0574* | 0.0437* | 0.4520 | 1.1079 | 0.6723 | 1.0526 |
| Segment 2 | 0.3235 | 0.1984 | 0.1973 | 0.1262* | 0.1251* | 0.6396 | 1.0056 | 0.7998 | 1.0028 |
| Segment 3 | 0.3044 | 0.2228 | 0.0072 | 0.2972* | 0.0816* | 41.2778 | 30.9444 | 6.4248 | 5.5628 |
| Segment 4 | 0.3035 | 0.1580 | 0.2097 | 0.0938* | 0.1455* | 0.4473 | 0.7535 | 0.6688 | 0.8680 |
| Mean | 0.2790[a] | 0.1800[a] | 0.1353[a] | 0.1437[a] | 0.0990[a] | 1.0617[b] | 1.3302[b] | 1.0304[b] | 1.1533[b] |

[a]Mean of the figures in the above column.
[b]Ratio of the column means identified in the calculation above.
*$F$-test of difference between models is significant at 0.01 level

effects. For example, in segments 1, 2, and 3 respectively corporation $R$ is 1.4, 0.9, and 1.8 times the industry $R$ (column labeled sqrt(2)/sqrt(3), $R/R$). The average ratio of $R$s is 1.3—Corporate ROA is 1.3 times as important as industry (Table 6).

But this calculation of the corporate and industry effect ignores the covariance between the two explanatory variables (corporation and industry). Under the *most conservative* assumptions where we attribute all of the jointly explained variance to industry, what is the size of the corporate effect? Following Theil (1971: 163–175), we calculate how much Corporate ROA adds to the variance explained by Industry alone (see Table 6). We subtract the $R^2$ of the equation with just industry from the $R^2$ of the equation with both industry and corporate variables to give a conservative estimate of the variance explained by the corporate variable (column labeled 1–3, incremental corporate $R^2$). For segment 1 this gives us an incremental corporate effect of 0.154 (0.2710 – 0.1171) which when divided by the industry effect of 0.117 (column labeled 3) gives a ratio of 1.3 (column labeled (1 – 3)/3—$R^2/R^2$, Corp. effect/ind. effect ratio). For segment 2 the equivalent ratio would be 0.5 and for segment 3 it would be 2.6.

The row labeled Mean presents the averages across the three equations. Using the most conservative assumptions expressed above, the ratio of corporation to industry is 0.0888/0.0725 = 1.225; corporation incremental $R^2$ is 1.2 times what industry explains—(average corporate incremental $R^2$)/(average industry $R^2$) (see column (1 – 3)/3, Table 6). The value of the incremental $R$ for corporation would be 1.1 times the $R$ for industry, which is an indicator of relative importance for this conservative approach. With more reasonable (not so conservative) assumptions, corporation explains 0.1296/0.0725 or 1.8 times what industry explains – (average corporate $R^2$)/(average industry $R^2$) (see column 2/3, Table 6). This same ratio in terms of incremental $R$ is 1.3. Thus there is a range for incremental corporate $R^2$ to Industry $R^2$ of 1.2 to 1.8 and a range of incremental corporate $R$ to industry $R$ of 1.1 to 1.3.

The lower portion of Table 6 reports results for corporations with four segments. Overall, these incremental $R^2$ results support a substantial explained variance for Corporate ROA. Analyses for firms with four segments indicate a range in ratios of $R^2$ from 1.1 for the incremental $R^2$ ratio to 1.3 for less conservative $R^2$ ratio. The same range for ratios of $R$s is 1.0 to 1.15 (Table 6).

While an instrumental variables technique provides consistent estimates of the parameters, it underestimates the explained variance. The instrument is not identical to the actual variable and introduces measurement error which reduces its ability to explain the dependent variable. Because Corporate ROA in the Business Segment ROA equations is represented by an instrumental variable, it has inherent measurement error which reduces its ability to explain Business Segment ROA. For purposes of comparison with OLS estimates, we report an OLS regression of each equation separately in Tables 3 and 4 for three and four segments. Table 7 reports the explained variance results for these OLS estimates the same way that Table 6 reports this analysis for the two-stage least-squares estimates. The results show a stronger corporate effect relative to industry effect with OLS than with the simultaneous equation model. This confirms the presence of a possible bias in the results when a contemporaneous error is not removed from the endogenous variables.

To summarize, when using both standardized betas and explained variance to measure importance, estimates suggest Corporate ROA has a slightly larger influence than Industry ROA on business segment profitability.

## Further explorations: Business segment dummy variables

While the estimates above provide substantial evidence for the influence of corporations on business segment performance, the model differs substantially from others in the literature in that it omits explicit variables to represent business segment effects. This section remedies that omission.

Including business segment dummy variables in the models above presents some serious issues. Let us illustrate with a simple model. Suppose that corporations differ in their returns but the returns are constant over time (Corporate $\text{ROA}_{J,T}$ = Corporate $\text{ROA}_J$ for all $T$). Suppose also that there is no business segment effect—all business segments in a corporation have the same returns as the corporation (with some minor random noise): Segment $\text{ROA}_{I,J,K,T}$ = Corporate

Table 7. Incremental $R^2$ analysis for three- and four-segment firms with OLS analysis

| | 1 Corp. and industry $R^2$ | 2 Corporate only $R^2$ | 3 Industry only $R^2$ | (1 − 3) Incremental corporate $R^2$ | (1 − 2) Incremental industry $R^2$ | (1 − 3)/ 3—$R^2/R^2$ Incremental corp./ind. effect ratio | (2/3)—$R^2/R^2$ Corp. effect/ind. effect Ratio | Sqrt(1 − 3)/ sqrt(3) $R/R$ | Sqrt(2)/ sqrt(3) $R/R$ |
|---|---|---|---|---|---|---|---|---|---|
| **Firms with three business segments** | | | | | | | | | |
| Segment 1 | 0.3217 | 0.2678 | 0.1171 | 0.2046* | 0.0539* | 1.7472 | 2.2869 | 1.3218 | 1.5123 |
| Segment 2 | 0.1313 | 0.0827 | 0.0718 | 0.0595* | 0.0486* | 0.8287 | 1.1518 | 0.9103 | 1.0732 |
| Segment 3 | 0.1089 | 0.0997 | 0.0286 | 0.0803* | 0.0092* | 2.8077 | 3.4860 | 1.6756 | 1.8671 |
| Mean | 0.1873[a] | 0.1501[a] | 0.0725[a] | 0.1148[a] | 0.0372[a] | 1.5834[b] | 2.0699[b] | 1.2584[b] | 1.4387[b] |
| **Firms with four business segments** | | | | | | | | | |
| Segment 1 | 0.1814 | 0.1295 | 0.1270 | 0.0544* | 0.0519* | 0.4283 | 1.0197 | 0.6545 | 1.0098 |
| Segment 2 | 0.3343 | 0.1883 | 0.1973 | 0.1370* | 0.1460* | 0.6944 | 0.9544 | 0.8333 | 0.9769 |
| Segment 3 | 0.3094 | 0.2434 | 0.0072 | 0.3022* | 0.0660* | 41.9722 | 33.8056 | 6.4786 | 5.8143 |
| Segment 4 | 0.2941 | 0.1266 | 0.2097 | 0.0844* | 0.1675* | 0.4025 | 0.6037 | 0.6344 | 0.7770 |
| Mean | 0.2798[a] | 0.1720[a] | 0.1353[a] | 0.1445[a] | 0.1079[a] | 1.0680[b] | 1.2709[b] | 1.0334[b] | 1.1273[b] |

[a] Mean of the figures in the above column.
[b] Ratio of the column means identified in the calculation above.
*$F$-test of difference between models is significant at 0.05 level (or lower)

$ROA_J + \epsilon_{I,J,K,T}$. If the model includes dummy variables for each segment and no Corporate ROA variable, the segment dummy variables would fully and completely pick up the corporate effect. Parameter estimates for all the dummies for segments in a given corporation would equal the Corporate ROA effect. If we add a stable business segment effect, a similar result appears. That is, if Segment $ROA_{I,J,K,T}$ = Segment $ROA_{I,J,K}$ + Corporate $ROA_J$ + $\epsilon_{I,J,K,T}$, business segment dummy variables could completely reflect both corporate and business segment effects. Nothing remains for stable corporate effects to explain.

In the real world, the corporate effect should be a reasonably constant influence with perhaps a transient influence that varies by year. Well-managed corporations should have some premium in returns over time and poorly managed some permanent deficit. In that case, estimating the model with dummy variables for business segments and a continuous variable for Corporate ROA may underestimate the corporate effect. The yearly Corporate ROA variable in the model would largely represent the transient influence while the dummy variables would pick up any stable level effects within the corporation and business segments. Consequently we would expect this model to underestimate corporate effects.

We estimate the following model for segment ROA:

$$\begin{aligned}\text{Segment ROA}_{IJ,I,T} &= \delta_1 \\ &+ \beta_{01} D_1 + \beta_{02} D_2 + \ldots + \beta_{0K} D_K \\ &+ \beta_1 \text{ Corporate ROA}_{J,T} \\ &+ \gamma_1 \text{ Industry ROA}_{I,T} + \epsilon_{I,J,I,T}\end{aligned}$$

where $D_1$ to $D_K$ are dummy variables for each business segment.

The results for these estimates appear in Tables 8 and 9. For the most part, these estimates agree with the estimates in the previous model. Corporate ROA has positive parameter estimates in all of the segment ROA equations and six out of seven are statistically significant. Industry ROA has positive parameters in six out of seven estimates and all five statistically significant estimates are positive. While the average size of the parameters on both Corporate ROA and Industry ROA have been reduced by the introduction of the segment dummy variables, they remain substantial and Corporate ROA continues to have a sizable effect compared to Industry ROA. The ratio of the average standardized coefficient on Corporate ROA to that on Industry ROA is 1.04, and 1.11 for the samples with three and four segments respectively.

To summarize, the introduction of dummy variables for each business segment did not eliminate the substantial corporate and industry effects in these models nor did it change the relation that the corporate effect exceeded the industry effect.

The incremental adjusted $R^2$ for the business effect is still much larger than either the corporate or the industry effect. Given the large number of parameters associated with the business segments, some adjustment for degrees of freedom appears needed when comparing segments to corporations and industries. Consequently, we examine adjusted $R^2$ rather than simply $R^2$. Note that adjusted $R^2$ may not perfectly correct for differing numbers of regressors, but is better than not correcting at all.

In the three-segment sample, adding business segment dummies increased the average adjusted $R^2$ from 0.16 (corporate and industry together) to 0.75 (an increase of 0.54, calculated from Tables 3 and 8). The analogous incremental change for business effects for the four-segment sample is 0.43. (calculated from Tables 4 and 9). In the metric of relative incremental $R^2$, the business effects clearly dominate the other two.

Given the results of Brush and Bromiley (1997), and because $R$ is consistent with correlation, which is a linear rather than a nonlinear measure of relative importance, we lean toward interpreting relative effects in terms of incremental $R$ rather than incremental $R^2$. In this case, the mean incremental business segment effects would be 0.77 and 0.66 for three- and four-segment samples respectively. The corporate and industry effects are 0.36 and 0.27 respectively in the three-segment sample and 0.42 and 0.36 for the four-segment sample. Using adjusted $R$, business effects are much smaller multiples of corporate and industry effects than in $R^2$ comparisons. Business segment effects are 2.1 and 1.6 times corporate effects (three- and four-segment samples). Business segment effects are 2.9 and 1.8 times industry effects (three- and four-segment samples). While business effects remain larger

Table 8. Estimates of simultaneous equation with three business segments. (Business segment dummy coefficients not reported[a])

| | Business segment 1 ROA (2SLS[b]) | Business segment 2 ROA (2SLS) | Business segment 3 ROA (2SLS) | Corporate ROA (2SLS) |
|---|---|---|---|---|
| Intercept | −0.028<br>(−1.182)<br>0.000 | 0.012<br>0.479<br>(−0.772)<br>0.000 | 0.162***<br>(6.579)<br>(1.644)<br>0.000 | 0.078***<br>(9.786)<br>−0.002 |
| Business segment dummies | 165 dummies | 165 dummies | 165 dummies | |
| Corporate ROA | 0.541***<br>(5.623)<br>0.243 | 0.365***<br>(3.687)<br>0.180 | 0.462***<br>(4.713)<br>0.199 | |
| Business segment 1's Industry ROA | 0.333***<br>(5.149)<br>0.235 | | | |
| Business segment 2's Industry ROA | | 0.284***<br>(5.151)<br>0.237 | | |
| Business segment 3's Industry ROA | | | 0.170**<br>(3.167)<br>0.136 | |
| Business segment 1 ROA | | | | 0.495***<br>(9.853)<br>0.409 |
| Business segment 2 ROA | | | | 0.527***<br>(7.717)<br>0.342 |
| Business segment 3 ROA | | | | 0.426***<br>(5.326)<br>0.232 |
| Corporate Debt/Assets | | | | −0.004<br>(−0.386)<br>−0.016 |
| Rho | −0.025 | −0.096^ | −0.049 | −0.444*** |
| $R^2$ | 0.8446 | 0.7942 | 0.8420 | 0.3110 |
| Adjusted $R^2$ | 0.7744 | 0.7014 | 0.7707 | 0.3058 |
| $N$ | 535 | 535 | 535 | 535 |

[a]In numerical cells, the parameter estimate appears over $t$-statistic in parentheses and then the standardized coefficient.
[b]Two Stage Least Squares (2SLS) with instruments and serial correlation correction.
***|Probability| > 0.001; **|Probability| > 0.01; *|Probability| > 0.05; ^|Probability| > 0.10

than corporate and industry effects, business segments appear almost approximately twice as important as corporate effects and 2.4 times as important as industry effects. Given Bowman and Helfat's (1997) argument that segment effects have positive biases (because they pick up any errors in industry classification), these ratios should be considered biased in favor of finding a large business segment effect.

In order to compare our findings using the simultaneous equation methodology to the variance component methodology, we estimate a variance components model on the same samples. Following McGahan and Porter (1997a) and Roquebert *et al.* (1996) we include terms for Year, Industry, Corporation, Business Segment and Error. Comparing the analysis for samples with three and four segments respectively, we find 10 and 15 percent of variance associated with industry, 5 and 15 percent with corporation, and 48 and 25 percent with business segment (See Table 10). Year was associated with 1 percent of the variance in both samples. The ratios of corporation to industry variance components are around 0.55 : 1 and 1 : 1 in the two samples respectively. Since Brush and Bromiley (1997) recommend evaluating relative size of effects by the square roots of the variance components, we

Table 9. Estimates of simultaneous equation with four business segments[a]. (Business segment dummy coefficients not reported[b])

| | Business segment 1 ROA (2SLS[b]) | Business segment 2 ROA (2SLS) | Business segment 3 ROA (2SLS) | Business segment 4 ROA (2SLS) | Corporate ROA (2SLS) |
|---|---|---|---|---|---|
| Intercept | −0.020 | −0.020 | 0.056 | −0.134** | 0.086*** |
| | (−0.396) | (−0.439) | (1.188) | (−2.774) | (7.143) |
| | 0.000 | −0.001 | 0.000 | −0.000 | 0.000 |
| Business segment dummies | 68 dummies | 68 dummies | 68 dummies | 68 dummies | |
| Corporate ROA | 0.818** | 0.334 | 0.323 | 0.758** | |
| | (2.825) | (1.387) | (1.262) | (2.872) | |
| | 0.332 | 0.183 | 0.155 | 0.287 | |
| Business segment 1's Industry ROA | 0.009 | | | | |
| | (0.052) | | | | |
| | 0.006 | | | | |
| Business segment 2's Industry ROA | | 0.575*** | | | |
| | | (6.623) | | | |
| | | 0.550 | | | |
| Business segment 3's Industry ROA | | | 0.052 | | |
| | | | (0.367) | | |
| | | | 0.037 | | |
| Business segment 4's Industry ROA | | | | 0.337*** | |
| | | | | (4.286) | |
| | | | | 0.259 | |
| Business segment 1 ROA | | | | | 0.521*** |
| | | | | | (5.487) |
| | | | | | 0.364 |
| Business segment 2 ROA | | | | | 0.741*** |
| | | | | | (7.000) |
| | | | | | 0.437 |
| Business segment 3 ROA | | | | | 0.459** |
| | | | | | (3.277) |
| | | | | | 0.218 |
| Business segment 4 ROA | | | | | 0.349* |
| | | | | | (2.531) |
| | | | | | 0.151 |
| Corporate Debt/Assets Standard $\beta$ | | | | | −0.026^ |
| | | | | | (−1.706) |
| | | | | | −0.126 |
| Rho | 0.033 | −0.203* | −0.123 | −0.048 | −0.258** |
| $R^2$ | 0.8414 | 0.7568 | 0.7870 | 0.8792 | 0.4899 |
| Adjusted $R^2$ | 0.7351 | 0.5939 | 0.6547 | 0.7982 | 0.4746 |
| $N$ | 173 | 173 | 173 | 173 | 173 |

[a]Two Stage Least Squares (2SLS) with instruments and serial correlation correction.
[b]In numerical cells, the parameter estimate appears over $t$-statistic in parentheses and then the standardized coefficient.
***|Probability| > 0.001; **|Probability| > 0.01; *|Probability| > 0.05; ^|Probability| > 0.10

Table 10. Variance component estimates for samples of firms with three and four business segments

| | Var-Comp | % of sum | Sq. rt. Var-Comp | % of sum | Var-Comp | % of sum | Sq. rt. Var-Comp | % of sum |
|---|---|---|---|---|---|---|---|---|
| | 3 segments only | | | | 4 segments only | | | |
| Year | 0.93 | 1.14% | 0.96 | 5.51% | 0.61 | 0.77% | 0.78 | 4.34% |
| Industry | 7.86 | 9.67% | 2.80 | 16.06% | 12.16 | 15.32% | 3.49 | 19.31% |
| Corporation | 4.12 | 5.07% | 2.03 | 11.63% | 11.52 | 14.52% | 3.39 | 18.80% |
| Business segment | 39.02 | 48.04% | 6.25 | 35.79% | 19.94 | 25.13% | 4.47 | 24.73% |
| Error | 29.30 | 36.08% | 5.41 | 31.03% | 35.12 | 44.26% | 5.93 | 32.82% |
| Sum | 81.222 | 100.00% | 17.454473 | 100.00% | 79.355 | 100.00% | 18.05607 | 100.00% |
| *N* | 1857 | | | | 862 | | | |

examined these as well. Ratios of corporate to industry square roots of variance components are 2.03/2.80 = 0.73 : 1 and 3.39/3.49 = 0.97 : 1. While not radically different from the simultaneous equation results, the variance component results suggest industry is somewhat more important than corporation while the simultaneous equation results suggest the opposite.

## CONCLUSIONS AND IMPLICATIONS FOR FUTURE RESEARCH

This study applies a new way to investigate the relative importance of corporate and industry effects. We use a continuous variable model, as an alternative to the more conventional ANOVA or VCA. This approach estimates the coefficients of corporation and industry effects on business segment returns while explicitly removing the simultaneous effects that might cause inconsistent estimates. We find a sizable corporate effect on business segment performance, one which appears to be greater than the industry effect. These estimates only use data from corporations with three or four business segments and so may not generalize to other samples.

We also investigate a complex null hypothesis that accounting relations explain the statistical findings. We can reject this.

Overall, corporate performance explains more variance in segment returns than industry performance. With the most reasonable estimates, the ratios of corporate to industry $R^2$ were 1.8 in three segments and 1.3 in four for an average of 1.6 (1.3, and 1.2 respectively in ratios of $R$s). With the most conservative approach, which allocated all shared variance to industry, the ratios were 1.2 in three segments, and 1.1 in four segments, for an average of 1.15 (1.1 and 1.0 respectively in ratios of $R$s for an average of 1.05). Furthermore, the average ratios of corporation to industry standardized coefficients (1.6, and 3.5 respectively for three- and four-segment samples) result in an average of 2.5. Thus, all these approaches ($R^2$, $R$, conservative and less conservative, and standardized coefficients) support a corporate effect somewhat larger than the industry effect but generally under twice the industry effect.

One might consider the debate over relative importance of corporation and industry effects as largely an argument about which of two small effects is smaller. However, when we measure importance using incremental adjusted $R$s rather than $R^2$s, a different picture emerges. Using this metric on our results, corporate and industry effects remain smaller than business segment effects, but appear half to four tenths the size of business effects respectively. Rather than inconsequential, corporation and industry effects remain important. Note also that these regressions have high levels of overall fit ($R^2$ in Tables 8 and 9 about 0.80), which suggests most of the variation in segment returns comes from the included factors (corporate, industry, and business segment) rather than some unexplained error term.

These results can be compared with a variety of results in the field—both variance components estimates by Rumelt (1991), Roquebert *et al.* (1996), and McGahan and Porter (1997a), and regression approaches by Hansen and Wernerfelt

(1989), Lang and Stulz (1994), and James (1996) and (See Table 11). Let us consider each in turn.

*Rumelt (1991)*

Based on associated variances, Rumelt found that the corporation was anywhere from 10 percent as important as industry in his Sample A to 41 percent as important as a much smaller industry effect in his Sample B. But he preferred to view the corporate effect as essentially zero (to paraphrase, present but not important), given his acknowledgment of error in the calculation of variance-component estimates. Thus, our results question Rumelt's interpretation.

*McGahan and Porter (1997a)*

McGahan and Porter (1997a) revisit Rumelt's analysis by using VCA and incorporating an autoregressive term to control for serial correlations—which reflects temporal persistence. They find corporate effects that are roughly one fourth the size of industry effects, and corporate effects are about 4 percent of total variance. When they apply Rumelt's model to their data, their results are very similar to those of Rumelt (1991).

*Roquebert, Phillips, and Westfall (1996)*

Our results agree with those of Roquebert *et al.* (1996), despite using a different method of analysis. Across their 10 samples, the percentage of variance explained by the corporate variance component averaged 1.8 times the percentage for industry (average effect of 10.1% for industry and 17.9% for corporation). This agrees well with our less conservative estimates of 1.8, 1.3 and 1.3 for corporations with three, four, and five segments.

Our analysis differs from Roquebert *et al.* (1996) in that our samples include firms with only three and four segments, while the main sample in Roquebert *et al.* (1996) combines corporations with two or more segments with an average number of segments of 4.01. They find the percent variance explained by the corporation declined as they eliminated corporations from the sample which have fewer segments, i.e., moving from samples with two or more, to three or more and four or more, etc.

In our sample, the average corporate effect and average incremental corporate effect did not decline consistently as we moved from samples with three to four segments (see Table 6). Nor do our standardized coefficients on Corporate ROA decline consistently (Tables 3 and 4).

*Hansen and Wernerfelt (1989)*

Related work by Hansen and Wernerfelt (1989) compares organizational influences on corporate performance. They find in a sample of 60 corporations that organizational climate appeared to have a greater influence on corporate performance than industry profitability.

*Lang and Stultz (1994)*

Lang and Stultz's (1994) related work investigates whether the market valuation of firms correlates with degree of diversification. They compare the Tobin's $q$ of diversified firms through the late 1970s and 1980s to single-industry firms and find that the market values single-industry firms more highly than diversified firms. Our results do not speak to this issue directly, since we are investigating samples of diversified firms with three and four segments. Nonetheless, among diversified firms we do find a corporate effect, that the corporation influences the performance of the business segment, which, at face value, seemingly contradicts the inference that one might derive from Lang and Stulz (1994).

*James (1996)*

In recent work James (1996) examines corporate strategies (low cost or differentiation), learning approach (exploration vs. exploitation), and industry effects. She finds corporate strategy interacting with learning approach explains double the variance that industry dummy variables explain.

Taken all together these results present a serious problem. While ANOVA, our regression approach, and the behavioral work of Hansen and Wernerfelt (1989) and James (1996) demonstrate a corporate effect equal or greater than the industry effect, Rumelt (1991) and McGahan and Porter (1997a) find small corporate effects using VCA. Roquebert *et al.* (1996) finds a substantial corporate effect using VCA on a sample with COMPUSTAT data.

Table 11. Studies investigating the relative contribution of industry, corporate and business unit effect for firm or business unit performance

| | Sample (data base, year, restrictions) | Unit of analysis and variables | Method | Findings |
|---|---|---|---|---|
| Schmalensee (1985) | FTC data base<br>1975 (single year)<br>Manufacturing firms | FTC Business Unit | OLS, $F$-tests and inc. adj. $R^2$ of nested equations<br>Variance Components analysis | Corporate-parent effect is negligible<br>Industry membership explains 20% of total firm performance<br>Business unit effect is small and significant |
| Wernerfelt and Montgomery (1988) | Trinet Large Firm Database<br>10K reports<br>FTC LOB for Industry Variables<br>1976 | Business Unit<br>Tobin's $q$ (10K) for dependent variable | OLS, $F$-tests and incremental $R^2$ of nested equations | Firm focus (a measure of firm diversification) explains 2.6% of total variance<br>2-digit SIC industry membership explains 20% to 12.3% depending on controls<br>Market share explains 1% |
| Rumelt (1991) | FTC data base<br>1974–1977<br>Manufacturing firms | Business unit | Random effects Variance Components analysis<br>Fixed effect ANOVA with $F$-tests and inc. adj. $R^2$ of nested equations | Corporate parent effect explains 1–2%<br>Industry membership explains 9–16%<br>Business unit effect explains 44–46% of variation |
| Roquebert *et al.* (1996) | COMPUSTAT Business Segment Tapes<br>1985–1991<br>Manufacturing firms<br>Excludes single-business firms | Business segment<br>Sample restricted to firms with at least 2 business segments | Random effects<br>Variance<br>Components analysis | Corporate parent effect explains 17.9% of variance in business segment performance<br>Industry explains 10% of variation in business unit performance |
| McGahan and Porter (1997a) | COMPUSTAT Industry Segment Tapes<br>1981–1994<br>All sectors except finance<br>Includes single-business firms | Business segment | Random effects<br>Variance<br>Components analysis<br>Sequential ANOVA with $F$-tests and $R^2$ of nested equations | Corporate parent explains 4.33%<br>Industry explains 18.68%<br>Business segment explains 31.71%<br>Year effect explains 2% |
| Current | COMPUSTAT Industry Segment Tapes<br>1986–1995<br>All sectors except finance | Business segment<br>Sample restricted to firms with 3 and 4 segments | Two-stage least-squares<br>$F$-tests and $R^2$ of nested equations | Ratio of corporate effect to industry effect is 1.7 for standardized coefficients<br>Ratio of corporate effects to industry effects in terms of $R^2$ and $R$ is greater than 1 |

Roquebert *et al.* (1996) offer three interpretations of the difference between their results (substantial corporate effect) and Rumelt's (no corporate effect). They suggest the time periods of the data differ, the methods differ in minor ways, and the sample differs in what appears to be level of diversification. They find the corporate effect appears to decline with the number of segments in the corporation. Rumelt's sample consisted of firms with many more lines of business.

These comparisons present some difficulties. Rumelt's categories come from the FTC data and do not correspond directly to the COMPUSTAT business segment data. The FTC line of business data is supposed to define business units in terms of sales in a particular 3.5-digit SIC code but may combine multiple corporate divisions if they sell in the same industry. COMPUSTAT segments, on the other hand, may combine businesses from several different 4-digit SIC codes. Thus one expects differences in the results derived from these two data sets.

On the other hand, Bowman and Helfat's (1997) review of work in the area offers an intriguing observation. Of McGahan and Porter's (1997a: 22) 7003 corporations, only 1791 were diversified. With this sample they get results quite close to Rumelt's (1991) although with a slightly larger corporate effect. Roquebert *et al.* (1996) eliminate all corporations with only one segment. They do not expect single-business firms to have a corporate effect that would be different from a business effect. The small corporate effects in Rumelt (1991) and McGahan and Porter (1997a) may come from an estimate where most of the corporate effects are constrained to be zero—one-business companies. Alternatively, as suggested in McGahan and Porter (1997b), excluding the single-business firms to get a better estimate of corporate effects may create sample selection bias problems resulting in biased estimates of business effects or industry effects.

Rumelt (1991) and McGahan and Porter's (1997a) ANOVA results find substantial corporate effects. The estimates vary depending on order and model specification but corporate effects appear roughly the same magnitude as the industry effects (particularly when one takes the different number of degrees of freedom used into account).

To summarize, this paper provides a new estimate of the influence of industry and corporation on business segment performance. Differing radically from Rumelt's VCA estimates, we find corporations do matter greatly. When considered along with other technical issues and results in the field, we think the evidence to date supports a conclusion that corporate parentage explains slightly more variance in business unit performance than industry membership. Corporations matter as much or more than industry.

## ACKNOWLEDGEMENTS

We are grateful for detailed comments on an earlier draft from Paul Wolfson, the Strategic Management Research Group of the University of Minnesota, and the Management Department at the Wharton School, University of Pennsylvania.

## REFERENCES

Balakrishnan, S. and I. Fox (1993). 'Asset specificity, firm heterogeneity, and capital structure', *Strategic Management Journal*, **14**(1), pp. 2–16.

Belsley, D. A., E. Kuh and R. E. Welsch (1980). *Regression Diagnostics*. Wiley, New York.

Bowman, E. H. and C. Helfat (1997). 'Does corporate strategy matter', working paper, Department of Management, Wharton, University of Pennsylvania.

Bromiley, P. (1991). 'Testing a causal model of corporate risk-taking and performance', *Academy of Management Journal*, **34**(1), pp. 37–59.

Brush, T. H. and P. Bromiley (1997). 'What does a small corporate effect mean? A variance components simulation of corporate and business effects', *Strategic Management Journal*, **18**(10), pp. 825–835.

Carroll, G. R. (1993). 'A sociological view on why firms differ', *Strategic Management Journal*, **14**(4), pp. 237–249.

Christensen H. K. and C. A. Montgomery (1981). 'Corporate economic performance: Diversification strategy versus market structure', *Strategic Management Journal*, **2**(4), pp. 327–243.

Demsetz, H. (1973). 'Industry structure, market rivalry, and public policy', *Journal of Law and Economics*, **16**, pp. 1–9.

Dielman, T. E. (1989). *Pooled Cross-Sectional and Time Series Data Analysis*. Marcel Dekker, New York.

Federal Trade Commission (1985). 'Statistical report: Annual line of business report 1977', *Report of the Bureau of Economics*, April, Washington, DC.

Financial Accounting Standards Board (1988). *Account-*

*ing Standards: Original Pronouncements, July 1973–June 1, 1988*. Irwin, Homewood, IL.

Fomby, T. B., R. C. Hill and S. R. Johnson (1988). *Advanced Econometric Models*. Springer-Verlag, New York.

Ghemawat, P. and J. E. Ricart I. Costa (1993). 'The organizational tension between static and dynamic efficiency', *Strategic Management Journal*, Winter Special Issue, **14**, pp. 59–73.

Hansen, G. S. and B. Wernerfelt (1989). 'Determinants of firm performance: The relative importance of economic and organizational factors', *Strategic Management Journal*, **10**(5), pp. 399–412.

Hoskisson, R. E., C. W. L. Hill and H. Kim (1993a). 'The multidivisional structure: Organizational fossil or source of value?', *Journal of Management*, **19**(2), pp. 269–298.

Hoskisson, R. E., M. A. Hitt, R. A. Johnson and D. D. Moesel (1993b). 'Construct validity of an objective (entropy) categorical measure of diversification strategy', *Strategic Management Journal*, **14**(3), pp. 215–235.

Ijiri, Y. and H. A. Simon (1977). *Skew Distributions and the Sizes of Business Firms*. North-Holland, Amsterdam.

James, C. R. (1996). 'In search of firm effects: The managerial and behavioral implications of competitive advantage', working paper, Anderson School of Management, University of California, Los Angeles.

Jarnagin, B. D. (1994). *Financial Accounting Standards: Explanation and Analysis* (16th ed.). CCH Incorporated, Chicago, IL.

Judge, G. G., R. C. Hill, W. E. Griffiths, H. Lutkepohl and T. Lee (1985). *Theory and Practice of Econometrics* (2nd ed.). Wiley, New York.

Kennedy, P. (1985). *A Guide to Econometrics*. Basil Blackwell, Oxford.

Lang, L. H. P. and R. M. Stulz (1994). 'Tobin's q, corporate diversification, and firm performance', *Journal of Political Economy*, **192**(6), pp. 1248–1280.

Lubatkin, M. and S. Chatterjee (1991). 'Strategy–shareholder value relationships: Testing temporal stability across market cycles', *Strategic Management Journal*, **12**(4), pp. 251–270.

Maddala, G. S. (1977). *Econometrics*. McGraw-Hill, New York.

Matyas, L. and P. Sevestre (1996). *The Econometrics of Panel Data*. Kluwer Academic Publishers, New York.

McGahan, A. M. and M. E. Porter (1997a). 'How much does industry really matter?', *Strategic Management Journal*, Summer Special Issue, **18**, pp. 15–30.

McGahan, A. M. and M. E. Porter (1997b). 'What do we know about variance in accounting profitability?', working paper, Harvard Business School.

Peters, T. and R. H. Waterman, Jr. (1982). *In Search of Excellence: Lessons from America's Best-Run Companies*. Harper & Row, New York.

Powell, T. C. (1992). 'Organizational alignment as competitive advantage', *Strategic Management Journal*, **13**(2), pp. 119–134.

Roquebert, J. A., R. L. Phillips and P. A. Westfall (1996). 'Markets vs. management: What "drives" profitability?', *Strategic Management Journal*, **17**(8), pp. 653–664.

Rumelt, R. P. (1982). 'Diversification strategy and profitability', *Strategic Management Journal*, **3**(4), pp. 359–369.

Rumelt, R. P. (1991). 'How much does industry matter?', *Strategic Management Journal*, **12**(3), pp. 167–185.

Savage, L. J. (1954). *The Foundations of Statistics*. Wiley, New York.

Schmalensee, R. (1985). 'Do markets differ much?', *American Economic Review*, **75**(3), pp. 341–351.

Searle, S. R. (1971). *Linear Models*. Wiley, New York.

Standard and Poor's Compustat (1994). *Compustat User's Guide*. McGraw-Hill, New York.

Theil, H. (1971). *Principles of Econometrics*. Wiley, New York.

Wernerfelt, B. and C. A. Montgomery (1988). 'Tobin's q and the importance of focus in firm performance', *American Economic Review*, **78**(1), pp. 246–249.

## APPENDIX 1: VCA and ANOVA compared

ANOVA estimates models of the following form:

$$Y_i = \beta_0 + \beta_1\, D1_1 + \beta_2\, D1_2 + \ldots + \beta_n\, D1_n + \alpha_1\, D2_1 + \alpha_2\, D2_2 + \ldots + \alpha_m\, D2_m + \epsilon_i \tag{7}$$

where $D1_1$ to $D1_n$ are dummy variables corresponding to the $n$ classes of the first kind (e.g., corporations) and $D2_1$ to $D2_m$ are dummy variables corresponding to the $m$ classes of the second kind (e.g., industries). The error $\epsilon_i$ is assumed to be normally distributed $(0,\sigma^2)$. The importance of an explanatory factor (e.g., corporation or industry) is associated with the variance explained by the set of dummy variables for that factor.

VCA estimates models of the following form:

$$Y_{n,m,t} = \mu_n + \gamma_m + \epsilon_{n,m,t} \tag{8}$$

where $\mu_n$ and $\gamma_m$ are random individual effects with $E(\mu_n)=0$, $E(\mu_n^2)=\sigma_\mu^2$, $E(\gamma_m)=0$ and $E(\gamma_m^2)=\sigma_\gamma^2$. It is also assumed that $E(\mu_i \times \mu_j)=0$ if $i \neq j$ and $E(\gamma t \times \gamma_s)=0$ if $t \neq s$, also $\mu_n$, $\gamma_m$, and $\epsilon_{n,m,t}$ are all uncorrelated (Fomby *et al.*, 1988). That is, $\mu_n$ and $\gamma_m$ are effects for each class of $\mu$ and $\gamma$, for instance, corporation and industry. Rather than estimating each value, i.e., $\mu_i$, $\gamma_j$, the technique estimates $\sigma_\mu^2$ and $\sigma_\gamma^2$ which Rumelt (1991) and others interpret as reflecting the importance of that class, for example corporation or industry.

## APPENDIX 2: Continuous vs. Dummy Variable Models

The dummy variable approaches such as ANOVA and variance components (which is often called random effects ANOVA) basically examine whether the mean of the dependent variable varies across differing explanatory categories (e.g., by corporation or industry). This discrete or dummy variable approach uses many degrees of freedom since it uses a parameter for each level of each factor.

If we have a plausible way of measuring the level of the explanatory variables, we can replace the dummies with these measures. In place of a dummy variable and parameter for each corporation, industry, or business segment, we only need one parameter for each continuous explanatory variable. For example, in McGahan and Porter (1997a: Table 5), the model takes up over 12,298 degrees of freedom, about 21 percent of the total observations. A continuous variable representation would use 4 or 5 degrees of freedom for the model.

This leaves us with the question of what would be a good proxy for the industry or corporation. While we see the mean returns for the industry as a very obvious choice for the performance impact of that industry, the point can be derived more analytically.

Assume that the VCA representation is correct. Consistent with assumptions of VCA, we assume that Corporation, Industry and Year are randomly drawn from independent normal distributions. Using non-Greek notation and only including the industry, corporate and year effects, Rumelt's general representation of a variance components model is (Equation 2, Rumelt 1991):

$$\mathrm{ROA}_{ikt} = \mathrm{Industry}_i + \mathrm{Corporation}_k + \mathrm{Year}_t + \epsilon_{ijt}$$

In a regression framework using dummy variables, one would represent this model using a separate dummy variable for each level of Industry, Corporation, and Year. But this is not inherent in the assumptions of the model. It is just as legitimate to think of Industry as a column vector that takes on the value $\mathrm{Industry}_i$ for business segments in industry $i$. Similarly, one can think of corporation as a column vector with the value of $\mathrm{Corporation}_k$ for all business units in corporation $k$, and likewise for year.

If we use the values for $\mathrm{Industry}_i$, $\mathrm{Corporation}_k$, and $\mathrm{Year}_t$, then we could see this as the following regression model:

$$\mathrm{ROA}_{ikt} = \beta_1\,\mathrm{Industry}_i + \beta_2\,\mathrm{Corporation}_k + \beta_3\,\mathrm{Year}_t + \epsilon_{ijt}$$

with the hypotheses that $\beta_1 = \beta_2 = \beta_3 = 1$. We can now show that Industry mean returns provides a good estimate for $\mathrm{Industry}_i$.

Consider the following data set where we have three corporations each of two segments which operate in two industries. On ROA and the error, the first subscript is industry, the second is corporation, and the third is year. For simplicity, we omit the grand mean but note the mean of each factor's values is zero, as is the mean of ROA. For each segment we have four annual observations:

*Corporation 1*

$\mathrm{ROA}_{111} = \mathrm{Industry}_1 + \mathrm{Corporation}_1 + \mathrm{Year}_1 + \epsilon_{111}$
$\mathrm{ROA}_{112} = \mathrm{Industry}_1 + \mathrm{Corporation}_1 + \mathrm{Year}_2 + \epsilon_{112}$
$\mathrm{ROA}_{113} = \mathrm{Industry}_1 + \mathrm{Corporation}_1 + \mathrm{Year}_3 + \epsilon_{113}$
$\mathrm{ROA}_{114} = \mathrm{Industry}_1 + \mathrm{Corporation}_1 + \mathrm{Year}_4 + \epsilon_{114}$

$\mathrm{ROA}_{211} = \mathrm{Industry}_2 + \mathrm{Corporation}_1 + \mathrm{Year}_1 + \epsilon_{211}$
$\mathrm{ROA}_{212} = \mathrm{Industry}_2 + \mathrm{Corporation}_1 + \mathrm{Year}_2 + \epsilon_{212}$
$\mathrm{ROA}_{213} = \mathrm{Industry}_2 + \mathrm{Corporation}_1 + \mathrm{Year}_3 + \epsilon_{213}$
$\mathrm{ROA}_{214} = \mathrm{Industry}_2 + \mathrm{Corporation}_1 + \mathrm{Year}_4 + \epsilon_{214}$

*Corporation 2*

$\mathrm{ROA}_{121} = \mathrm{Industry}_1 + \mathrm{Corporation}_2 + \mathrm{Year}_1 + \epsilon_{121}$
$\mathrm{ROA}_{122} = \mathrm{Industry}_1 + \mathrm{Corporation}_2 + \mathrm{Year}_2 + \epsilon_{122}$
$\mathrm{ROA}_{123} = \mathrm{Industry}_1 + \mathrm{Corporation}_2 + \mathrm{Year}_3 + \epsilon_{123}$
$\mathrm{ROA}_{124} = \mathrm{Industry}_1 + \mathrm{Corporation}_2 + \mathrm{Year}_4 + \epsilon_{124}$

$\mathrm{ROA}_{222} = \mathrm{Industry}_2 + \mathrm{Corporation}_2 + \mathrm{Year}_1 + \epsilon_{222}$
$\mathrm{ROA}_{222} = \mathrm{Industry}_2 + \mathrm{Corporation}_2 + \mathrm{Year}_2 + \epsilon_{222}$
$\mathrm{ROA}_{223} = \mathrm{Industry}_2 + \mathrm{Corporation}_2 + \mathrm{Year}_3 + \epsilon_{223}$
$\mathrm{ROA}_{224} = \mathrm{Industry}_2 + \mathrm{Corporation}_2 + \mathrm{Year}_4 + \epsilon_{224}$

*Corporation 3*

$\mathrm{ROA}_{131} = \mathrm{Industry}_1 + \mathrm{Corporation}_3 + \mathrm{Year}_1 + \epsilon_{131}$
$\mathrm{ROA}_{132} = \mathrm{Industry}_1 + \mathrm{Corporation}_3 + \mathrm{Year}_2 + \epsilon_{132}$
$\mathrm{ROA}_{133} = \mathrm{Industry}_1 + \mathrm{Corporation}_3 + \mathrm{Year}_3 + \epsilon_{133}$
$\mathrm{ROA}_{134} = \mathrm{Industry}_1 + \mathrm{Corporation}_3 + \mathrm{Year}_4 + \epsilon_{134}$

$$\mathrm{ROA}_{232} = \mathrm{Industry}_2 + \mathrm{Corporation}_3 + \mathrm{Year}_1 + \epsilon_{232}$$
$$\mathrm{ROA}_{232} = \mathrm{Industry}_2 + \mathrm{Corporation}_3 + \mathrm{Year}_2 + \epsilon_{232}$$
$$\mathrm{ROA}_{233} = \mathrm{Industry}_2 + \mathrm{Corporation}_3 + \mathrm{Year}_3 + \epsilon_{233}$$
$$\mathrm{ROA}_{234} = \mathrm{Industry}_2 + \mathrm{Corporation}_3 + \mathrm{Year}_4 + \epsilon_{234}$$

Given this data set, we could estimate an ANOVA model with Industry, Corporation, and Year effects and would expect to find estimates that approximate the values above (i.e., the estimate of the effect for Industry One would be approximately $\mathrm{Industry}_1$ above).

Alternatively, if we can provide a proxy that has a value close to $\mathrm{Industry}_1$ for segments in Industry One, and close to $\mathrm{Industry}_2$ for segments in Industry Two, we should get roughly the same results with a continuous variable model using the proxy.

Consider the mean ROA for an industry as a proxy for the Industry effect in the VCA representation. In the example here, there are 12 observations for each industry, which means the mean for Industry One is:

$$\mathrm{IndustryMean}_1 = \frac{1}{12}\sum_{t=1} \mathrm{ROA}_{i,c,t}$$
$$= \frac{1}{12}\sum_{t=1} \mathrm{Industry}_i + \mathrm{Corporation}_c + \mathrm{Year}_t + e_{i,c,t}$$
$$= \frac{1}{12}\sum_{t=1} \mathrm{Industry}_i + \frac{1}{12}\sum_{t=1} \mathrm{Corporation}_c$$
$$+ \frac{1}{12}\sum_{t=1} \mathrm{Year}_t + \sum_{t=1} \frac{1}{12} e_{i,c,t}$$

Consider the expectation of the values of the right-hand side. Since Corporation, Industry and Year are randomly drawn from independent normal distributions, the expected values $\mathrm{Corporation}_c$, $\mathrm{Year}_t$, and $e_{i,c,t}$ are all zero. This gives the following equation:

$$\mathrm{IndustryMean}_1 = \frac{1}{12}\sum_{t=1} \mathrm{Industry}_i$$
$$= \mathrm{Industry}_1$$

In other words, the mean of the segment ROAs within a given industry provides an unbiased estimate of the industry effect for that industry. An identical logic follows for the corporate effects.

Thus, mean industry or corporate returns provide good proxies for the industry and corporate effects. Under VCA assumptions, the expected results from a continuous variable model should be approximately equal to those from the discrete variable approaches.

In addition, since we can take industry and corporate mean returns by year, we do not need a year effect. Any general year factors that influence all segments certainly should influence all segments in a given industry and so will be picked up by the industry effect. Actually, the annual industry mean value should provide a proxy for both the general year effect and an interaction between year and industry.

To summarize, the continuous variable approach using mean returns as proxies follows directly from the arithmetic under VCA assumptions. The main difference between the continuous variable approach and ANOVA/VCA is that continuous variable models have a substantial advantage in power. Whereas the ANOVA for the model above would need independent parameters associated with three corporations, 4 years, and two industries (nine parameters for 24 observations), a continuous variable representation would only need two parameters (one for corporation and one for industry).