

The background of the entire page is a grayscale photograph of a modern university building. The building features a prominent glass facade with vertical window columns. In the foreground, there is a paved courtyard with several concrete benches and young trees. The overall scene is bright and clear.

# KRANNERT GRADUATE SCHOOL OF MANAGEMENT

Purdue University  
West Lafayette, Indiana

Comparing Alternative Methods to  
Estimate Corporate and Industry Effects

by

Thomas H. Brush  
Constance R. James  
Philip Bromiley

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Thomas H. Brush  
Krannert School of Management  
Purdue University  
West Lafayette, Indiana  
47906  
(765) 494-4441  
(765) 494-1526 fax

Constance R. James  
Pepperdine University  
Malibu, California  
90265  
(310) 317-7371  
(310) 456-0437 fax

Philip Bromiley  
Carlson School of Management  
University of Minnesota  
Minneapolis, MN 55402  
(612) 624-5746  
(612) 626-1316 fax



# COMPARING ALTERNATIVE METHODS TO ESTIMATE CORPORATE AND INDUSTRY EFFECTS

## Abstract

Recent studies of the relative size of corporate and industry effects have used ANOVA, Variance Components Analysis and Simultaneous Equations (Roquebert, Phillips and Westfall 1996; McGahan and Porter, 1997a; 1997b, Brush, Bromiley and Hendrikx, forthcoming). This paper provides a comprehensive evaluation of the advantages and disadvantages of these techniques for evaluating the relative importance of effects. Using a Monte Carlo approach, we empirically compare these techniques. Based on bias and precision of estimation, the simultaneous equation estimates and particularly standardized beta provide the best estimates of effect size.



# COMPARING ALTERNATIVE METHODS TO ESTIMATE CORPORATE AND INDUSTRY EFFECTS

## Introduction

In recent years, a controversy has arisen over the relative importance of corporate, business unit or industry effects on business unit profitability (Schmalensee, 1985; Rumelt, 1991; Powell, 1996; Roquebert, Phillips & Westfall, 1996; McGahan & Porter, 1997a). The underlying issues center on differing approaches to explaining performance. Strategic management scholars have emphasized corporate portfolio and corporate management along with organizational capabilities at the business unit level (Chandler, 1991, 1992; Prahalad & Hamel, 1990). In contrast, work drawing most heavily from industrial organization economics and the structure-conduct-performance paradigm emphasizes the importance of industry positioning as a determinant of performance (Bain, 1951, 1956; Porter, 1980).

Efforts to assess the relative importance of corporate, industry, and business effects have relied on three statistical techniques -- analysis of variance (ANOVA), variance components analysis (VCA), and simultaneous equations systems. Although controlling for sample characteristics reduces the differences in findings (Bowman & Helfat, 1998), some remaining differences in findings appear to depend on the researchers' choice of statistical technique (McGahan and Porter, 1997a; McGahan and Porter, 1997b; Rocquebert, et al, 1996). We use a Monte Carlo simulation to compare the three approaches and to determine which approach(es) provide the best estimates of relative importance.

ANOVA and VCA have been most widely used in empirical studies assessing effect size. Both techniques have problems when interpreted as measuring the relative importance of the effects of industry, corporate and business units. 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 that under many circumstances, VCA lacks the power to find effects even when they are imposed to be present in the data. Another issue revolves around the interpretation of variance component effects – according to Brush and Bromiley (1997) the square root of variance components should be used when interpreting the relative importance of effects. ANOVA presents difficulties because corporate effects must be entered into the model before business unit effects which gives an upper bound on the relative importance of corporation (Rumelt, 1991). For example, Rumelt (1991) finds a substantial corporate effect when he enters corporation before business unit. In addition to the debate over corporate, industry, and business unit effects, the underlying issue of estimating importance of an effect has wide impact in business research.

Brush, Bromiley and Hendrickx (forthcoming) use a simultaneous equation model to assess relative importance. They claim this method provides reliable estimates of effects and solves some of the difficulties posed by assumptions in the other estimation approaches (Brush, Bromiley and Hendrickx, forthcoming). While Brush, Bromiley and Hendrickx (forthcoming) focus on the use of continuous performance variables to estimate corporate and industry effects, they still use dummy variables to control for business unit effects.

We use Monte Carlo simulation to compare ANOVA, VCA and simultaneous equations techniques in their ability to estimate the relative importance of effects. The comparisons evaluate both bias and precision of the estimators.

## **The Alternative Techniques: Variance Components Analysis versus ANOVA**

Two schools of thought contest the source of business unit profitability. The classical school of industrial organization economists uses the structure-conduct-performance paradigm (Bain 1951, 1956), while a school of revisionists argue for firm efficiency (Demsetz, 1973; Conner, 1991). The classical school argues that firms earn abnormal profits due to their industry structure and market power (Bain 1951, 1956); the revisionist school argues that efficient and well-managed firms grow to dominate industries (Wernerfelt, 1984; Rumelt, 1984, 1987).

Most empirical studies testing whether industry or firm effects matter more for business unit performance use two techniques, ANOVA and variance components analysis (VCA). Several studies include both, but the authors demonstrate a preference for one method over the other by relying more heavily on one than the other in deriving conclusions. These studies are descriptive rather than positive; they seek to identify the magnitude of a particular effect rather than test an explanation for the effects. These studies often use broad measures, such as dummy variables, to capture industry and firm effects. While industry effects have been modeled consistently across the studies, differing representations of corporate and business effects have been presented.

Schmalensee (1985) provides the first major study of industry, corporate, and business effects, using both VCA and ANOVA, though clearly preferring VCA for determining importance of effects. He attempts to determine the relative importance of industry or firm on 1974 FTC line-of-business data for manufacturing firms. Using ANOVA to measure the significance of each effect, he finds that firm effects (the same as Rumelt's corporate effects) are insignificant and concludes that firm management does not matter. Using VCA to compare the relative importance of each effect, he finds that corporate effects do not exist, important industry



effects existed and explained 19% of the variance in rates of return, and market share effects exist but are trivial in magnitude. Schmalensee (1985: 349) says the absence of a corporate effect "merely means that knowing a firm's profitability in market A tells nothing about its likely profitability in a randomly selected market B." His study supports the classical view of industry structure, but provides no details into the characteristics behind these effects.

Schmalensee's use of VCA to measure importance presents at least two potential methodological problems. First, the management and economics literatures are largely silent on how to interpret VCA. Second, Schmalensee uses the variance of each component rather than the more standard practice of measuring importance with an estimated parameter.

Intrigued by the non-existence of a corporate effect, Kessides (1987) and Wernerfelt and Montgomery (1988) use similar methods on Schmalensee's data in follow-up studies. Their results agree with Schmalensee's on industry effects, but not on the corporate effect. By excluding corporations with fewer than three business units, Kessides (1987) finds a larger corporate effect than Schmalensee's. Using Tobin's  $q$  to measure performance and adding diversification focus, Wernerfelt and Montgomery (1988) find a small corporate effect in the form of diversification focus strategies which are measured with a continuous variable.

Rumelt (1991) respecifies Schmalensee's (1985) model to decompose 1974-1977 FTC line-of-business profitability variance over time using both VCA and ANOVA. Rumelt (1991) adds a different specification of business unit effects (industry corporate interactions), year effects and industry-year interaction effects to Schmalensee's (1985) model. Rumelt's model allows him to identify business-units as an independent effect rather than Schmalensee's method that used market share as a proxy for business-unit effects. Both Schmalensee and Rumelt use VCA and ANOVA to estimate their models, but while Schmalensee emphasizes the role of

ANOVA for showing that corporate effects are not significant, Rumelt primarily emphasizes his VCA findings. Rumelt argues that "it is only by estimating the variances of effects that relative importance can be assessed." (Rumelt, 1991: 173).

Rumelt's results agree with Schmalensee in finding a very small corporate effect and a modest industry effect, but Rumelt also finds a strong business effect which in Schmalensee (1985) was part of the error term. Rumelt finds that business effects are much larger than either the corporate or industry effects.

Rumelt (1991) discusses the small corporate effect 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 is formally based on the size of his estimated variance component, he suggests that corporate strategy may be relatively unimportant for explaining business unit performance.

In addition to more general concerns about VCA (see Brush & Bromiley, 1997), the small corporate effect in VCA may come from structural assumptions in Rumelt's (1991) variance components model. He decomposes the total variance of business unit profitability ( $\sigma^2_\gamma$ ) into variance and covariance terms:

$$\sigma^2_\gamma = \sigma^2_\alpha + \sigma^2_\beta + \sigma^2_\gamma + \sigma^2_\delta + \sigma^2_\phi + \sigma^2_\epsilon + 2C_{\alpha\beta(3)}$$

in which  $\sigma^2_\alpha$  is the variance of stable industry effects,  $\sigma^2_\beta$  is the variance of stable corporate effects,  $\sigma^2_\gamma$  is the variance of the year effect,  $\sigma^2_\delta$  is the variance of the business effects,  $\sigma^2_\phi$  is the variance of transient industry effects,  $\sigma^2_\epsilon$  is the variance of transient corporate effects, and

$C_{\alpha\beta}$  is the covariance between  $\alpha$  and  $\beta$ . The covariance term captures covariance between the corporation and the industry consistent with Schmalensee. This would be equivalent to the contribution from firms picking profitable industries (Schmalensee, 1985). However, Rumelt does not include the possibility that corporate effects may also covary with business effects in his model. Rumelt imposes the assumption that corporate and business unit effects are uncorrelated, i.e., across corporations, corporate effects cannot correlate with business unit effects.

Strategic management may argue for an association between business-unit and corporate effects if well-managed corporations both pick profitable businesses to enter and manage them well. For example, if high performance corporations achieve such performance by selecting high performance business units, this corporate effect might be masked as a business effect using VCA. While corporate strategy emphasizes activities that should create associations between business unit and corporate effects, VCA does not capture this correlation as part of its corporate effect. That is, if corporations differ in their ability to pick high performance business units, this capability will not necessarily be picked up as a corporate effect. Thus, one questions the underlying structural assumptions of using this model, without adjusting for this possibility.

More recent studies of industry, corporate and business effects use data from COMPUSTAT (Roquebert, et al, 1996; McGahan & Porter, 1997a). COMPUSTAT provides more recent data on a larger sample of firms, but defines the "business" according to the accounting treatment of business segments rather than the FTC's line of business approach. Business segments tend to include business units with similar product lines. Given the size of the business segment, the use of business segments should produce a large business effect and reduce the corporate effect (McGahan & Porter, 1997a), yet these studies produce larger

corporate effects than Schmalensee's and Rumelt's. These studies result in a large range of corporate effects from 4% to 18%.

To understand this range of effects, McGahan and Porter (1997a) use sequential ANOVA analysis entering industry before corporate effects and vice versa. When industry enters first, the corporate effect is 9.1% versus 11.9% when corporate enters first. James (1998) finds a similar issue between corporate and business effects. Corporate effects decline from 15% to 5% when entered last using continuous variables (James, 1988).

Both VCA and ANOVA present problems. Researchers using VCA interpret the magnitude of the variance component as "importance". This contrasts with standard practice in other areas of management research in which researchers interpret estimated parameters (standardized beta) as importance rather than explained variance. In addition, the comparison of the size of the variance of each component may be misleading. Brush and Bromiley (1997) have shown that square roots of variance components more accurately reflect the relative importance of each component. Studies using variance components without taking the square root will obtain biased estimates and the biases increase with smaller effects (Brush & Bromiley, 1997). Thus, while Schmalensee's industry effects explain 19% of the variance in business unit profitability, their relative importance is approximately 4.5% using the square root of the variance. Similar interpretation problems appear in all previous VCA analyses of this issue.

In addition to interpretation, Brush and Bromiley (1997) find that VCA does not provide very reliable estimates. They find that multiple runs of the same underlying model (simulated data with the same parameters) can result in a wide variance in estimates which means the technique is not reliable in any single application (Brush & Bromiley, 1997).

ANOVA also has its pros and cons. On the positive side, management researchers understand its assumptions and interpretation better than VCA. On the other hand, order of entry matters because ANOVA allocates covariance effects to the first variable entered in the pair. Whether corporate effects enter before industry effects will influence which appears larger. Furthermore, because business units (and segments) naturally nest within corporations and industries, corporations and industries must be entered before business units. In addition, ANOVA uses many degrees of freedom. Thus, we are left with a conundrum of VCA giving us unreliable corporate effects and interpretations that underreport the relative size of smaller effects, with ANOVA giving us a range of corporate effects depending on the order of entry

### **Simultaneous Equations**

In addition to VCA and ANOVA, some researchers have used regression models to measure the importance of one variable over another. Brush, Bromiley and Hendrickx (forthcoming) argue for continuous variable models which in this case implies a simultaneous equation system. Thus, they establish a simultaneous equations model that addresses the relative importance of corporate and industry effects. They also estimate these effects while controlling for business effects.

Brush and Bromiley's (forthcoming) simultaneous equation model allows for the influence of corporate profitability on business-unit profitability and the influence of business-unit profitability on corporate profitability. The model avoids the problem of whether the corporation or industry term should enter first (ANOVA), or the imposition of orthogonality of estimated effects (VCA). They claim that the lower number of parameters should provide more reliable estimates of the magnitude of effects than VCA and ANOVA which use many more parameters.

As with VCA and ANOVA, the simultaneous equation model has some drawbacks. It requires functional specification of the relations which may create problems. It also loses some observations due to the need for instrumental variables. Prior to this study, to our knowledge simultaneous equations using continuous variables to assess importance have not been compared to those of VCA and ANOVA. Hence we explore this comparison further.

Given an important issue (relative importance) which has both specific impact on this topic and more general impact in the management area (where other researchers are using similar techniques to estimate importance), we decided to evaluate the three techniques empirically.

### **Research Design**

Given three approaches to estimating the same thing, comparing the estimators appeared essential. Our approach begins by simulating data with known characteristics. Then, we estimate the VCA, ANOVA, and simultaneous equation models using this data. By repeating the process many times, the relative performance of the differing estimators can be compared. To maintain comparability with previous research in the area, our design follows the standard Monte Carlo simulation approach as outlined in Brush and Bromiley (1997). We develop a sample with known properties and then estimate that sample using the alternative techniques. Let us begin with a review of the three techniques.

ANOVA estimates models of the following form:

$$Y_i = \beta_0 + \beta_1 D1_1 + \beta_2 D1_2 + \dots + \beta_n D1_n + \alpha_1 D2_1 + \alpha_2 D2_2 \dots + \alpha_m D2_m + \varepsilon_i \quad [1]$$

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  $\varepsilon_i$  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:

$$Y_{n,m,t} = \mu_n + \gamma_m + \varepsilon_{n,m,t} \quad [2]$$

Where the  $\mu_n$  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  $E(\mu_i * \mu_j) = 0$  if  $i \neq j$  and  $E(\gamma_t * \gamma_s) = 0$  if  $t \neq s$ , also  $\mu_n$ ,  $\gamma_m$ , and  $\varepsilon_{n,m,t}$  are all uncorrelated (Fomby and Johnson, 1994).  $\mu_n$  and  $\gamma_m$  are effects for each class of  $u$  and  $\gamma$ , for instance, corporation and industry. Rather than estimating each value, i.e.,  $\mu_n$  and  $\gamma_m$ , 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.

Brush, Bromiley and Hendrickx (forthcoming) estimate a model of the following form:

$$\text{Segment } ROA_{1,J,1,T} = \delta_1 + \beta_1 \text{ Corporate } ROA_{J,T} + \gamma_1 \text{ Industry } ROA_{1,T} + \varepsilon_{1,J,1,T} \quad [3.1]$$

$$\text{Segment } ROA_{2,J,2,T} = \delta_2 + \beta_2 \text{ Corporate } ROA_{J,T} + \gamma_2 \text{ Industry } ROA_{2,T} + \varepsilon_{2,J,1,T} \quad [3.2]$$

$$\text{Segment } ROA_{3,J,3,T} = \delta_3 + \beta_3 \text{ Corporate } ROA_{J,T} + \gamma_3 \text{ Industry } ROA_{3,T} + \varepsilon_{3,J,1,T} \quad [3.3]$$

$$\text{Corporate } ROA_{J,T} = \phi_1 + \alpha_1 w_{1,J,T} \text{ Segment } ROA_{1,J,K,T} + \alpha_2 w_{2,J,T} \text{ Segment } ROA_{2,J,K,T} + \alpha_3 w_{3,J,T} \text{ Segment } ROA_{3,J,K,T} + \alpha_4 \text{ Debt/Total Assets }_{J,T} + u_{J,T} \quad [4]$$

According to Brush, Bromiley and Hendrickx (forthcoming), equation 4 allows the construction of an instrument for *Corporate ROA<sub>J,T</sub>* that allows consistent estimation of equations 3.1, 3.2 and 3.3. In the COMPUSTAT data, equation (4) is not an identity because the Financial Accounting Standards Board guidelines specify that several items will not be allocated to segments. Furthermore, some areas of the business may not pass the tests to be reported as separate segments.

Two primary criteria are used to compare the quality of estimators. First, on average does the technique provide parameters that equal the true value either within finite sample sizes (unbiased) or asymptotically (consistent)? Second, what is the dispersion of the estimates around the true value (precision)? Within a Monte Carlo simulation, these issues can be easily handled. For an unbiased estimator, the mean of a set of estimates should be approximately equal to the true value. Dispersion of the estimators (precision) can be assessed by absolute value of the difference, or square of the difference, between the estimated parameter and the true value.

### **Method**

We compared the estimation techniques by estimating a set of simulated data using each technique. Throughout, we use a model where performance is determined by corporate, industry and business-unit effects along with an error term. Adding more effects would unduly complicate the analysis without capturing more of the problem we wish to examine. The simulation and estimation were written within the SAS package.

We constructed data using the following model:

$$\text{BUPerformance}_{i,j,k,t} = \textit{scale} \text{ Corporation}_i + \text{Industry}_j + \text{Business-unit}_{i,k} + \varepsilon_{i,j,k,t} \quad [2]$$

where  $i$  indexes the corporation,  $j$  the industry within which the business unit competes,  $i,k$  the business-unit and  $t$  the year. *Scale* is a scalar parameter which we will use to vary the influence of the corporate effect on performance to investigate the sensitivity of the estimation techniques to different true levels of the underlying effect. That is, we can examine the effect of truly different corporate effects by multiplying the corporate random numbers by a scale factor. In our data, the largest corporate effect is when *scale* equals 1 and the smallest is when *scale* is zero.



The simulation began by developing industry effects. Two hundred and fifty normal random numbers were generated and stored to be "industry effects". As with all other random variables in the simulation, the numbers were normal (0,1).

Next a random variable was generated for the effect of Corporation 1 and then values for each of the four business-units within the corporation. Then, for each business-unit we generated four random error terms, one for each annual "observation". Using a uniform random selection process, one of the 250 industry effects was associated with each business unit. Thus each corporation has sixteen observations: four years for each of four business-units. Four business-units per corporation approximates Rumelt's Sample B (4.56 business-units per corporation). Each simulation run included data for 200 corporations which means 3200 observations. All simulations were run five hundred times with the same parameters.

We varied the importance of corporate effects relative to business-unit effects by changing the value of corporate scale parameter (*scale*), while leaving the size of business-unit, industry, and error effects constant. In each model we try four levels of the corporate scale parameter (*scale*), 0, .2, .6, and 1. With *scale* equal zero, no corporate effect exists. With *scale* equal 1, the corporate effect contributes just as much to the business-unit's performance as the industry and business-unit do.

Following Brush and Bromiley (1997), we added one additional indicator of importance. We selected the top and bottom quartiles for corporate and industry effects and then calculated the mean ROA for these quartiles. The difference in means between the top and bottom quartiles provides an alternative measure of the size of effect for the corporation or business-unit.

The comparison required contrasting the results from variance components, ANOVA, and regression approaches. Since Brush, Bromiley and Hendrickx (forthcoming) primarily focuses

on estimates of effects for corporation and industry, our comparison focuses on the relative magnitudes for these two effects.

Estimation used standard procedures from SAS. The variance component estimation used Proc Varcomp with business unit performance as the dependent variable and corporation, industry, and business unit as the estimated components. The ANOVA estimation used the ANOVA procedure within Proc GLM since it is more appropriate for unbalanced designs than Proc ANOVA. Since the industry and corporate effects were independent by construction, we did not have a problem with which to enter first. We compared the explained variance from using only industry to the explained variance from using only corporation.

For the simultaneous equation regression estimates, we attempted to follow Brush and Bromiley's (forthcoming) approach. We began by developing an instrument for corporate performance. Business unit returns were added to create corporate returns. Then the corporate returns variable was regressed on the corporate effect variable ( $Corporation_i$  above) to create an instrument for the corporate performance. As might be expected, the fit of the regression to create the instrument varied substantially across the different values of scale with an average  $R^2$  of .05 when scale is .2, .32 when scale is .6 and .58 when scale is one. Finally, the returns for each business-unit were regressed on the corporate instrument and the industry effect. Parameter values were averaged across the four business-units in each corporation.

### **Empirical Results**

The empirical results appear in Tables 1 to 4. Results appear under columns "Variance Components" and "Square Root of Variance Components" for VCA, ANOVA  $R^2$  and ANOVA R for ANOVA, and "Regression Standardized Beta", "Regression  $R^2$ " and "Regression R" for simultaneous equations. Table 1 presents the mean of the estimates of the ratio of firm to

industry for each of the alternative estimation techniques. While interesting, the later sections provide much more useful representations for contrasting the estimators. Let us consider three different but closely related measures of the quality of the estimates. Note that the estimates of relative importance based on the ratios of means (top to bottom quartile) match with the values of *scale* quite reasonably suggesting that *scale* provides an appropriate metric for the "true" ratio.

Table 2 presents the mean estimation errors: the true value minus the estimate averaged across the 500 runs of the simulation. This estimates the bias in the estimates. In the tables, regression refers to the results from simultaneous equation regression estimation. In the discussion that follows, we will refer to the standardized regression coefficient as beta.

Three of the estimators have low mean errors: the square root of the variance component (SqrtVC), the standardized regression coefficient (beta), and the regression R. With the exception of *scale* equal to zero for the SqrtVC, these three have mean errors under .1 for all values of *scale*. They also have the three lowest average errors across the values of *scale*. Overall, the mean error for beta (.0062) is smaller than that of the SqrtVC and the regression R. The difference is largest at *scale* of zero. This reflects the fact that SqrtVC and regression R can only take on positive values and thus must be biased estimators when *scale* equals zero (assuming they take on any value other than zero). At *scale* of zero, the mean error for regression R and for SqrtVC are *four times* the mean error for beta. In addition, the mean error for regression R and for SqrtVC are three times larger at *scale* of zero than at *scale* of .2, .6, and 1. We ran an ANOVA to test differences in mean error across the estimators using the 500 runs as observations. The differences between beta and SqrtVC and between beta and regression R are statistically significant. SqrtVC and regression R do not differ at statistically significant levels. All other estimators have significantly higher mean errors.

The four highly biased estimators (Variance Components, ANOVA R, ANOVA R<sup>2</sup>, and regression R<sup>2</sup>) have somewhat different biases. Variance components provides reasonable estimates for *scale* of zero or one, but is strongly biased for intermediate values of scale. This agrees with Brush and Bromiley's (1997) claim that variance components provide an estimate of the square of importance -- the square and the true value will be the same at zero and one. Particularly for low values of scale (i.e., smaller corporate effects) ANOVA provides gross over-estimates of the corporate effect. This may simply reflect that ANOVA R<sup>2</sup> and ANOVA R will increase as the number of categories increase -- with many categories even a random assignment of categories may provide substantial ANOVA R<sup>2</sup>. The errors for regression R<sup>2</sup> match those for variance components being particularly far off for medium values of the corporate effect. Indeed, the magnitudes of the errors for regression R<sup>2</sup> and VCA agree closely.

The second criterion is precision - the dispersion of estimates around the true value. This approximates how close any particular estimate is likely to be to the true value. We examined the mean of the absolute errors (the average distance between the estimate and the true value), and the mean squared error (the square of the true value minus the estimate). These measures include both the bias and the variation around the bias.

Using Mean Absolute Errors (the absolute value of difference between the estimate and the true value averaged across the 500 runs), the results (Table 3) resemble those for mean error (Table 2). Regression standardized beta has the lowest mean absolute error and that mean differs statistically significantly from the next best estimator, the regression R. The regression R has a statistically significant lower mean absolute error than the SqrtVC which is significantly better than the remaining estimators. The magnitudes of the estimates indicate a substantively

important difference - the mean absolute error for the regression standardized beta is two thirds the size of the regression R and half the size of the square root of the variance component.

As with bias, variance components, ANOVA R, ANOVA  $R^2$ , and regression  $R^2$  provide very poor estimates. Variance components and regression  $R^2$  are very poor for moderate values of scale (.2 and .6) while ANOVA R and ANOVA  $R^2$  are poor for low values of scale. The similarity of these results to the ones on bias suggests that most of the problem is not variance in the estimators but rather bias.

Finally, we examine the Mean Squared Errors (Table 4). This weights errors by the square of their magnitude thus weighting large errors much more heavily than smaller ones. Regression beta and regression R have the lowest mean squared errors. By this criterion, standardized beta and regression R do not differ significantly from one another but do have significantly lower error than all the other estimators. The SqrtVC is next and it differs significantly from the remaining estimators. Beta (.0037) and regression R (.0057) have substantially lower values than the SqrtVC (.0175). The mean squared error for beta is less than one fourth of that for SqrtVC.

While the magnitudes differ from the previous measures of quality, the problems with variance components, ANOVA R, ANOVA  $R^2$ , and regression R remain. The ANOVA estimates are poor for low values of *scale* and the others are poor for moderate values of *scale*.

These analyses provide clear results. Regression beta provides the best estimator of relative importance having both lower bias and greater precision than the other estimators. Second best is the regression R. SqrtVC is clearly third best but substantially less accurate than the regression results. The other four estimators, variance components, ANOVA R, ANOVA  $R^2$ ,

and regression R, provide quite misleading estimates of relative importance. These four estimators have very large biases which render them useless for comparing magnitudes.

Two factors appear to influence the biases. First, given the numbers are fractions, the squared effects (variance components and regression  $R^2$ ) are biased towards zero. Examining Table 1, we see both estimators grossly underestimate the effect for moderate values of the *scale*. Second, all of the estimators except beta cannot be negative. This creates positive biases when the true value is zero. For the two squared effects (variance components and regression  $R^2$ ), this results in "good" (close to zero) estimates when the true value is zero because the square of a small fraction will always be smaller than the fraction.

We compare the estimators on the same number of observations, but in practice a study using variance components normally will have more observations than one with regression. Often, missing data on the regressors and other issues associated with estimation (e.g., losing observations to create instrumental variables) will lower sample size in a regression. Consequently, we examine whether increasing the number of observations for a VCA substantially improved the error variance of those estimates.

We construct a data set using the same procedures as before with the following changes: (i) 2000 (instead of 200) firms were simulated for a sample size of 32,000 observations per run, (ii) scale values were 0 and .2, and (iii) the full procedure was repeated 50 times instead of the 200 used in the previous estimates. Using 2000 firms instead of 200 provides a massive data advantage to variance components. Although variance components estimates often have larger sample sizes than regression estimates, sample size differences of this magnitude will come from substantive choices concerning what firms to sample, how to handle outliers, and so forth, rather than the differing requirements of the two techniques. With 32,000 observations, the variance

components estimates took a long time so additional restrictions were used to reduce estimation time (to about 40 hours). We chose scale of 0 and .2 since they appeared the most problematic for the estimators. Fifty runs should be sufficient to provide reliable estimates of the means of the measures of quality.

Comparing the SqrtVC with 32,000 observations to regression estimates with 3,200 observations, we get the following results. At *scale* equal to zero, the mean error for SqrtVC (-.065) now lies between those for the standardized beta (-.022) and regression R (-.084). At *scale* equal to .2, SqrtVC has larger mean error (.010) than the two regression estimators (.005 and .002 for beta and R). These relations also hold for mean absolute errors with SqrtVC between standardized beta and R at *scale* of zero but above both at *scale* of .2. SqrtVC has larger mean squared errors (.0087 and .0032) than standardized beta (.0015 and .0019) and regression R (.0080, .0026) at both *scale* values (zero and .2). In terms of magnitude, on all three criteria the errors of SqrtVC are at least twice as large as those of standardized beta.

To summarize, SqrtVC with 10 times as many observations as regression estimates provides poorer estimates than the standardized beta using all three quality measures and both values of *scale*. SqrtVC did provide lower mean error and lower absolute errors than the regression R (with one tenth the sample size) at *scale* of zero but had higher mean error and absolute error at *scale* of .2 and higher mean squared error at both values of *scale*. Overall, even with substantially larger data sets, SqrtVC performs worse than standardized beta and regression R.

### **Implications**

We have shown that two models and three measures provide reasonable estimates of the importance of an effect. The continuous variable regression model provides the best estimates of

effect size using either R or standardized beta. The VCA model with square root of variance components as the measure of importance is also reasonable. The other approaches and measures (ANOVA R, ANOVA R<sup>2</sup>, regression R<sup>2</sup>, and variance components) have large biases and provide misleading estimates.

In addition to providing better estimates of effect size, continuous variable models facilitate the testing of structural explanations or representations for such effects. Continuous variable models provide a natural way to represent causal arguments concerning how factors influence performance. Furthermore, continuous variable models use fewer parameters which facilitates testing moderation or interaction hypotheses. For example, an interaction between corporation and industry would use one additional parameter in regression but immensely more parameters (the number of corporations times the number of industries) in ANOVA. Studies using VCA and ANOVA can attempt to test structural explanations by comparing estimates on differing samples, but sampling-based approaches have inherent limitations. The sampling approach forces particular representations -- the explanations must be categorical. If the underlying causal story is not discrete, a discrete approximation will be inefficient and crude. Furthermore, sampling-based approaches have trouble differentiating among different ways two samples might differ. Instead of a clear theoretical tie to an explanatory variable, one has the less direct tie to a category.

Comparisons of VCA estimates on different samples is growing more common (McGahan and Porter, 1997a; McGahan and Porter, 1997b; Roquebert *et al*, 1996) when compared to earlier studies (Rumelt, 1991; Schmalansee, 1985). In addition, Balakrishnan and Fox (1993) and Mauri and Michaels (1998) compare different dependent variables using the same sample. To our knowledge, *testing* of differences between VCA estimates on different



samples has not been reported. The superiority of continuous variable techniques, for testing structural hypotheses, unbiased estimates, and high precision of estimates, has long been acknowledged in social science since the "revolution" when regression replaced correlation and ANOVA for many social science applications.

If one wants to study both effect size and structural properties, regression seems to be the only useful choice. VCA does not allow testing of structural properties for the most part. ANOVA provides very poor estimates of effect size. The only model that provides structural interpretations that also gives reasonable estimates of effect size/ importance is the continuous variable model.

To summarize our results, the simulation has shown clearly:

1. To estimate relative importance, only the square root of the variance component, regression standardized beta, and regression R provide meaningful estimates. Variance components and ANOVA and regression  $R^2$  provide misleading estimates of relative importance.
2. Standardized beta provides the best estimates. Since all the other estimators are constrained to be positive, *for values near zero*, standardized beta provides the only unbiased estimates. Both regression R and SqrtVC have substantial bias near zero. In addition, standardized beta beats regression R and the square root of the variance components across the range of *scale* values and on all three measures of estimator quality. Regression R provides better estimates than the square root of the variance components for most values and evaluation criteria.
3. Even if the variance component is run on a massively larger data set, it remains less precise than the regression approaches.

Overall, researchers who want to determine relative importance should rely on continuous variable approaches whenever possible.

Table 1: Mean of Estimates of the Ratio of Firm to Industry Effects

SCALE	Means of First to Fourth Quartile	Variance Components	Square Root of Variance Components	ANOVA R <sup>2</sup>	ANOVA R	Regression Standardized Beta	Regression R <sup>2</sup>	Regression R
0.0	-0.00251	0.02708	0.10562	0.40198	0.63330	0.02189	0.01086	0.08354
0.2	0.19734	0.04709	0.16698	0.42396	0.65042	0.19479	0.04884	0.19810
0.6	0.58319	0.34962	0.58438	0.61068	0.78065	0.58427	0.34860	0.58241
1.0	0.97908	0.96035	0.97301	0.91009	0.95293	0.97433	0.95558	0.97403

Table 2: Mean Estimation Errors\*: True Value (Scale) Minus Estimate

SCALE	Variance Components	Square Root of Variance Components	ANOVA R <sup>2</sup>	ANOVA R	Regression Standardized Beta	Regression R <sup>2</sup>	Regression R
0.0	-0.0271	-0.1056	-0.4020	-0.6333	-0.0219	-0.0109	-0.0835
0.2	0.1529	0.0330	-0.2240	-0.4504	0.0052	0.1512	0.0019
0.6	0.2504	0.0156	-0.0107	-0.1807	0.0157	0.2514	0.0176
1.0	0.0397	0.0270	0.0899	0.0471	0.0257	0.0444	0.0260
Mean	0.104	-0.0075	-0.1367	-0.3043	0.0062	0.109	-0.0095

$$* \text{ MeanError} = \frac{1}{500} \sum_{Rtm=1}^{500} \text{Scale} - (\text{FirmEffect} / \text{IndustryEffect})$$

Table 3: Mean Absolute Errors\*: Absolute Value of True Value Minus Estimate

SCALE	Variance Components	Square Root of Variance Components	ANOVA R <sup>2</sup>	ANOVA R	Regression Standardized Beta	Regression R <sup>2</sup>	Regression R
0.0	0.0271	0.1056	0.4020	0.6333	0.0303	0.0109	0.0835
0.2	0.1536	0.1218	0.2240	0.4504	0.0351	0.1512	0.0407
0.6	0.2512	0.0737	0.0453	0.1807	0.0472	0.2515	0.0520
1.0	0.1878	0.0957	0.1050	0.0545	0.0713	0.1394	0.0720
Mean	0.1549	0.0992	0.1941	0.3297	0.046	0.1383	0.0621

$$* \text{ Mean Absolute Error} = \frac{1}{500} \sum_{Run=1}^{500} |\text{Scale} - (\text{FirmEffect} / \text{IndustryEffect})|$$

Table 4: Mean Squared Error \*

SCALE	Variance Components	Square Root of Variance Components	ANOVA R <sup>2</sup>	ANOVA R	Regression Standardized Beta	Regression R <sup>2</sup>	Regression R
0.0	0.0024	0.0271	0.1631	0.4020	0.0015	0.0002	0.0080
0.2	0.0260	0.0203	0.0517	0.2038	0.0019	0.0233	0.0026
0.6	0.0736	0.0084	0.0032	0.0339	0.0036	0.0685	0.0042
1.0	0.0558	0.0143	0.0155	0.0042	0.0077	0.0291	0.0079
mean	0.0395	0.0175	0.0584	0.161	0.0037	0.0303	0.0057

$$* \text{ Mean Squared Error} = \frac{1}{500} \sum_{Rim=1}^{500} [\text{Scale} - (\text{FirmEffect} / \text{IndustryEffect})]^2$$

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