DIVISION BY ZERO:
Disaggregation in the Analysis of Accounting Profits, 1984-1994¹

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ABSTRACT

Organizations researchers have long debated the substantive importance of internal and external sources of variation in firm performance. In particular, the relative size of industry-level and firm-level determinants of accounting profitability has been a consistent and important stream within strategy research. In this paper, I argue that much research in this tradition has overlooked a fundamental characteristic of the categorical explanatory variables that are central to the variance decomposition approach so often used in this literature. The number of within-category distinctions in an explanatory variable is positively correlated with the amount of variance it explains in ways that are not fully accounted for by variance decomposition analyses. Given a lack of information about the appropriate level of aggregation at which constructs such as time, market conditions, and business-level and corporate strategy should be measured, prior estimates of the importance of predictors corresponding to these constructs may be over or underestimated. I illustrate these arguments using ANOVA and ordinary least squares analyses of Compustat Business Segment Report data for U. S. firms from 1984-1994.

Keywords: categories; strategy; performance; variance decomposition; industry structure
INTRODUCTION

Organizations researchers across a variety of disciplines have persistently asked whether firms embedded in a particular environment differ very much, either in their structure or in their performance. One set of approaches to answering this question has focused environmental (Hannan and Freeman 1977, Dobrev and Carroll 2003, Hsu 2006, Hannan, Pólos and Carroll 2007) and institutional (DiMaggio and Powell 1983, Ruef and Scott 1998, Dobbin and Dowd 2000) forces that cause populations of organizations to converge in structure and performance. An alternative perspective has emphasized the importance of variation in organizational capabilities and resources in accounting for performance differences (Wernerfelt 1984; Barney 1991; Eisenhardt and Martin 2000; Adner and Helfat 2003). Though these two approaches are not explicitly in conflict, they reflect a broader question about whether or not substantive differences in firm performance have more to do with individual characteristics of organizations or the characteristics of the environment that these organizations are embedded in.

This broader empirical question has specifically been addressed by a research stream within strategic management that has as its objectives the determination of different sources of variation firm performance (Schmaelnsee 1985, Rumelt 1991, Rocquebert, Phillips and Westfall 1996, McGahan and Porter 2002, Bowman and Helfat 2001) and explaining the persistence of such variation (Cubbin and Geroski 1987, Rumelt 1991, Waring 1996, McGahan and Porter 1997, Villalonga 2004, Lenox et. al 2006, Bou and Satorra 2007). By investigating potential sources of performance variation related to features and characteristics of individual business units, the corporations they are
organized into, the industries in which they compete, or the macroeconomic, political or social conditions at the time of their operation, this research stream proposes an account of the degree to which firm performance differs in substantively important ways.

The primary justification for this research has either been the identification of areas of likely fruitful research, or demonstrating that more detailed study given area is unlikely to be helpful in identifying strong drivers of firm performance. For instance, theoretical claims about the relationship between market power and industry-level entry barriers (Porter 1980, Sutton 1991) may show strong statistical significance, but are unlikely to provide useful insights to practitioners if the potential variance explained by these industry-level constructs is minimal. Similarly, the value of understanding unique resources and capabilities associated with individual firms and business units (Barney 1991, Eisenhardt and Martin 2000) is magnified to the extent that there are large identifiable firm-level differences in performance. Given this logic, the principal thrust of this largely empirical body of work has been to identify the amount of variance in performance that might be explained by differences in industries, time periods, individual business units, and corporations or firms.

It would be premature to say that there is a consensus within this body of research about the relative contribution of each of these classes of explanatory variables to performance, though recently a few convergent themes have emerged. Those studies of firm performance using the variance decomposition approach that estimate an effect for business units or business segments overwhelmingly find that this effect explains more
variance than other effects examined (Rumelt 1991; Rocquebert et al 1996, McGahan and Porter 1997, 2001, Chang and Singh 2000). More recent studies have found statistically significant evidence for both industry and corporate-parent effects, with some consensus that firm effects are more important than industry effects (Bou and Satorra 2007: 707).

While most of these studies find negligible if significant period effects, many studies have concluded that individual effects appear to persist over time. Collectively, these results could be used to argue that strategy research seeking to explain performance would be well-served by focusing on features internal to business units, and less so, for instance, on features of the markets and industries in which they compete.

While there seems to be a growing consensus among empirical research in this tradition about the relative importance of different classes of predictors of business unit performance, I argue in this paper that insufficient attention has been paid to a particular assumption embedded in the analyses. The evaluation of performance determinants through variance decomposition using categorical explanatory variables makes a set of strong assumptions that has rarely been addressed. While categorical explanatory variables might well be appropriate descriptors of the underlying constructs assumed to affect the performance of businesses, firms and industries, there is certainly a relationship between the degree of aggregation with which a given construct is measured and the amount variance that it is able to explain. This relationship is particularly concerning in a body of research in which the number of distinctions captured by different explanatory variables ranges from a handful to several thousand.
In this paper I argue that it may be difficult to draw strong empirical conclusions from a variance decomposition analysis about the importance of various classes of explanatory variables without information about the appropriate level of aggregation at which these explanatory variables should be measured. I illustrate this issue by comparing a set of results from a variance decomposition analysis of Compustat Business Segments Reports data to a parallel set of results from an extended synthetic data set created by expanding the Compustat data with uninformative distinctions. I conclude by discussing the implications of these results for the study of determinants of organizational performance, and for the use of categorical constructs in strategic research.

EVALUATING DETERMINANTS OF ACCOUNTING PROFITABILITY

The empirical objective of this study is to determine whether prior analyses of the determinants of accounting profitability have appropriately considered the potential impact of variation in the level of aggregation with which categorical explanatory variables in the analysis are measured. The specific concern is that the empirical objective of this work—identifying the relative impact of different classes of explanatory variables on performance—may rest critically on decisions made by researchers in identifying categorical constructs. For all of its advantages, the variance decomposition approach essentially takes for granted the validity of categorical distinctions in the analyzed data, potentially leading to substantial inflation or deflation of effect sizes. This feature of variance decomposition analysis may have led this stream of research to overstate the relative empirical importance of “segment” effects simply because of a relatively fine grain
of distinction in the identification of business units as compared to other explanatory variables.

The presumed contribution of the variance decomposition approach is that, by employing a descriptive rather than a structural model, it has the potential to establish upper bounds on the contribution of different classes of explanatory variables to variation in a given dependent variable. In the context of studies of accounting profitability, establishing a sense of the empirical contribution of different classes of variables is a critical step in resolving whether or not internal features such as CEO performance play a more important role than context features such as industry structure in determining firm performance (e.g. Mackey 2008). The key insight of taking a descriptive approach is that it affords an opportunity to avoid measurement issues associated with specific structural models in favor of simply establishing the maximum potential impact that a particular class of explanatory variable might have (Schmalensee 1985: 343).

Variance decomposition is not, of course, the only way to attempt to assess the importance of a particular class of variables on business unit profitability. It would for instance be possible to attempt to assess the importance of corporate strategy by measuring several features of each corporate parent or firm in an analysis that has been theorized to affect its performance. Such measures could include its activity in patenting and publishing (Henderson and Cockburn 1994), production and sales experience to new and existing markets (King and Tucci 2002), or level of intangible resources (Villalonga 2004). That said, it would be difficult to enumerate and measure with certainty every variable associated with the influence that a corporate parent might have on the performance of
business unit. While the association of a fixed or random effect with each corporate parent\(^2\) does nothing to measure individual mechanisms, it does pose the distinct advantage of capturing the maximum variance potentially explained by variables of this class. By this logic, all variation in explanatory variables can be captured by a model in which every entity (year, industry, firm, or business segment) in the analysis is allowed to have its own separate impact on profitability, without imposing a need for measure of every explanatory variable associated with a class of potential effects.

While this proposition is an attractive one, it rests on a key presumption—that the entities identified in the analysis in fact correspond meaningfully to the mechanisms of economic performance\(^3\). It could at least in principle be the case that the mechanisms of interest operate at either higher or lower levels of aggregation than indicated by the units of analysis in a given study. The potential consequences of units measured at too coarse of a level of aggregation on variance decomposition analyses has been noted several times, particularly in the case of evaluating industry or market conditions. The discourse ranges from broad questions about the value of arbitrary aggregations that industry and market boundaries may often reflect (Geroski 1998: 678), to more narrow observations of the sensitivity of variance decomposition analyses to the number of observations in a given industry (Roquebert et. al 1996: 657, Bowman and Helfat 2001: 15), to the specific claim that performance variation would be best explained with correctly, which is to say narrowly, defined industries (Chang and Singh 2000: 749). Put simply, these critiques

\(^2\) Or, perhaps, year-parent effects in the case of dynamic capabilities (e.g. Eisenhardt and Martin 2000; Adner and Helfat 2003: 1014).

\(^3\) This presumption rests, in turn, on a second one—that there are in fact identifiable entities in the analysis at all. Addressing this presumption is outside of the scope of this study.
reflect the very reasonable concern that across instances in any given data set, there may be significant variation in the market conditions faced by business segments identified as being in the same industry category (e.g. a 4-digit SIC industry) that might be important to understand in accounting for their respective levels of performance.

Concerns about over-aggregation, of course, need not be limited to the way that industry or market conditions have been treated in these analyses. McGahan and Porter (1997: 16) note that differences in the level of aggregation of the units that make up a firm (business units v. business segments, in this case) play a key role in determining the amount of influence accorded to this class of explanatory variables. Moreover, the very inclusion of firms along with business segments or units in these analyses suggests a question about the appropriate level of aggregation at which to analyze mechanisms presumed to be internal to the firm. It is also clearly the case that years could at least in principle be disaggregated into quarters, months, weeks or days, and that this would increase the variance explained by the class of explanatory variables associated with time.

A parallel concern might be raised about under-aggregation—the extent to which entities identified as distinguishable in a given empirical analysis in fact correspond to multiple observations of the same fundamental unit of interest. Proponents of the idea of strategic groups (Caves and Porter 1977, Porter 1979, Peteraf and Shanley 1997, Porac et al. 1999, Short et. al 2007, DeSarbo and Grewal 2008) suggest that there are groups of firms that have similar characteristics that experience similar performance outcomes. If the causal agent that explains the impact of a given business unit or corporate parent is the selection
of a particular type of strategy, then associating separate business unit or corporate effects with the same strategic type would inflate the amount of variance explained by these classes of explanatory variables. Other researchers have contributed to this line of argument by demonstrating how categories figure explicitly into audience-mediated performance outcomes for these economic entities (Porac et al. 1999, Zuckerman 1999, 2000, Hsu 2006). Taken collectively, this body of research suggests that the appropriate level of analysis may well be at a higher level of aggregation than that which is represented by any particular data set.

Given an understanding of variance decomposition studies in this light, there is a potentially troubling relationship in prior empirical analyses between the number of within-category distinctions associated with a given explanatory variable and the amount of variance it is purported to explain. Many of the studies within this stream evaluate extensions of a general model articulated by McGahan and Porter (2002)

\[ r_{ikt} = \mu + \gamma_t + \alpha_i + \beta_k + \phi_{ik} + \epsilon_{ikt}, \]  

(1)

where \( r_{ikt} \) is the accounting profitability of a business unit in industry \( i \) under a corporate parent \( k \) in a year \( t \), \( \mu \) is the mean level of profitability in the period under study, \( \gamma_t \) are year effects, \( \alpha_i \) are industry effects, \( \beta_k \) are corporate-parent effects, \( \phi_{ik} \) are business unit effects, and \( \epsilon_{ikt} \) is an error term. Equation 1 has been estimated primarily using one of two methodological approaches. In an ANOVA analysis, the equation is estimated in full and restricted forms, in order to determine the contribution of each class of variables. In a
variance components or components-of-variance (COV) analysis, it is estimated as a realization of a random-effects model, and the variance associated with each class of random effects is treated as an indication of the magnitude of its explanatory power.

Models of this type using both of these approaches have come to a variety of conclusions about the relative and absolute importance of each of these classes of effects. To the extent that the problem of aggregation is addressed, it is through the use of adjusted $R^2$ statistics or $F$-tests to evaluate statistical differences among entire classes of effects, but rarely employed in directly assessing the importance of a class of effects. Specifically, for given class of effect, such as an “industry effect”, a categorical variable can take on a certain number of levels. Thus, the categorical variable “industry” might take on many levels if industry is defined in a relatively fine-grained way, or somewhat fewer levels is industries are defined at a higher level of aggregation. In this sense, the number of levels taken on by a categorical explanatory variable indicates the degree of aggregation across possible values of the concept of interest.

The question addressed in the subsequent analysis is whether conclusions that have been drawn about the effect of different classes of explanatory variables on business unit performance have properly taking into consideration the potential effect of the level of aggregation within these classes—particularly given wide variation in the number of levels associated with these categorical explanatory variables both between and within studies. The data in Table 1 and the corresponding graph in Figure 1 reflect the findings of some of these prior studies (Rumelt 1991, Roquebert et al. 1996, McGahan and Porter 1997),
viewed in relation to information about the number of levels of each explanatory variable considered. As these empirical studies vary significantly in their empirical scope, Table 1 reports for each year, industry, corporate parent, and segment-specific or business unit effect, the variance explained by each of these effects, the explained variance as a percentage of the total variance explained by the model, the number of levels of the independent variable, and ratio of the number of levels of the independent variable to the number of observations analyzed. Figure 1 depicts these results graphically.

**TABLE 1: Estimated Effect Sizes and Category Granularity**

<table>
<thead>
<tr>
<th>Study</th>
<th>Effect</th>
<th>Levels</th>
<th>Variance</th>
<th>Observations</th>
<th>Observations</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td>Effect</td>
<td>Model</td>
<td>%</td>
</tr>
<tr>
<td>Rumelt</td>
<td>Year</td>
<td>4</td>
<td>0.03</td>
<td>63.33</td>
<td>0.05</td>
</tr>
<tr>
<td></td>
<td>Industry</td>
<td>242</td>
<td>17.9</td>
<td></td>
<td>28.26</td>
</tr>
<tr>
<td></td>
<td>Firm</td>
<td>457</td>
<td>14.8</td>
<td></td>
<td>23.37</td>
</tr>
<tr>
<td></td>
<td>Segment</td>
<td>1774</td>
<td>46.37</td>
<td></td>
<td>73.22</td>
</tr>
<tr>
<td>Roquebert</td>
<td>Industry</td>
<td>237.5</td>
<td>10.2</td>
<td>68</td>
<td>15</td>
</tr>
<tr>
<td></td>
<td>Firm</td>
<td>105.1</td>
<td>17.9</td>
<td></td>
<td>26.32</td>
</tr>
<tr>
<td></td>
<td>Segment</td>
<td>421</td>
<td>37.1</td>
<td></td>
<td>54.56</td>
</tr>
<tr>
<td>McGahan &amp; Porter</td>
<td>Year</td>
<td>14</td>
<td>2.39</td>
<td>51.6</td>
<td>4.63</td>
</tr>
<tr>
<td></td>
<td>Industry</td>
<td>628</td>
<td>18.68</td>
<td></td>
<td>36.2</td>
</tr>
<tr>
<td></td>
<td>Firm</td>
<td>7003</td>
<td>4.33</td>
<td></td>
<td>8.39</td>
</tr>
<tr>
<td></td>
<td>Segment</td>
<td>12296</td>
<td>31.71</td>
<td></td>
<td>61.45</td>
</tr>
</tbody>
</table>

While there are clearly too few observations to draw strong statistical conclusions from these data, they are at the very least suggestive of the possibility that the identified strength of each class of effects may be related to the number of levels of a given effect in the data analyzed. For instance, while each of these studies finds substantially more variance explained by segments or business units than is explained by other effects, it is
also the case that in each of these studies there are substantially more category levels per observation for business units and segments than there are for other explanatory variables. The relationship is less clear when comparing results for industry effects and corporate-parent effects, though the mean results across the three studies are still suggestive of a monotonic relationship.

These data suggest at least two approaches to comparing the relative effect of time, industry, firm and business unit effects on performance. One general approach might be to carefully re-evaluate the underlying assumptions of the methods used in prior studies regarding the relationship between the levels of categorical explanatory variables and the
conclusions of variance decomposition approaches (Schwarz 1978, Raftery 1995). The alternative and perhaps more straightforward approach taken in this study is to fix the number of levels across potential explanatory variables in the analysis. This approach will allow the comparison of the relative size of each effect while taking into account any influence due to the degree of information contained within a categorical explanatory variable.

DATA

In order to maximize comparability to earlier work, the data used in this study closely match those used by McGahan and Porter (1997, 2002) in their analyses of accounting profitability. I analyze business segment data from the Compustat Database, covering business units from 1984-1994. A critical difference between these data and that analyzed in earlier studies is that SIC information appears not to be available for observations prior to 1984 in the Compustat data available from Wharton Research Data Services. As a result, while I am able to present analyses with qualitatively similar results as prior research, I am unable to precisely replicate earlier results in illustrating the effect of aggregation on variance decomposition analyses.

In order to match earlier analyses as closely as possible, I screen the 119,956 observations available in the Compustat data following conventions substantively similar to those applied by McGahan and Porter (1997, 2002). A total of 14,893 business segments associated with an industry with “not elsewhere classified” in the title were removed under the assumption that these designations refer to collections of business units less similar
than those assigned to other designations. Similarly, 449 business segments industries in government (SIC codes in the 9000s) were removed, as were 14,595 identified as depository institutions (SIC codes in the 6000s). 28,410 small segments were deleted because they were associated with business segments with either less than $10 million in sales or $10 million in assets. Business segments were also deleted if they were the only segment in their SIC classification for a given year, or if they appeared for only a single year in the data set. Business segments that only appear for a single year are often anomalous because they can represent the disposal of assets by a firm just before it exits.

This process retained a sample of 59,637 business segment-year observations for further analysis. Notably, these data cover eleven distinct years, 6,300 corporate parents, 640 four-digit SIC industries. The Compustat data allows each firm to identify up to 10 distinct lines of business in a given year associated with a primary and in some cases secondary 4-digit SIC industry classification. In the analyses presented here, a business segment is defined as all activities associated with a firm in a given year with the same primary 4-digit SIC industry—there are 9,909 distinct business segments in the data analyzed.

ANALYSIS

As Figure 1 and Table 1 suggest, the amount of variance explained by a given categorical explanatory variable may be determined in part by the number of distinct levels that variable takes on. The analyses presented here attempt to address this issue by fixing the number of levels of across all variables. An ideal test would be to perform a variance decomposition analysis on a data set in which the number of levels for each variable is
exactly the same. Unfortunately, a data set in which, for instance, the number of distinct business units is precisely the same as the number of distinct time periods would be prohibitively difficult to identify. In particular, by definition the number of distinct corporate parents in a data set must be no greater than the number of business units, unless business units are associated with more than a single corporate parent across time periods.

While it may not be possible to identify a data set that has equivalent levels of aggregation across the categorical variables of interest, it is possible to construct a “synthetic” data set that has the desired properties. For instance, in the Compustat data, there are 9,909 distinct business segments, but only 640 distinct industries. In an ideal setting, a researcher could examine specific details about the industries in which these business units competed in order to come up with a more fine-grained classification with 9,909 levels in order to perform a less-biased variance decomposition analysis. The alternative approach taken in the analyses presented here is to randomly assign different observations of a given industry to different values, in order to create a new “synthetic industry” variable.

Figure 2 schematically illustrates this process for a subset of the observations in the sample. In this example, five distinct industries in the original data are expanded to ten distinct industries in the synthetic data by expanding each original industry by a factor of up to three. This process allows for the possibility that, for instance, market conditions associated with an “industry effect” for the Pizza Restaurants segment of A&M Food
FIGURE 2: Creation of Synthetic Variables

<table>
<thead>
<tr>
<th>Corporate Parent</th>
<th>Segment</th>
<th>Year</th>
<th>Original Industry</th>
<th>Synthetic Industry</th>
<th>ROA</th>
</tr>
</thead>
<tbody>
<tr>
<td>A&amp;M Food Srvcs</td>
<td>1: Pizza Restaurants</td>
<td>1984</td>
<td>5812</td>
<td>5812.2</td>
<td>11.6%</td>
</tr>
<tr>
<td>A&amp;M Food Srvcs</td>
<td>1: Pizza Restaurants</td>
<td>1985</td>
<td>5812</td>
<td>5812.1</td>
<td>13.3%</td>
</tr>
<tr>
<td>AA Importing Co.</td>
<td>1: Antique Reproductions</td>
<td>1986</td>
<td>5932</td>
<td>5932.1</td>
<td>13.3%</td>
</tr>
<tr>
<td>AA Importing Co.</td>
<td>1: Antique Reproductions</td>
<td>1987</td>
<td>5712</td>
<td>5712.3</td>
<td>-2.5%</td>
</tr>
<tr>
<td>AA Importing Co.</td>
<td>1: Antique Reproductions</td>
<td>1988</td>
<td>5712</td>
<td>5712.1</td>
<td>-26.8%</td>
</tr>
<tr>
<td>AA Importing Co.</td>
<td>1: Antique Reproductions</td>
<td>1989</td>
<td>5712</td>
<td>5712.2</td>
<td>-23.0%</td>
</tr>
<tr>
<td>AAR Corporation</td>
<td>3: Com.-Military Aviation</td>
<td>1984</td>
<td>5088</td>
<td>5088.2</td>
<td>22.7%</td>
</tr>
<tr>
<td>AAR Corporation</td>
<td>3: Com.-Military Aviation</td>
<td>1985</td>
<td>5088</td>
<td>5088.3</td>
<td>19.3%</td>
</tr>
<tr>
<td>AAR Corporation</td>
<td>5: Bus.-Private Aviation</td>
<td>1984</td>
<td>5088</td>
<td>5088.1</td>
<td>-8.0%</td>
</tr>
<tr>
<td>AAR Corporation</td>
<td>5: Bus.-Private Aviation</td>
<td>1985</td>
<td>4581</td>
<td>4581.1</td>
<td>4.3%</td>
</tr>
<tr>
<td>AAR Corporation</td>
<td>6: Com. &amp; Military Aviation</td>
<td>1986</td>
<td>5088</td>
<td>5088.1</td>
<td>15.8%</td>
</tr>
<tr>
<td>AAR Corporation</td>
<td>6: Com. &amp; Military Aviation</td>
<td>1987</td>
<td>5088</td>
<td>5088.2</td>
<td>15.3%</td>
</tr>
</tbody>
</table>

Services differ in 1984 from those in 1985. This process allows a variance decomposition analysis to pick up on some level of continuity of industry effects. In the original Compustat data, the Business-Private Aviation segment of AAR Corporation was identified as being in the Transportation Equipment and Supplies industry (SIC 5088) in 1984, as was the Commercial & Military Aviation segment in 1986. In the synthetic data set presented in Figure 2, these two segments are still represented as being in the same industry (Synthetic SIC 5088.1). By employing random assignment to synthetic industries, this process permits a fairly direct test of the effect of disaggregation per se on the ability of a categorical variable to explain variance in profitability.

The process illustrated in Figure 2 is applied to the year, industry and firm independent variables in the original data set in order to construct a synthetic data set in which each of these variables takes on 9,909 distinct values, corresponding to the number of distinct values observed for business units in the original data. Having made assignments to
synthetic variables at equal levels of disaggregation, I follow prior studies (McGahan and Porter 1997, 2002, Rumelt 1991) and estimate Equation 1 using nested ANOVA techniques\(^4\). ANOVA results are produced through ordinary least squares regression, which allows for a direct examination of both the increase in explained variance for each model and also the distribution of individual fixed effects for each categorical explanatory variable.

RESULTS

In this section, I present estimates of Equation 1 based on both the original Compustat data and the synthetic data set, using nested ANOVA and direct estimation of variance from the full ordinary least squares model. Table 2 reports the level of explained variance for each of the sixteen\(^5\) models possible based on inclusion or exclusion of each of the four

As expected, given the additional degrees of freedom implied by the disaggregated variables in the synthetic data as compared to the original Compustat data, the overall level of explained variance for each model is higher for the former than it is for the latter. Of particular interest, however, is the extent to which variables with relatively few levels in the original data explain significantly more variance in the synthetic data. For instance, a

\(^4\) I also follow the convention of constraining firm/corporate-parent effects to zero for firms that only have a single business segment in a given year (McGahan and Porter 2002: 839). To maximize comparability, in the synthetic data, these effects are set to zero for all observations in which they are also set to zero in the original data set.

\(^5\) Prior research, such as McGahan and Porter (1997) have reported less than the full possible set of sixteen models implied by four independent classes of effects because some of models in these studies completely subsume other models. For instance, a model that includes both business unit effects and corporate-parent effects adds no new information to a model that only includes business unit effects when fixed-effects are entered into the model for all business units. This logic does not hold when fixed-effects are entered for disaggregated firms, industries, and years. Under these conditions, business units are not strictly nested within higher-level constructs. For this reason, I am able to identify 16 separate models in this study.
model that only includes year effects for the 11 year levels in the original data explains 0.34% of the variance in accounting profitability. In the synthetic data, where arbitrary distinctions are introduced to these 11 actual year levels, the year variable is associated with 17.56% of explained variance.

Table 3 presents estimates of effect sizes for each variable in both the original and synthetic data sets based on nested ANOVA analyses. As many prior studies have noted, effect sizes determined on the basis of nested ANOVA are dependent on the order in which variables are entered into the analysis—any covariance between variables will be

<table>
<thead>
<tr>
<th>Source</th>
<th>Original Data</th>
<th>Synthetic Data</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>d.f.</td>
<td>Incr. $R^2$</td>
</tr>
<tr>
<td>Year</td>
<td>10</td>
<td>0.0034</td>
</tr>
<tr>
<td>Industry</td>
<td>639</td>
<td>0.1034</td>
</tr>
<tr>
<td>Firm</td>
<td>6,299</td>
<td>0.1445</td>
</tr>
<tr>
<td>Segment</td>
<td>9,908</td>
<td>0.3346</td>
</tr>
<tr>
<td>MODEL</td>
<td>16,856</td>
<td>0.5859</td>
</tr>
<tr>
<td>Error</td>
<td>22,776</td>
<td>0.4141</td>
</tr>
<tr>
<td>TOTAL</td>
<td>59,637</td>
<td></td>
</tr>
</tbody>
</table>

(A) Ordering of effects: year, industry, firm, segment

| Year            | 10   | 0.0034      | 20.31*    | 9,908 | 0.1756      | 1.06*     |
| Firm            | 6,299| 0.1837      | 1.91*     | 9,908 | 0.2455      | 3.10*     |
| Industry        | 639  | 0.0642      | 7.07*     | 9,908 | 0.1389      | 1.28*     |
| Segment         | 9,908| 0.3346      | 3.49*     | 9,908 | 0.0895      | 0.76      |
| MODEL           | 16,856| 0.5859      |           | 39,632| 0.7646      |           |
| Error           | 22,776| 0.4141      |           | 20,005| 0.2354      |           |
| TOTAL           | 59,637|            |           | 59,637|            |           |

(B) Ordering of effects: year, firm, industry, segment

*p<0.0001
associated with the first variable entered. Following McGahan and Porter (1997), I present analyses based on two entry orders. The first panel of Figure 3 reflects the canonical order used in most studies, in which year effects are entered first, followed by industry, firm, and segment effects. The second panel presents results from an alternative but consistent ordering in which year effects are entered first, followed by firm, industry, and segment effects.

The first three columns of panel A and B reflect a replication of the analysis by McGahan and Porter (2002) subject to caveats induced by the small differences between the data sets analyzed. The results of these analyses show few substantive differences with earlier results. F-tests for each variable are strongly significant (p<0.0001), independent of the order of entry, suggesting that there are in fact statistical differences between years, industries, firms and segments. In the canonical order of variable entry, year, industry, firm and business units explain 0.34%, 10.34%, 14.45% and 33.46% of variance respectively, values quite close to the 0.80%, 9.6%, 12.0% and 37.7% reported by McGahan and Porter (2002: 844).6

The last three columns of Table 3 present estimates of variance from Equation 1 based on the synthetic data. A significant difference in the analysis of the synthetic data is that the F-test rejects the hypothesis that there are significant differences among segment effects. This result may be in part due to the increased variance explained by the synthetically disaggregated explanatory variables for year, industry and firm. To the extent that there is

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6 In the alternative order of entry, McGahan and Porter (2002) report increases of 15.9% and 5.7% for firm and industry effects, respectively, also consistent with the 18.37 and 6.42% increases reported here.
covariance between any of these variables and segment effects, the additional variance explained by segment effects would be underestimated, leading to a lower $F$-value. That notwithstanding, these results at the very least illustrate a substantively different conclusion that might be drawn about the determinants of accounting profitability in a study in which data about time, corporate strategy and market conditions were available at a more fine-grained level of detail. Precisely the same methods and empirical context as that used in earlier research can produce a result that suggests there are no important differences between business units with respect to profitability.

ANOVA results based on the synthetic data also provide evidence in support of the hypothesis that effect size estimates are at least partially driven by the level of disaggregation of a categorical explanatory variable\(^7\). Gains in explained variance are most pronounced for industry and year effects—two constructs measured at particularly high level of aggregation in the original data. Conclusions about the relative importance of different effects drawn from the synthetic data are substantively different from those that would be drawn from the original data, in that these results suggest that industry, year and firm effects are substantially more important than business unit effects. To be clear, the only difference between the original data and the synthetic data is the addition of noise in the latter. The different substantive conclusions drawn from the analyses of these two data

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\(^7\) ANOVA results presented throughout these analyses reflect unadjusted $R^2$ rather than adjusted $R^2$ values. The standard intuition for using adjusted $R^2$ as a measure of explained variance is that unadjusted $R^2$ are higher for models that include variables that are uninformative with respect to the dependent variable. The implication of this logic is that adding uninformative explanatory variables to a model should, on expectation, neither increase nor decrease the adjusted $R^2$ measure of explained variance. Analyses not reported in full here do not support this intuition. Adjusted $R^2$ statistics for models including only year, industry and firm effects respectively on the synthetic data are 0.34%, 6.59% and 27.08%. As these results are both higher and lower than unadjusted $R^2$ statistics for the corresponding models in the original data, it is not clear precisely what adjusted $R^2$ is measuring in this context.
sets are, as such, only attributable to features of the variance decomposition method employed.

An alternative to the incremental assessment of variance resulting from nested ANOVA analysis is to directly estimate the variance of each class of effects in the full model represented by Equation 1 (Rumelt 1991, Roquebert et al. 1996, McGahan and Porter 1997, Bou and Satorra 2007). Having estimated Equation 1 using ordinary least squares, variances and covariances can be directly estimated by fixing $\gamma_t$, $\alpha_t$, $\beta_k$, and $\phi_{ik}$ at their estimated values. Results from this analysis are presented in Tables 4 and 5.

### TABLE 4: Variance and Co-Variance in Full Model – Original Data

<table>
<thead>
<tr>
<th></th>
<th>Year</th>
<th>Industry</th>
<th>Firm</th>
<th>Segment</th>
</tr>
</thead>
<tbody>
<tr>
<td>Year</td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Industry</td>
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<td>0.0001</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Firm</td>
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<td>0.0000</td>
<td>0.0033</td>
<td></td>
</tr>
<tr>
<td>Segment</td>
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<td>0.0000</td>
<td>-0.0028</td>
<td>0.0170</td>
</tr>
</tbody>
</table>

### TABLE 5: Variance and Co-Variance in Full Model – Synthetic Data

<table>
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<th>Year</th>
<th>Industry</th>
<th>Firm</th>
<th>Segment</th>
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</thead>
<tbody>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Industry</td>
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<td></td>
<td></td>
</tr>
<tr>
<td>Firm</td>
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<tr>
<td>Segment</td>
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<td>-0.0057</td>
<td>0.0206</td>
</tr>
</tbody>
</table>

Prior models assessed with the components-of-variance method capture a broader variety of effects—particularly those associated with the persistence of differences over time (Rumelt 1991, McGahan and Porter 1997, Bou and Satorra 2008) than are captured by the model analyzed here. Accordingly, the results presented in Table 4 differ both in model, method, and empirical context from other published results. In very broad terms, these
results are consistent with prior analyses that have found that segment-specific effects are associated with significantly more variance than year, industry or firm effects. The result of central interest to the question addressed by this study concerns the differences between Table 4 and Table 5. The results from the analysis of variance in the synthetic data suggests that not only that significantly more variance may be associated with year, industry and firm effects, but in particular that industry and firm effects may be of roughly the same magnitude as segment effects. The results also suggest substantial variance between industry, firm and segment effects. Effects in the synthetic data are of course driven by non-informative distinctions introduced into the original data, so it is difficult to draw direct substantive conclusions on the basis of these particular results. These results do, however, raise the possibility that prior results concerning the lack of importance of corporate strategy due to the absence of covariance between these effects may have been driven in part by the degree of aggregation at which these underlying categorical constructs were measured.

DISCUSSION AND CONCLUSION

The objective of this study was to reconsider the set of empirical conclusions that have been drawn about the comparative importance of various kinds of explanatory variables on business unit profitability. While other studies have certainly raised concerns about the use of variance decomposition methods in addressing this question (Brush and Bromiley 1997), this study was intended to draw attention to a specific set of issues arising from the treatment of categorical variables in these analyses. The results presented here suggest that a significant fraction of the variance attributed to firm and business unit effects may be
due simply to the relatively high degree of disaggregation with which these constructs have been measured in many studies within this tradition.

The key feature of these analyses is that the distinctions made among observations in the synthetic data in terms of year, industry, and firm effects are completely arbitrary in that, in principle, they add no actual information about performance. One way to interpret the increase in explained variance associated with each variable expanded in the synthetic data set is to consider it as a lower bound on the additional variance that would be explained by an informative measure of any of the explanatory constructs considered here. The random assignment procedure employed in this study makes it extremely unlikely that, for instance, two business units actually experiencing exactly the same industry or market condition would be assigned to the same level, or by the same logic, that two business units assigned to the same synthetic level would actually have faced exactly the same market or industry conditions. Accordingly, a categorical schema that measures industry using meaningful rather than random distinctions that has 9,909 levels should explain no less variance than the synthetic variable constructed here.

A second interpretation of these results is that the additional variance explained variance by the synthetic variables corresponds purely to an artifact of ANOVA and variance components methods having to do strictly with the number of levels associated with a categorical explanatory variable, and having nothing to do with the extent to which the distinctions reflected in the additional levels are informative about the underlying concept of interest. Viewed in this light, the results presented here raise a number of doubts about
the kinds of conclusions that can be drawn from the currently employed set of variance decomposition tools with respect to assessing the importance of the determinants of business unit performance.

For instance, Schmalensee (1985: 344) argues that $F$-tests can be used to test for the existence of a class of effects, or specifically for the cases presented here, whether or not the effects for individual levels within a given categorical explanatory variable are statistically distinguishable from one another. While this is a perfectly reasonable tool to assess, for instance, whether industries or markets statistically differ from one another in terms of the opportunities they provide for profitability, this says little about the internal structure of differentiation within a category schema. As the results presented here demonstrate, while an $F$-test can indicate that there is differentiation within a class of effects, it cannot say that every distinction within a class is a meaningful or informative one. Accordingly, $F$-tests can provide little evidence to address the appropriateness of the level of aggregation of a given categorical measure.

Were it the case that a clear answer about the appropriate level of disaggregation could be assessed by an $F$-test or other statistical means, the importance of those effects would presumably be measured by assessing the variance of the population from which those effects were drawn. Unfortunately, the results presented here suggest that variance estimates using either a nested ANOVA approach or even direct variance estimation through ordinary least squares are sensitive to the number of distinctions made within a category, even when the distinctions are known not to correspond to meaningful or
informative variance. Given a lack of tools available with which to assess the appropriate level of aggregation at which to perform an analysis (Wheat 2005, 2008), these results make it difficult to refute the possibility that any estimate of explained variance based on categorical explanatory variables is not inflated due to uninformative disaggregation.

These analytic difficulties should not be taken to suggest that aggregate categorical constructs should be abandoned in favor of constructs that can be measured using interval or ratio scales. Quite to the contrary, a growing body of research suggests that categorical phenomena play significant roles determining organizational outcomes (Porac et al. 1990, 1995, 1999; Zuckerman 1999, 2000, Carroll and Swaminathan 2000, Hsu 2006, Hannan, Pólos and Carroll, 2007). Theoretical and methodological approaches for identifying appropriate levels of aggregation will become increasingly important to the extent that organizational researchers continue to theorize that categorical phenomena play informative and meaningful roles in determining performance outcomes.

To this end, this work could most usefully be extended by developing categorical distinctions about industries, business unit strategies, and corporate strategies that are not only meaningful to the actors involved in making decisions that lead to firm performance, but are also empirically identifiable to researchers. Judgments about the relative importance of different classes of explanatory variables based upon variance decomposition analyses may prove increasingly useful when the underlying categorical distinctions are both empirically and theoretically supported. The results of analyses performed in this context would not only answer questions about whether or not
industries, firms, or business segments differ in meaningful ways with respect to profitability, but they would also provide useful steps forward in identifying the specific mechanisms that explain these performance differences.
REFERENCES

*Strategic Manage. J.* 24 1011-1025.


