How Much Do Industry, Corporation, and Business Matter, Really? A Meta-Analysis

Bart S. Vanneste
University College London, UCL School of Management, b.vanneste@ucl.ac.uk

May 12, 2017

Forthcoming in *Strategy Science*
Available at https://doi.org/10.1287/stsc.2017.0029

The academic field of strategy seeks to explain differences in firm performance. A consensus exists that industry, corporate, and business effects together account for most performance differences, but there is debate over how much each factor explains. Previous studies have used three different effect size measures: sum of squares, variance, or standard deviation. These measures yield different results for a given sample, which precludes direct comparison. Using simulation analysis, I show that the sum-of-squares measure is sensitive to sample dimensions (e.g., the number of industries, the number of businesses per industry). Using 25 samples from 9 studies ($N = 212{,}112$), I find that this sensitivity is strong in practice: knowing only the dimensions of a sample is sufficient to predict well the sum-of-squares measure. A meta-analysis is conducted using the variance and standard deviation measures instead (18 samples from 16 studies, $N = 225{,}183$). With the variance measure, the effect sizes are 0.08 for industry, 0.14 for corporate, and 0.36 for business; effect sizes with the standard deviation measure are 0.28 for industry, 0.36 for corporate, and 0.59 for business. Thus business effects have about twice the explanatory power of corporate effects, and corporate effects explain somewhat more than do industry effects.

Key words: industry effect; corporate effect; business effect; variance decomposition; meta-analysis

1. Introduction

The academic field of strategy seeks to explain differences in firm performance (Rumelt et al. 1994, Nag et al. 2007). Consider, for example, Procter & Gamble's business of manufacturing diapers for babies and Boeing's business of building military aircraft for governments. Studies have found that three factors typically account for most of the performance differences between such businesses (Schmalensee 1985, Hansen and Wernerfelt 1989, Rumelt 1991, Roquebert et al. 1996, McGahan and Porter 1997): the *industry* in which the business operates (here, baby care vs. defense industry); the *corporate* parent, if any, to which the business belongs (e.g., Procter & Gamble vs. Boeing); and the *business* itself (i.e., the specifics of each business). Although consensus exists that industry, corporate, and business effects together explain most differences in performance, there is ongoing debate about how much each of these factors explains (Hough 2006, Misangyi et al. 2006, Bou and Satorra 2010, Karniouchina et al. 2013, Stavropoulos et al. 2015, Zavosh and Dibiaggio 2015).

I argue that achieving consensus requires consistent measures to quantify the contribution of industry, corporate, and business factors to firm performance. Studies have used three different effect size measures: sum of squares, variance, or standard deviation. These various measures yield different results for a given sample, which precludes the direct comparison of samples using different measures. Whereas the variance and standard deviation measures are easy to convert from one to the other, this is not the case for the sum-of-squares and variance measures—which are the measures used most often.

I employ simulation analysis to show that the sum-of-squares measure is sensitive to sample dimensions (e.g., the number of industries, the number of businesses per industry), which limits its usefulness as effect size measure. For example, the industry sum-of-squares measure will be higher with stronger industry effects or with more industry degrees of freedom. It follows that we obtain a different sum of squares when changing the degrees of freedom (e.g. by picking a sample with different dimensions) even when the strength of industry effects is held constant. Using 25 samples from 9 empirical studies ($N = 212{,}112$), I find that this sensitivity is strong in practice: knowing only the dimensions of a sample is sufficient to predict well the sum-of-squares measure.

To assess the explanatory power of industry, corporate, and business effects, I conduct a meta-analysis using not the sum-of-squares measure of effect size but instead the variance and standard deviation measures. Using 18 samples from 16 studies ($N = 225{,}183$), the variance findings are 0.08 for industry, 0.14 for corporate, and 0.36 for business effects; the standard deviation findings are 0.28 for industry, 0.36 for corporate, and 0.59 for business. Thus, business effects explain about twice what industry and corporate effects do and corporate effects explain somewhat more than do industry effects.

These results contribute in two ways to answering the question of how much of performance differences is explained by each of these factors. First, the effect size for business is substantially greater than for industry and corporate, but that difference depends on the measure employed. For example, the average effect size for business is more than four times that of industry when measured in variances but only twice as large when measured in standard deviations. Indeed, under the standard deviation measure, industry and corporate effects together explain as least as much as do business effects. The variance measure is based on squared distances, so differences between factors are amplified (Brush and Bromiley 1997, Hunter and Schmidt 2004); taking the square root of the standard deviation measure reduces that amplification. Thus the question of explanatory power is as much a question about the strength of particular effects as it is about the effect size measure itself.

Second, corporate effects are somewhat greater than industry effects. This finding does not depend on whether the variance or instead the standard deviation measure is used. Two reasons may explain why this result has not previously been established in the literature. First of all, the corporate effect is greater than the industry effect in most samples but not in all samples. It is more difficult to separate signal from noise in a single sample than in a large set of samples, as is employed here. In the second place, the industry factor has received more attention than the corporate factor. All studies in the empirical literature include industry effects but several do not include corporate effects. In the theoretical literature, most debate concerns the merits of adopting an external (industry) perspective versus an internal (business) perspective rather than a corporate perspective. Hence this finding reinforces the relevance of corporate effects for the understanding of performance differences.

2. Measures

2.1. Background

The empirical approach to explaining firm performance amounts to *describing at which level* performance differences occur. Here "performance" is usually measured as return on assets and less frequently as return on sales, return on invested capital, or market share. The levels investigated most often are industry, corporate parent, and business. An *industry* is the set of businesses that sell similar goods or services. Similarity is often captured via an industry classification, such as the Standard Industrial Classification (SIC) or its successor, the North American Industry Classification System (NAICS). Thus we can distinguish among the industries of rail transportation (NAICS 4821), insurance carriers (NAICS 5241), and electric power generation, transmission and distribution (NAICS 2211). A *corporate parent* is a legal entity that owns and operates one or more businesses (Rumelt 1991).[1] For example, Berkshire Hathaway owns and operates many businesses, including a rail transportation business, an insurance business, and an electric power generation business. The businesses of a corporate parent are demarcated such that each business operates in one and only one industry. It follows that a *business* is interpreted from a market perspective (i.e., as a business segment) and not from an organizational perspective (i.e., not as a business unit) (McGahan and Porter 1997). Even if the operations of rail transportation and electric power generation were organized in a single business unit, they would still count as two businesses for the purposes of performance analysis. Insurance operations that are distributed between two business units would still be considered a single business.

[[INSERT FIGURE 1 ABOUT HERE]]

[1] Business ownership can be partial as in the case of business groups (e.g. Khanna and Rivkin 2001).

Figure 1 gives examples of performance differences occurring at different levels. Consider four businesses, each belonging to one of two corporate parents (ovals in the figure) and one of two industries (triangles). Our aim is to characterize the occurrences of high-performing businesses (gray squares) and low-performing businesses (white squares). Therefore, explaining "firm" performance is equivalent to explaining the performance of businesses, which belong to corporate parents and industries. *Industry* effects are such that performance differences occur between industries. In Example I, all high-performing businesses are in the industry on the figure's left side while all low-performing businesses are on the right-side industry. *Corporate* effects are such that performance differences occur between corporate parents. So in Example II, all high-performing businesses belong to the left-side corporate parent and the low-performing businesses to the right-side corporate parent. *Business* effects are such that performance differences are related to the specifics of the business. In Example III, the leftmost and rightmost businesses are high-performing while those in the middle are low-performing. This pattern cannot be explained either by industry or corporate effects because each corporate parent and each industry has both a low-performing and a high-performing business.

These examples are simplifications. First of all, they are "pure" examples: in each case, a single factor accounts fully for the pattern of performance differences. In reality, the three effects co-occur; the result is complex performance patterns—especially when considering more than two industries, two corporate parents, and four businesses. Second, these examples ignore time. If we interpret Figure 1 as performance from a single year, then all the patterns may reflect nothing more than randomness. Only if these performance differences persist over longer periods can we meaningfully talk about industry, corporate, and business effects.

2.2. Basic Properties of Measures

Three different measures have been used to quantify the effect of year, industry, corporate, and business effects on performance. The first measure is based on the *sum of squares* of these effects (e.g., Goddard et al. 2009, Ma et al. 2013, Fitza 2014, Zacharias et al. 2015); the second on their *variances* (e.g., Chan et al. 2010, Karniouchina et al. 2013), and the third on their *standard deviations* (e.g., Brush and Bromiley 1997, Hough 2006). The sum-of-squares and variance measures have been used most frequently and the standard deviation measure least frequently.

These measures are related but usually yield different outcomes, which precludes aggregation. In general, a sum of squares is the sum of squared differences from a mean. A sum of squares divided by the degrees of freedom gives the variance, and the square root of a variance is the standard deviation. The sum of squares measure does not account for degrees of freedom. A larger sample yields a higher sum of squares but not a higher variance or higher standard deviation. Formally, we have:

$$
\begin{aligned}
SS(x) &= \sum_{i=1}^{n}(x_i - \bar{x})^2; \\
Var(x) &= \frac{SS(x)}{n-1}; \\
SD(x) &= \sqrt{Var(x)}.
\end{aligned}
\tag{1}
$$

To describe industry, corporate, and business effects, we can write the performance (p_{jkt}) of a business in corporation k, industry j, and year t in line with Rumelt (1991) as

$$
p_{jkt} = m + Y_t + I_j + C_k + B_{jk} + e_{jkt}. \tag{2}
$$

Here m is a constant (it signifies the mean performance of all businesses across all years), Y_t is the year effect for year t (i.e., the performance difference in year t relative to the mean), I_j is the industry effect for industry j (i.e., the performance difference in industry j relative to the mean), C_k is the corporate effect for corporation k (i.e., the performance difference of corporation k relative to the mean), B_{jk} is the business effect for a business in corporation k and industry j (i.e., the performance difference between that business relative to the mean), and e_{jkt} is an error term. For simplicity, the model does not include interaction effects (in addition to the business effect, which can be viewed as an interaction between the industry and corporate effects).

For industry, corporate, and business effects, calculation of the three measures is the same when transforming variance to standard deviation (the square root) but differs when transforming the sum of squares to variance (i.e., dividing the industry sum of squares by its degrees of freedom does not yield the industry variance). However, the general intuition holds. The sum of squares measure is sensitive to sample dimensions, e.g., the number of businesses per industry, and the variance and standard deviation are not (or much less so).

2.2.1. Measure 1: Sum of Squares. The total sum of squares (SST) is the sum of squared differences from the performance mean. The goal with this approach is to allocate the total sum of squares among the *sum of squares* of the effects: year, industry, corporate, and business. For example, the sum of squares industry (SSI) is that part of the total sum of squares arising from performance differences between industries, and the sum of squares business (SSB) is the part arising from performance differences between businesses. For comparison, effect sizes are expressed as a proportion of the total sum of squares: SSI/SST and SSB/SST. These ratios correspond to a regression's R^2 values that are due to (respectively) industry and business effects.

The sum-of-squares effect size measure depends not only on the strength of the effects but also on the sample dimensions (e.g., the number of industries, the number of businesses per industry). Even if the sum of squares business is greater than the sum of squares industry, we cannot then say that business is more important than industry because the difference could be due to the sample's dimensions and not to any difference in the relative strength of their effects. This property limits the measure's usefulness for aggregating results across samples, which is the goal here.

I illustrate the influence of sample dimensions with a simulation.[2] For simplicity (but without loss of generality), I focus on industry and business effects and ignore corporate and year effects. Let the performance (p_{jlt}) of business l in industry j and year t be written as

$$p_{jlt} = m + I_j + B_{jl} + e_{jlt}. \tag{3}$$

By construction, industry effects I_j and business effects B_{jl} are equally important in determining performance: both are normally distributed with mean 0 and standard deviation 1. The error (e_{jlt}) has the same distribution. The overall mean (m) is 0. The range of sample dimensions matches that of the studies included in the meta-analysis: the number of industries ranges from 5 to 2,375 and the number of businesses per industry from 2 to 167. The number of years is fixed at 8, which is the median of all the studies considered.

Most researchers use ANOVA for the sum-of-squares measure; I shall do likewise. For a given combination of parameters, each industry has the same number of businesses. The result is a balanced design (i.e., an equal number of observations per business and an equal number of businesses per industry). The sum of squares can therefore be calculated directly from the data without the need for regression analysis (which would give the exact same results but takes much longer to calculate) (Searle 1971).[3] For the sum-of-squares formulas, see column SS of Table 1 (or Kutner et al. 2005, 1096–99).

[[INSERT TABLE 1 ABOUT HERE]]

Figure 2 plots the explained sum of squares for industry and for business (SSI/SST and SSB/SST). Each data point represents the average of 1,000 randomly generated samples. In the figure's left panel, the number of business per industry is fixed at the studies' median (10); in the right panel, the number of industries is fixed at the studies' median (69). These results illustrate two points. First, the explained sum of squares for industry and business effects depends on the

[2] The R code of the simulation is provided in an online appendix.

[3] When taking into account that business is nested within industry, their respective order of entry in a regression is irrelevant because the data are balanced. Thus the sequential method (e.g., industry first and then business: $SS(I)$ and $SS(B|I)$) and the partial method (i.e, industry with business already included and next business with industry already included: $SS(I|B)$ and $SS(B|I)$) yield the same sum of squares and R^2 as in a regression.

sample dimensions. Second, despite the equal importance (by design) of industry and business effects, their sums of squares differ for most parameter combinations.

[[INSERT FIGURE 2 ABOUT HERE]]

The right panel of Figure 2 shows that, with two businesses per industry, business effects explain only about 19% of performance while industry effects explain 51%. Yet with 167 businesses per industry, the situation is reversed: business effects explain more than do industry effects (38% vs. 33%). The only difference in these two cases is the number of business effects, not their size. In the left panel, if there are five industries then industry effects explain about 29% of performance while business effects explain 38%. Yet for a higher number of industries, industry effects explain more than business effects: when there are 100 industries, the respective percentages are 37% and 34%. The only difference is that the sample size has increased. So if the sum of squares is taken as an indicator of importance for performance, then one could mistakenly conclude that industry matters less than business if few industries are sampled, and more if many are sampled.

This problem is not resolved by using adjusted R^2, which penalizes the addition of more variables, instead of R^2 (cf., Brush et al. 1999). I calculate the adjusted R^2 by adjusting the sum of squares with the appropriate degrees of freedom (see Figure 3). The derived values for adjusted R^2 are somewhat lower than those derived for R^2 (because of the penalty just described), but they lead to the same conclusion: notwithstanding equal industry and business effects, their adjusted sum of squares differ markedly for most parameter settings and are sensitive to sample dimensions.

[[INSERT FIGURE 3 ABOUT HERE]]

The problem arises as follows. Changing the degrees of freedom (e.g. the number of industries) will naturally lead to a change in the sum of squares (e.g. SSI), simply because a different number of squares need to be summed, see Table 1. At the same time, the total sum of squares (SST) will change, but not in the same magnitude. Hence, the ratio of the two will change (SSI/SST).[4] As I will show next, this problem is much diminished (or entirely absent) for ratios of variances or standard deviations.

2.2.2. Measure 2: Variance. The total variance is the variance in performance. The goal here is to allocate it among the *variances* of the effects: year, industry, corporate, and business. For purposes of comparison, the effect size is given as a proportion of the total variance—for example, σ_I^2/σ_p^2 for industry or σ_B^2/σ_p^2 for business. Unlike the sum-of-squares measure, the variance measure is not (or is only weakly) dependent on sample dimensions.

[4] The ANOVA literature emphasizes that the inclusion or exclusion of factors in a research design changes the denominator but not the numerator (Kennedy 1970, Cohen 1973). This problem is not unique to a ratio of the sum of squares; it occurs also for a ratio of variances or of standard deviations (Olejnik and Algina 2003, Fritz et al. 2012). However, the issue at hand here is not the inclusion or exclusion of factors (e.g, industry or business) but how many effects are included per factor (e.g., the number of industries or the number of businesses).

To illustrate this difference, I calculate the variance measure for the previously simulated data (which, by design, had equally strong industry and business effects). Using the simplified performance equation (3), which includes industry and business effects but not year and corporate effects, we can write (see e.g., Rumelt 1991)

$$\sigma_p^2 = \sigma_I^2 + \sigma_B^2 + \sigma_e^2. \tag{4}$$

Assuming independent effects, this expression decomposes the total variance (σ_p^2) into the variances of the effects (σ_I^2 for industry and σ_B^2 for business), and the variance of the error (σ_e^2). Following the extant literature, I use a random-effects assumption when calculating the variances of the effects. Hence these are expressed as population variances (σ_I^2 and σ_B^2) and not as sample variances (s_I^2 and s_B^2), which would apply with a fixed-effects assumption. However, the discussion that follows holds for both random- and fixed-effects.

For the variance measure, most researchers use either variance component analysis (VCA) or hierarchical linear modeling (HLM). The key difference between these methods is in how they account for multi-level data and the relationships between levels (Hough 2006, Misangyi et al. 2006). This distinction is less relevant to the simplified model here, which includes only industry and business effects. The data are nested (i.e., a business belongs to an industry) but not cross-classified (i.e., a business does not belong to an industry *and* a corporation). Because of ease of calculation, I use VCA to estimate the variances (Searle 1971). This procedure involves equating the calculated sum of squares with their expected values and then solving the system of equations.[5]

[[INSERT FIGURE 4 ABOUT HERE]]

Figure 4 plots the average explained variance for industry and business ($\hat{\sigma}_I^2/\hat{\sigma}_p^2$ and $\hat{\sigma}_B^2/\hat{\sigma}_p^2$); each explains about a third of the variance in performance. The number of businesses has no effect (left panel), but the number of industries has some effect when there are few industries (right panel). This is because it is difficult to estimate precisely the variance of a factor when limited levels are sampled (Kutner et al. 2005, Hox 2010).[6] That difficulty has been referred to as the problem of "data sparseness" (for further discussion, see Stavropoulos et al. 2015). Note that this problem arises only for a small number of levels and appears to be modest in size compared to

[5] The expected values for a sum of squares is the degrees of freedom (column *df* of Table 1) multiplied by the expected mean square (column $\mathbb{E}[MS]$—Random).

[6] The precision of the estimates ($SD(\hat{\sigma}_I^2)$ and $SD(1/\hat{\sigma}_p^2)$) matters beyond unbiasedness ($\mathbb{E}[\hat{\sigma}_I^2] = \sigma_I^2$ and $\mathbb{E}[1/\hat{\sigma}_p^2] = 1/\sigma_p^2$) because the effect size measure is a ratio of two random variables. Since $Cov(X,Y) = \mathbb{E}[XY] - \mathbb{E}[X]\mathbb{E}[Y]$, it follows that we can write $\mathbb{E}[\hat{\sigma}_I^2/\hat{\sigma}_p^2] = Cor(\hat{\sigma}_I^2, 1/\hat{\sigma}_p^2)SD(\hat{\sigma}_I^2)SD(1/\hat{\sigma}_p^2) + \mathbb{E}[\hat{\sigma}_I^2]\mathbb{E}[1/\hat{\sigma}_p^2]$. When estimate precision is low, typically $\mathbb{E}[\hat{\sigma}_I^2/\hat{\sigma}_p^2] \neq \mathbb{E}[\hat{\sigma}_I^2]/\mathbb{E}[\hat{\sigma}_p^2]$. Yet with high precision, $\mathbb{E}[\hat{\sigma}_I^2/\hat{\sigma}_p^2] \approx \mathbb{E}[\hat{\sigma}_I^2]/\mathbb{E}[\hat{\sigma}_p^2]$ because (i) any correlation ($Cor(\hat{\sigma}_I^2, 1/\hat{\sigma}_p^2)$) matters less given that both $SD(\hat{\sigma}_I^2)$ and $SD(1/\hat{\sigma}_p^2)$ are low; and (ii) by Jensen's inequality $\mathbb{E}[1/\hat{\sigma}_p^2]$ is closer to $1/\mathbb{E}[\hat{\sigma}_p^2]$.

the sum of squares. So provided the standard errors of the effects' estimates are not too high, the variance measure will be insensitive to sample dimensions.

[[INSERT FIGURE 5 ABOUT HERE]]

To compare the sum-of-squares and variance measures, Figure 5 shows the effect sizes for industry relative to business (SSI/SSB and $\hat{\sigma}_I^2/\hat{\sigma}_B^2$). The variance measure attributes roughly equal strength to industry and business irrespective of the sample dimensions; in contrast, the sum-of-squares measure's ranking depends on the sample dimensions.

2.2.3. Measure 3: Standard Deviation. The standard deviation measure is the square root of the variance measure. Expressed as a proportion of the performance standard deviation, we have for example σ_I/σ_p for industry and σ_B/σ_p for business. Like the variance measure, the standard deviation measure is relatively insensitive to sample dimensions.

The variance measure is based on squared distances, so differences in linear distances are amplified (Brush and Bromiley 1997, Hunter and Schmidt 2004). The square root of the standard deviation measure reduces that amplification.[7] To illustrate this dynamic, I intentionally make the business effects stronger than the industry effects. Thus I simulate data in which the business effects have been multiplied by a factor that ranges from 1 to 3 while leaving industry effects unchanged. The number of industries is fixed at the median (69), as is the number of businesses per industry (10); the other settings remain unchanged. I use VCA to obtain the variances and then take the square root to obtain the standard deviation.

[[INSERT FIGURE 6 ABOUT HERE]]

Figure 6 illustrates the effect size for business relative to industry using the variance and the standard deviation measures ($\hat{\sigma}_B^2/\hat{\sigma}_I^2$ and $\hat{\sigma}_B/\hat{\sigma}_I$, respectively). Making the business effect 3 times as strong yields an effect size—for business relative to industry—of 3 (with the standard deviation measure) and more than 10 (with the variance measure). Thus the variance measure amplifies differences between industry and business, making industry seem less important than it actually is. These results reflect the variance measure's use of squared distances. Because the sum-of-squares measure is also based on squares, it likewise displays such amplification.

2.3. Methods

The literature has active discussions on fixed- vs. random-effects assumptions and on methods. Here I describe how these discussions relate to the three measures.

The year, industry, corporate, and business effects can be described as random or fixed (Searle 1971). If random, then the effects are seen as coming from a larger population. If fixed, then

[7] Formally, if $0 < a < b$, then $\sqrt{b}/\sqrt{a} < b/a$ because $b/a = \sqrt{b}/\sqrt{a} \times \sqrt{b}/\sqrt{a}$ and $\sqrt{b}/\sqrt{a} > 1$. Thus, if $\hat{\sigma}_B^2 > \hat{\sigma}_I^2$, then the ratio of standard deviations ($\hat{\sigma}_B/\hat{\sigma}_I$) is less than that of the ratio of variances ($\hat{\sigma}_B^2/\hat{\sigma}_I^2$).

the effects are not seen as coming from a larger population. For instance, with a random-effects assumption, we can describe industry effects in terms of the population standard deviation (σ_I)—that is, how much all industries differ from each other. With a fixed-effects assumption, we can describe such effects only in terms of the sample standard deviation (s_I), or how much industries in the sample differ from each other.[8] Because it is not always obvious whether effects are fixed or random (Searle 1971), some variance decomposition studies have used fixed effects (e.g., Mackey 2008, Goddard et al. 2009, Ma et al. 2013) and others have used random effects (e.g., Roquebert et al. 1996, Chang and Singh 2000, Chan et al. 2010). These types have been used in separate models (e.g., Schmalensee 1985, Rumelt 1991, McGahan and Porter 1997) and also in the same model, as when some effects are fixed and others are random (i.e., mixed-effects) (e.g., Hough 2006, Misangyi et al. 2006).

The three measures can be calculated for both fixed and random effects (see Table 2). The sum-of-squares measure is the same for fixed and random effects. Sum of squares is a property of a sample, hence the presence or absence of a larger population is irrelevant. The variance and standard deviation measures differ for random versus fixed effects: for random effects, these measures refer to the population variance and standard deviation; for fixed effects, they refer to the sample variance and standard deviation.[9]

[[INSERT TABLE 2 ABOUT HERE]]

Even though the fixed versus random effects assumption does not limit one's choice of measure, in practice, however, nearly all studies have used either a fixed-effects assumption with the sum-of-squares measure or a random-effects (or mixed-effects) assumption with the variance and standard deviation measures (an exception is Brush et al. 1999). Table 3 illustrates this mapping between the effects assumption made and the measures used. It shows also the variety of methods employed, including analysis of variance (ANOVA), hierarchical linear modeling (HLM), two-stage least squares (2SLS), and variance components analysis (VCA). In the literature, debate has centered on the appropriateness of the fixed- versus random-effects assumption (columns in the table) and on the merits of the different methods (cells in the table). For a discussion, see for example Brush and Bromiley (1997), McGahan and Porter (2002, 2005), Ruefli and Wiggins (2003, 2005),

[8] The random- versus fixed-effects assumption is not indicative of whether the effects are constant over time. Either assumption can accommodate time-varying effects by including interactions between year effects and industry or corporate effects. Neither is the random- versus fixed-effects assumption the same as random- versus fixed-effects regressions, a distinction that indicates whether (unobserved) effects are assumed to be uncorrelated with the explanatory variables. In general, even if a random-effects assumption is made, one must still decide on the uncorrelatedness of the effects and the explanatory variables (Wooldridge 2003, 473). In the case of ANOVA with a random-effects assumption, the variance components can be estimated from a dummy variable regression (i.e., a fixed-effects regression); see Searle (1971, 443) or Method III in Henderson (1953).

[9] Even in a fixed-effects model, the notation used for performance is σ_p—and not s_p—because performance includes the error, which is always seen as coming from a population distribution (i.e., a random "effect").

Hough (2006), and Bou and Satorra (2010). Here the discussion has focused on the measures (rows in the tables).

[[INSERT TABLE 3 ABOUT HERE]]

3. Methods

3.1. Identification of Studies

Several steps were taken to identify studies for the meta-analysis. First, the Business Source Premier database and the Google Scholar database were searched using the following search terms: industry effect, corporate effect, or business effect; or variance, decomposition, and at least one of industry, corporate, and business. Second, the following journals were searched for any study containing at least two of industry, corporate, or business (anywhere in the text): *Academy of Management Journal*, *Administrative Science Quarterly*, *Global Strategy Journal*, *Journal of Business Research*, *Journal of International Business Studies*, *Journal of Management*, *Journal of Management Studies*, *Longe Range Planning*, *Management Science*, *Organization Science*, *Organization Studies*, *Strategic Management Journal*, *Strategic Organization*, and *Strategy Science*. Third, all studies citing the foundational study of McGahan and Porter (1997) were searched for the word "variance". Fourth, a request for unpublished (and published) studies was sent to strategy scholars via the BPS listserv. Fifth, all works cited in the identified studies were screened for their possible relevance.

Most meta-analyses in the strategy literature use as inputs sample estimates that do not depend on modeling choices (e.g., pairwise rather than partial correlations). Such model-free estimates are unavailable here. To ensure comparability among studies, I selected those that employ similar models (Hunter and Schmidt 2004). A study was included in the meta-analysis only if it met the following conditions. First, it had to include industry, corporate, and business effects. Second, it had to report an effect size in standard deviations, variances, or sums of squares (two studies excluded). Third, the study had to describe a model with no more than one interaction term involving year, industry, or corporate effects (in addition to the business effect) (three studies excluded). Fourth, for VCA or HLM, the study had to report a model without covariances (two studies excluded).

3.2. Selection of Analyses

Most studies report multiple analyses. For each study, only one is included per measure by sequentially applying the following criteria. First, for overlapping samples, choose the largest. Hence aggregate samples are chosen instead of subsamples of select industries, but also samples are selected such that single-business corporations are included rather than excluded. The latter selection may affect the estimates, especially those of the corporate effects, per Bowman and Helfat

(2001). I investigate the impact of including versus excluding single-business corporations in an additional analysis. Second, for the model, choose one without additional interaction effect (if one is provided). Third, for the method, choose HLM over VCA (only one study uses both). Note that the more recent studies reporting variances or standard deviations use HLM.

3.3. Calculation of Effect Sizes

Few studies report standard deviations; moreover, in those that do report them, the standard deviations of effects are relative to each other rather than to performance. So even for studies that do report standard deviations, I rely on the reported variances to calculate the standard deviations used here (by taking the square root). Sum-of-squares measures could conceivably be converted into variances using Henderson's (1953) "method III", but studies do not report data sufficient for conducting these calculations. For this reason, the sum-of-squares samples are reported separately.

The procedures just described yielded, for the standard deviation and variance measures, a set of 16 studies reporting on 18 samples with a total of $N = 225{,}183$ business-year observations. For the sum-of-squares measure, I obtain a (partially overlapping) set of 9 studies reporting on 25 samples with a total of $N = 212{,}112$ observations.

3.4. Non-independence

For a given sample, the effect sizes are not independent. For example, the business standard deviation (as a ratio of the total standard deviation) depends on the corporate standard deviation. To account for such non-independence, I treat the data as paired when testing for differences in effect size. For example, I analyze the distribution of the business *minus* the corporate standard deviation across samples.

Across samples, the effect sizes are unfortunately also not independent. This violates a key assumption of a meta-analysis. The problem arises because many samples are from the United States (12 of the 18 variance and standard deviation samples). Most of these US samples are from the Compustat database, and some with overlapping time periods. To address this non-independence, I provide an analysis restricted to the six non-US samples, which draw from different databases and cover different regions and time periods. Because the results are broadly consistent, I report all samples as the main analysis and the non-US samples as a supplementary analysis. Note that the reported confidence intervals for the main analysis are merely indicative and are probably too narrow.

4. Results

Table 4 lists the studies and samples. The three effect size measures are also reported; these measures are standardized relative to performance (e.g., industry/performance). The samples are sorted by industry effect size for the variance or standard deviation or (absent those measures) for the sum of squares. Three summary statistics are reported in the bottom rows. The sample size–weighted mean puts more weight on larger samples, whereas the unweighted mean gives equal weight to all samples; the median reduces the influence of any outliers.

[[INSERT TABLE 4 ABOUT HERE]]

4.1. Sum of Squares vs. Variance

4.1.1. Sensitivity to Sample Dimensions The sum-of-squares measure for actual samples is sensitive to sample dimensions. In Figure 7 the sum-of-squares samples (1, 14, 19–41) are represented by dots.[10] On the vertical axis is the explained sum of squares per factor; on the horizontal axis are the degrees of freedom used per factor as a proportion of the total degrees of freedom. If the degrees of freedom are not reported, then these are calculated for year, industry, and corporate effects as (respectively) the number of years minus 1, the number of industries minus 1, and the number of multi-business corporations minus 1. For business effects, missing degrees of freedom are approximated as the number of businesses minus the number of industries minus the number of multi-business corporations plus 1. In line with the simulations, more relative degrees of freedom corresponds to a higher explained sum of squares for a factor. For instance, a sample with more relative industry degrees of freedom displays (on average) a greater industry effect whereas a sample with more relative corporate degrees of freedom displays a greater corporate effect.

[[INSERT FIGURE 7 ABOUT HERE]]

The variance measure is much less sensitive to sample dimensions. The correlation between relative degrees of freedom and effect sizes is weak for the variance but is strong for the sum-of-squares measure (see the *df* columns in Table 5).[11] The "data sparseness" problem mentioned before with respect to the variance measure may manifest itself not with relative but rather with absolute degrees of freedom (Stavropoulos et al. 2015). However, correlations between effect sizes and the number of years, industries, multi-business corporations, and businesses (column n_k) or their natural logarithms (column $ln(n_k)$) remain weak.

[[INSERT TABLE 5 ABOUT HERE]]

4.1.2. Effect Size In the two samples that provide both measures, the effect sizes of the sum-of-squares measure differ noticeably from those of the variance measure (see Figure 8). In sample 1, the corporate effect's size as measured by sum of squares is more than twice its size as measured by variance. In fact, using sums of squares shows corporate effects to be greater than industry effects

[10] Due to incomplete information on sample dimensions, only 24 out of 25 samples are plotted for industry and corporate effects and 23 samples for business effects.

[11] These degrees of freedom are only approximations (Hodges and Sargent 2001).

whereas the opposite result obtains when variances are used. In sample 14, the ranking of effects is preserved; however, the industry effect size under sum of squares is more than double that under variance while the corporate effect size is less when the sum-of-squares measure is used.

[[INSERT FIGURE 8 ABOUT HERE]]

At the aggregate level, differences are more subtle. The weighted mean for the sum of squares measure is similar to that for the variance measure (see Table 6). This outcome is mainly driven by samples 31 and 35, which together account for more than 60% of all sum-of-squares observations. Looking instead at the unweighted mean, we see a notable difference for industry effects (0.127 vs. 0.090). This finding underscores the importance of using a common effect size measure.

4.2. Variance vs. Standard Deviation

For the variance and standard deviation samples (1–18) results are consistent across the three summary statistics (weighted mean, unweighted mean, median). I will focus on the weighted mean as an estimate of a population parameter (Hunter and Schmidt 2004).

The weighted mean for the variances are 0.01 for year, 0.08 for industry, 0.14 for corporate, and 0.36 for business effects. The weighted mean for the standard deviations are 0.08 for year, 0.28 for industry, 0.36 for corporate, and 0.59 for business effects.[12] Figure 9 and Table 6 report meta-analytic results with bootstrapped 95% confidence intervals based on 10,000 replications. We can informally interpret these variances and standard deviations as follows. An effect is defined as a performance deviation from an overall mean, and the estimates give an indication of the relative size of these performance deviations associated with each factor. On average, then, the deviations associated with corporate are somewhat greater than those associated with industry, and those associated with business are substantially greater. A formal interpretation would reference equation (2), where performance is the sum of four factors (and an error term). The effect sizes provide estimates of the distributions of these factors. For example, the industry effects can be seen as coming from a distribution with mean 0 and a variance of 0.08 or a standard deviation of 0.28. The year, corporate, and business effects each have their own mean 0 distribution with variance or standard deviation as reported above.

[[INSERT TABLE 6 ABOUT HERE]]

[[INSERT FIGURE 9 ABOUT HERE]]

Figure 10 shows the differences for variances (left) and standard deviations (right) between business and corporate effects, between corporate and industry effects, and between industry and year effects (for numbers, see Table 6). The figure plots the weighted mean differences and the

[12] Note that the standard deviations sum to more than 1. If $\sigma_p^2 = \sigma_Y^2 + \sigma_I^2 + \sigma_C^2 + \sigma_B^2 + \sigma_e^2$, then $\sqrt{\sigma_p^2} = \sqrt{\sigma_Y^2 + \sigma_I^2 + \sigma_C^2 + \sigma_B^2 + \sigma_e^2}$, which is less than $\sqrt{\sigma_Y^2} + \sqrt{\sigma_I^2} + \sqrt{\sigma_C^2} + \sqrt{\sigma_B^2} + \sqrt{\sigma_e^2}$ because the square-root function is concave. When dividing by $\sqrt{\sigma_p^2}$, it follows that $1 < \sqrt{\sigma_Y^2}/\sqrt{\sigma_p^2} + \sqrt{\sigma_I^2}/\sqrt{\sigma_p^2} + \sqrt{\sigma_C^2}/\sqrt{\sigma_p^2} + \sqrt{\sigma_B^2}/\sqrt{\sigma_p^2} + \sqrt{\sigma_e^2}/\sqrt{\sigma_p^2}$.

95% confidence intervals. No confidence interval overlaps with 0. Hence business effects are the strongest, followed by corporate, then industry, and finally year effects.

[[INSERT FIGURE 10 ABOUT HERE]]

Thus, the results are qualitatively similar for variance and standard deviation. In line with the simulation, the variance amplifies differences between factors. For the variance, the industry effect is ×10.5 (standard deviation: ×3.5) the year effect, the corporate effect is ×1.6 (standard deviation: ×1.3) the industry effect, and the business effect is ×2.6 (standard deviation: ×1.6) the corporate effect.

4.3. Additional Analyses for Standard Deviation

To determine how much of the differences between samples are due to sampling error or differences in underlying effects, we would need the standard errors of the sample estimates. These standard errors are neither reported nor can they be derived from the data provided. So instead, I explore the extent to which estimates differ by the following characteristics: sample, method, and model (see Table 7 and Figure 11). I report here the results for standard deviation (the results for variance are qualitatively similar).

[[INSERT FIGURE 11 ABOUT HERE]]

4.3.1. Sample: US vs. Non-US. In Panel A of Figure 11 (and in rows A1 and A2 of Table 7), the samples are split by region, which refers to the corporate parent's location. Most samples include the international businesses; for example, US samples contain businesses that operate beyond US borders. The results are fairly similar, although industry, corporate, and business effects are all somewhat lower in non-US than in US samples. The lack of substantial differences reduces concerns about the possible non-independence of the US samples.

4.3.2. Sample: Manufacturers Only. Due to data limitations, Rumelt (1991) restricted his analysis to manufacturing firms only. Nowadays, most data sets include non-manufacturing firms, too. Out of 18 samples, 4 are manufacturing firms only. The results of these 4 samples are similar to those of the other 14 (see Panel B of Figure 11 and rows B1 and B2 of Table 7).

4.3.3. Sample: Single- vs. Multi-business. For a single-business corporation, the business and corporate effects are indistinguishable. Some studies exclude such corporations whereas others include them. If they are included then, under VCA, an explicit assumption is needed. The convention in this regard is to estimate a business effect and then set the corporate effect to zero. This approach leads to underestimating the corporate effect and overestimating the business effect (Bowman and Helfat 2001). Under HLM, no such explicit assumption is required because the model can be estimated. It is difficult ex ante to state with high confidence whether or not the inclusion of single-business corporations leads to biases in the corporate or business effect. Our current knowledge on biases is based on simulations, not on analytical results (e.g., Baldwin et al. 2011). These simulations indicate that biases are small or nonexistent when the total number of groups (i.e., single-business *plus* multi-business corporations) is high, even if the percentage of "singletons" (single-business corporations) is high. The term "high" is 168 groups consisting of 57% singletons in Clarke and Wheaton (2007) and 500 groups consisting of 70% singletons in Bell et al. (2008, 2010). One reason for cautious optimism then is that the HLM samples have many corporations: even the smallest sample contains 136 corporations, and the second smallest has 998. Because of the different approaches for VCA and HLM, the comparison here is within method (i.e., either VCA or HLM). In the next section, the comparison is between methods (i.e., VCA versus HLM).

Only one VCA sample includes single-business corporations. Its corporate effect (sample 18: 0.084) is, as anticipated, the lowest across all samples; it is also substantially below the sample with the second-lowest VCA sample (sample 8: 0.225). In contrast, only one HLM sample excludes singletons. Its corporate effect (sample 17: 0.550) is the highest across all samples and substantially above the second-highest HLM sample (sample 14: 0.449). The sample without single-business corporations differs from the others not only in sample selection but also in model specification: it views the corporate effect as consisting of a business-invariant and a business-variant component. Hence from this single and atypical sample we cannot infer the impact of single business corporations, when using HLM. Below, I provide an analysis for samples with the same model specification.

4.3.4. Method: VCA vs. HLM. Among the 18 samples, 11 use VCA and 7 use HLM. Panel C of Figure 11 (and rows C1 and C2 of Table 7) show that industry effects are somewhat lower and that corporate effects are somewhat higher with the HLM than with the VCA method. As a result, the difference between industry and corporate effects is more pronounced under HLM. One distinction is that the VCA samples typically exclude single-business corporations whereas these are included in the HLM samples. Yet in light of the simulation results mentioned previously, this distinction may not actually explain the differences in effects. Furthermore, if HLM with single business corporations overestimates the corporate effect then we should expect it to underestimate the business effect; but the business effect is, if anything, greater under HLM than under VCA. Thus further investigation comparing these two approaches is needed.

4.3.5. Model: Year, Industry, Corporate, and Business Effects Only. Model specifications differ across samples. In particular, half of the samples employ models with only year, industry, corporate, and business effects ("YICB only"). Studies in the other half also include such terms as country, region, and/or an interaction effect between industry and year. Panel D of Figure 11 (and rows D1 and D2 of Table 7) show that the year, industry, and corporate effects differ little across alternative model specifications. The business effect becomes weaker when additional terms are included, which might be explained by the business effect picking up influences that are fixed for a business but vary across industry or corporations. For example, a business may operate in a single region even as its industry and corporation span multiple regions. In that case, omitting region from the specification will lead to a higher business effect.

Thus, a consistent pattern emerges across alternative samples, methods, and models: the industry effect is about half that of the business effect, and the corporate effect is slightly greater than the industry effect.

5. Discussion

Based on Cohen's f^2 (1988) criteria yielding 0.02, 0.13, and 0.26 for (respectively) small, medium, and large explained variance, we can classify the effect sizes for industry and corporate as "medium" and for business as "large".[13] There are two striking aspects of the findings reported here. First, business effects explain the most, but their explanatory power relative to industry and corporate effects depends on whether the variance measure or instead the standard deviation measure is used. Second, the effect size for corporate effects is somewhat greater than for industry effects; that relation has not been well established in existing research, regardless of the measure used.

When analyzing industry, corporate, and business effects, one should bear three cautionary statements in mind. First, the size of an effect does not equal its importance. A small performance difference can be enough to spell the death (or survival) of a business, and a small difference in return on assets may represent a big difference in absolute returns. Second, neither is size of an effect the same as its influence (Bowman and Helfat 2001, McGahan and Porter 2005). Thus an effect does not, in itself, reveal the managerial actions required to generate the performance difference. For example, if a successful corporate parent consistently picks profitable industries to enter, then this upside will be viewed as an industry effect rather than as a corporate effect. In other words, the empirical approach identifies correlates, not causes, of performance.

Third, it follows that the observed effects are not causal effects. The literature on variance decomposition defines an "effect" as a performance deviation from a mean (Rumelt 1991, McGahan and Porter 1997)—for example, the mean performance of the businesses of one corporate parent

[13] Cohens f^2 is defined as the variance accounted for by a factor over the *unaccounted* variance (Cohen 1988: 410). The effect sizes for (respectively) small, medium, and larger are 0.02, 0.15, and 0.35 (p. 413-414). Explained variance is the variance accounted for by a factor over the *total* variance. Explained variance is then equivalent to $f^2/(1+f^2)$ (p. 412), from which we obtain the following effect sizes for (respectively) small, medium, and large: 0.02, 0.13, and 0.26.

relative to an overall mean performance. Both types of performances are observable. In contrast, a causal effect is interpreted as the difference between factual and counterfactual performance (Rubin 1974, Morgan and Winship 2015); an example here is the performance of a business of a given corporate parent relative to the performance of the same business *if* it were under different ownership. By definition, factual and counterfactual performances cannot be observed simultaneously. So then what can be learned from this empirical approach? Most importantly, it offers a set of stylized facts (McGahan and Porter 2005). If the field of strategy seeks to explain differences in firm performance, then we need to identify those differences and the level at which they occur.

This study has the following implications for the choice of effect size measure. The variance and standard devation should be favored over the sum of squares as an effects measure. "An effect-size measure is a standardized index and estimates a parameter that is independent of sample size" (Olejnik and Algina 2003, 434)—and, I would add, independent of sample dimensions. The sum-of-squares measure does not satisfy this criterion. Chang and Singh (2000) show that the level of industry aggregation (e.g., 3- versus 4-digit industry classification) matters. Yet here the argument is that, for a given level of industry aggregation, the sum of squares is sensitive to sample dimensions. As mentioned previously, sum-of-squares measures are well predicted using only the number of years, industries, corporations, and businesses in the sample. The unfortunate consequence is that relative effect sizes can differ between samples simply because of their different dimensions. For this reason, the preference of standard deviation over sum of squares is clear.

The variance measure is (mostly) insensitive to sample dimensions, so the choice between the standard deviation and variance measures is more subjective. One downside of the variance measure is that large effects are amplified and small effects are compressed, which may reduce the latter's perceived importance. For example, the weighted average variance for year effects is less than 0.01. Most scholars would be reluctant to claim that the year is irrelevant, but this is what the variance measure seems to suggest. Similarly, the weighted average variance for industry is only 0.08, which could create the false impression that industry does not matter. At a minimum, it makes industry appear to matter less than it actually does. For instance, one of the most popular strategy textbooks notes that "[i]t appears that industry environment is a relatively minor determinant of a firm's profitability. Studies of the sources of interfirm differences in profitability have produced very different results [. . .] but all acknowledge that industry factors account for a minor part (less than 20%) of variation in return on assets among firms" (Grant 2016, 90). Although the author then proceeds to defend industry analysis, it is unclear whether a defense is needed (recall that, under Cohen's criteria, a small effect is around 2% and a medium effect around 13%). One upside of the variance measure is that it has a long tradition in the social sciences, which facilitates comparability.

This study suggests two opportunities for further research in this area. First, it was found that the ranking of the industry, corporate, and business effects was fairly constant across samples, methods, and models (using the standard deviation measure). Even so, each factor separately exhibited variability across studies. A subgroup analysis was used here to explore that variability. Future studies can analyze the same question using individual samples and possibly subsamples. The second research opportunity is that—given the robust findings on industry, corporate, and business effects—it would be interesting to identify which industries, corporations, and business are overperformers and which are underperformers. We could then move from a factor to an individual effect (e.g., from the corporate factor to a specific corporation).

Acknowledgments

I am grateful to Caroline Koekkoek for excellent research assistance. For discussions and comments, I thank Karla Diaz-Ordaz, Isabel Fernandez-Mateo, Colin Fisher, Rouba Ibrahim, Noemi Kreif, Phebo Wibbens, and Miros Zohrevand as well as participants in the INSEAD Corporate Strategy Camp and the UCL School of Management reading group. I also thank the editor Dan Levinthal and the reviewers for the insightful and constructive comments.

References

Adner, R, CE Helfat. 2003. Corporate effects and dynamic managerial capabilities. *Strategic Management J.* **24**(10) 1011–1025.

Baldwin, SA, DJ Bauer, E Stice, P Rohde. 2011. Evaluating models for partially clustered designs. *Psychological Methods* **16**(2) 149–165.

Becerra, M, J Santaló. 2003. An empirical analysis of the corporate effect: The impact of the multinational corporation on the performance of its units worldwide. *Management Internat. Rev.* **43**(2) 7–25.

Bell, BA, JM Ferron, JD Kromrey. 2008. Cluster size in multilevel models: The impact of sparse data structures on point and interval estimates in two-level models. *JSM Proceedings* 1122–1129.

Bell, BA, GB Morgan, JD Kromrey, JM Ferron. 2010. The impact of small cluster size on multilevel models: A Monte Carlo examination of two-level models with binary and continuous predictors. *JSM Proceedings* 4057–4067.

Bou, JC, A Satorra. 2010. A multigroup structural equation approach: A demonstration by testing variation of firm profitability across EU samples. *Organ. Res. Methods* **13**(4) 738–766.

Bowman, EH, CE Helfat. 2001. Does corporate strategy matter? *Strategic Management J.* **22**(1) 1–23.

Brush, TH, P Bromiley. 1997. What does a small corporate effect mean? A variance components simulation of corporate and business effects. *Strategic Management J.* **18**(10) 825–835.

Brush, TH, P Bromiley, M Hendrickx. 1999. The relative influence of industry and corporation on business segment performance: An alternative estimate. *Strategic Management J.* **20**(6) 519–547.

Chaddad, FR, MP Mondelli. 2013. Sources of firm performance differences in the US food economy. *J. of Agricultural Econom.* **64**(2) 382–404.

Chan, CM, S Makino, T Isobe. 2010. Does subnational region matter? Foreign affiliate performance in the United States and China. *Strategic Management J.* **31**(11) 1226–1243.

Chang, S-J, J Hong. 2002. How much does the business group matter in Korea? *Strategic Management J.* **23**(3) 265–274.

Chang, S-J, H Singh. 2000. Corporate and industry effects on business unit competitive position. *Strategic Management J.* **21**(7) 739–752.

Clarke, P, B Wheaton. 2007. Addressing data sparseness in contextual population research using cluster analysis to create synthetic neighborhoods. *Sociological Methods & Res.* **35**(3) 311–351.

Cohen, J. 1973. Eta-squared and partial eta-squared in fixed factor anova designs. *Educational and Psychological Measurement* **33**(1) 107–112.

Cohen, J. 1988. *Statistical Power Analysis for the Behavioral Sciences*. 2nd ed. Erlbaum, Hillsdale, NJ.

Fitza, MA. 2014. The use of variance decomposition in the investigation of CEO effects: How large must the CEO effect be to rule out chance? *Strategic Management Journal* **35**(12) 1839–1852.

Fritz, CO, PE Morris, JJ Richler. 2012. Effect size estimates: Current use, calculations, and interpretation. *J. of Experimental Psychology: General* **141**(1) 2–18.

Fukui, Y, T Ushijima. 2011. What drives the profitability of Japanese multi-business corporations? A variance components analysis. *J. of The Japanese and Internat. Econom.* **25**(2) 1–11.

Furman, J. 2000. Does industry matter differently in different places? Evidence from four OECD countries. *Working paper* 1–43.

Goddard, J, M Tavakoli, JOS Wilson. 2009. Sources of variation in firm profitability and growth. *J. of Business Res.* **62**(4) 495–508.

Grant, RM. 2016. *Contemporary Strategy Analysis*. 9th ed. John Wiley & Sons, Chichester, U.K.

Hansen, GS, B Wernerfelt. 1989. Determinants of firm performance: The relative importance of economic and internalization factors. *Strategic Management J.* **10**(5) 399–411.

Henderson, CR. 1953. Estimation of variance and covariance components. *Biometrics* **9**(2) 226–252.

Hodges, JS, DJ Sargent. 2001. Counting degrees of freedom in hierarchical and other richly-parameterised models. *Biometrika* **88**(2) 367–379.

Hough, JR. 2006. Business segment performance redux: A multilevel approach. *Strategic Management J.* **27**(1) 45–61.

Hox, JJ. 2010. *Multilevel analysis: Techniques and applications*. Routledge, New York.

Hunter, JE, FL Schmidt. 2004. *Methods of Meta-Analysis: Correcting Error and Bias in Research Findings*. Sage, Thousand Oaks, CA.

Iurkov, V, A Sasson. 2015. How much do alliance networks matter? *Working paper* 1–40.

Karniouchina, EV, SJ Carson, JC Short, DJ Ketchen. 2013. Extending the firm vs. industry debate: Does industry life cycle stage matter? *Strategic Management J.* **34**(8) 1010–1018.

Kennedy, JJ. 1970. The eta coefficient in complex anova designs. *Educational and Psychological Measurement* **30**(4) 885–889.

Khanna, T, JW Rivkin. 2001. Estimating the performance effects of business groups in emerging markets. *Strategic Management Journal* **22**(1) 45–74.

Kutner, MH, CJ Nachtsheim, J Neter, W Li. 2005. *Applied Linear Statistical Models*. 5th ed. McGraw-Hill, Singapore.

Lieu, P-T, C-W Chi. 2006. How much does industry matter in Taiwan? *Internat. J. of Business* **11**(4) 387–402.

Ma, X, TW Tong, M Fitza. 2013. How much does subnational region matter to foreign subsidiary performance? Evidence from Fortune Global 500 corporations' investment in China. *J. of Internat. Business Stud.* **44**(1) 66–87.

Mackey, A. 2008. The effect of CEOs on firm performance. *Strategic Management J.* **29**(12) 1357–1367.

Makino, S, T Isobe, CM Chan. 2004. Does country matter? *Strategic Management J.* **25**(10) 1027–1043.

McGahan, AM, ME Porter. 1997. How much does industry matter, really? *Strategic Management J.* **18**(S1) 15–30.

McGahan, AM, ME Porter. 2002. What do we know about variance in accounting profitability? *Management Sci.* **48**(7) 834–851.

McGahan, AM, ME Porter. 2005. Comment on "Industry, corporate and business-segment effects and business performance: A non-parametric approach" by Ruefli and Wiggins. *Strategic Management J.* **26**(9) 873–880.

Misangyi, VF, H Elms, T Greckhamer, JA Lepine. 2006. A new perspective on a fundamental debate: A multilevel approach to industry, corporate, and business unit effects. *Strategic Management J.* **27**(6) 571–590.

Morgan, SL, C Winship. 2015. *Counterfactuals and Causal Inference*. 2nd ed. Cambridge University Press, New York.

Nag, R, DC Hambrick, M-J Chen. 2007. What is strategic management, really? Inductive derivation of a consensus definition of the field. *Strategic Management J.* **28**(9) 935–955.

Olejnik, S, J Algina. 2003. Generalized eta and omega squared statistics: Measures of effect size for some common research designs. *Psychological Methods* **8**(4) 434–447.

Roquebert, JA, RL Phillips, PA Westfall. 1996. Markets vs. management: What 'drives' profitability? *Strategic Management J.* **17**(8) 653–664.

Rubin, DB. 1974. Estimating causal effects of treatments in randomized and nonrandomized studies. *J. of Educational Psychology* **66**(5) 688–701.

Ruefli, TW, RR Wiggins. 2003. Industry, corporate, and segment effects and business performance: A non-parametric approach. *Strategic Management J.* **24**(9) 861–879.

Ruefli, TW, RR Wiggins. 2005. Response to McGahan and Porter's commentary on "Industry, corporate and business-segment effects and business erformance: A non-parametric approach". *Strategic Management J.* **26**(9) 881–886.

Rumelt, RP. 1991. How much does industry matter? *Strategic Management J.* **12**(3) 167–185.

Rumelt, RP, DE Schendel, DJ Teece. 1994. *Fundamental Issues in Strategy: A Research Agenda*. Harvard Business School Press, Boston, MA.

Schmalensee, R. 1985. Do markets differ much? *Amer. Econom. Rev.* **75**(3) 341–351.

Searle, SR. 1971. *Linear Models*. John Wiley & Sons, New York.

Stavropoulos, S, MJ Burger, D Skuras. 2015. Data sparseness and variance in accounting profitability. *Organ. Res. Methods* **18**(4) 656–678.

Tarziján, J, C Ramirez. 2011. Firm, industry and corporation effects revisited: A mixed multilevel analysis for Chilean companies. *Applied Econom. Letters* **18**(1) 95–100.

Wooldridge, JM. 2003. *Introductory Econometrics: A Modern Approach*. 2nd ed. Thomson, Mason, OH.

Zacharias, N, B Six, D Schiereck, RM Stock. 2015. CEO influences on firms' strategic actions: A comparison of CEO-, firm-, and industry-level effects. *Journal of Business Research* **68**(11) 2338–2346.

Zavosh, G, L Dibiaggio. 2015. How much does corporate effect matter? Definition of business-variant corporate effect. *Academy of Management Proceedings* **2015**(1).

Zavosh, G, L Dibiaggio. 2016. How much does corporate effect matter? Definition and estimation of business-variant corporate effect. *Working paper* 1–36.

Table 1 Sum of squares and variances for simulation

Source of variation	SS	df	MS	$\mathbb{E}[MS]$ Fixed	$\mathbb{E}[MS]$ Random
Industry	$SSI = LT\sum(\bar{p}_{j..} - \bar{p}_{...})^2$	$J-1$	MSI	$\sigma_e^2 + LTs_I^2$	$\sigma_e^2 + T\sigma_B^2 + LT\sigma_I^2$
Business	$SSB = T\sum\sum(\bar{p}_{jl.} - \bar{p}_{j..})^2$	$J(L-1)$	MSB	$\sigma_e^2 + Ts_B^2$	$\sigma_e^2 + T\sigma_B^2$
Error	$SSE = \sum\sum\sum(p_{jlt} - \bar{p}_{jl.})^2$	$JL(T-1)$	MSE	σ_e^2	σ_e^2
Total	$SST = \sum\sum\sum(p_{jlt} - \bar{p}_{...})^2$	$JLT-1$			

Note: Dot indicates summation over that subscript; $\bar{p}$ indicates the sample mean.

Table 2 Effect size measures for fixed and random effects

Effect size measure based on	Performance	Factor Fixed	Factor Random	Effect size measure Fixed	Effect size measure Random
Sum of squares	SST	SSY	SSY	SSY/SST	SSY/SST
		SSI	SSI	SSI/SST	SSI/SST
		SSC	SSC	SSC/SST	SSC/SST
		SSB	SSB	SSB/SST	SSB/SST
Variance	σ_p^2	s_Y^2	σ_Y^2	s_Y^2/σ_p^2	σ_Y^2/σ_p^2
		s_I^2	σ_I^2	s_I^2/σ_p^2	σ_I^2/σ_p^2
		s_C^2	σ_C^2	s_C^2/σ_p^2	σ_C^2/σ_p^2
		s_B^2	σ_B^2	s_B^2/σ_p^2	σ_B^2/σ_p^2
Standard deviation	σ_p	s_Y	σ_Y	s_Y/σ_p	σ_Y/σ_p
		s_I	σ_I	s_I/σ_p	σ_I/σ_p
		s_C	σ_C	s_C/σ_p	σ_C/σ_p
		s_B	σ_B	s_B/σ_p	σ_B/σ_p

Table 3 Methods for fixed, mixed, and random effects

Effect size measure based on	Factor Fixed-effects	Factor Mixed-effects	Factor Random-effects
Sum of squares	ANOVA partial (Ma et al. 2013) ANOVA sequential (Goddard et al. 2009)	—	2SLS (Brush et al. 1999)
Variance	—	HLM (Misangyi et al. 2006)	HLM (Karniouchina et al. 2013) VCA (Chan et al. 2010)
Standard deviation	—	HLM (Hough 2006)	—

Table 4 Studies, samples, and their effect sizes

Sample	Study		Sample		
ID	Authors	Source	Country	Period	Performance
1	Becerra and Santaló (2003)	Compustat	USA	1991–1994	ROA
2	Chang and Singh (2000)	Trinet	USA	1981–1989	Market share
3	Brush et al. (1999)	Compustat	USA	1986–1995	ROA
4	Chan et al. (2010)	METI Trend	USA	1996–2005	ROS
5	Tarziján and Ramirez (2011)	Economatica	Chile	1998–2007	ROA
6	Chan et al. (2010)	METI Trend	China	1996–2005	ROS
7	Roquebert et al. (1996)	Compustat	USA	1985–1991	ROA
8	Brush et al. (1999)	Compustat	USA	1986–1995	ROA
9	Chang and Hong (2002)	KIS	Korea	1985–1996	ROIC
10	Misangyi et al. (2006)	Compustat	USA	1984–1999	ROA
11	Chaddad and Mondelli (2013)	Compustat	USA	1984–2006	ROA
12	Makino et al. (2004)	METI Trend	Japan	1996–2001	ROS
13	Iurkov and Sasson (2015)	Compustat	USA	1990–2013	ROA
14	Hough (2006)	Compustat	USA	1995–1999	ROA
15	Fukui and Ushijima (2011)	Nikkei NEEDS	Japan	1998–2003	ROA
16	Karniouchina et al. (2013)	Compustat	USA	1978–1994	ROA
17	Zavosh and Dibiaggio (2016)	Compustat	USA	2001–2009	ROA
18	Lieu and Chi (2006)	TEJ	Taiwan	1994–2000	ROS
19	Furman (2000)	Worldscope	Canada	1992–1996	ROA
20	Khanna and Rivkin (2001)	Datastream Int.	Philippines	1992-1997	ROA
21	Khanna and Rivkin (2001)	Datastream Int.	Israel	1992-1997	ROA
22	Khanna and Rivkin (2001)	Datastream Int.	Argentina	1990-1997	ROA
23	Furman (2000)	Worldscope	Australia	1992–1996	ROA
24	Khanna and Rivkin (2001)	ICMD	Indonesia	1993-1995	ROA
25	Khanna and Rivkin (2001)	SVS	Chile	1988-1996	ROA
26	Khanna and Rivkin (2001)	Datastream Int.	Mexico	1988-1997	ROA
27	Furman (2000)	Worldscope	USA	1992–1996	ROA
28	Khanna and Rivkin (2001)	Datastream Int.	Taiwan	1990-1997	ROA
29	Furman (2000)	Worldscope	UK	1992–1996	ROA
30	Rumelt (1991)	FTC	USA	1974–1977	ROA
31	McGahan and Porter (2002)	Compustat	USA	1982–1994	ROA
32	Khanna and Rivkin (2001)	Datastream Int.	Turkey	1988-1997	ROA
33	Khanna and Rivkin (2001)	Datastream Int.	Peru	1991-1997	ROA
34	Khanna and Rivkin (2001)	KCH	Korea	1991-1995	ROA
35	McGahan and Porter (1997)	Compustat	USA	1982–1994	ROA
36	Khanna and Rivkin (2001)	Datastream Int.	Brazil	1990-1997	ROA
37	Mackey (2008)	Compustat	USA	1992–2002	ROA
38	Khanna and Rivkin (2001)	McGregor	South Africa	1993-1996	ROA
39	Khanna and Rivkin (2001)	Datastream Int.	Thailand	1992-1997	ROA
40	Adner and Helfat (2003)	FRS	USA	1977–1997	ROA
41	Khanna and Rivkin (2001)	CME	India	1989-1995	ROA

Continued

ID	Measure		Method	Table	Model	Sample		
	Sum of squares	Variance				Single business corporations	*YICB* only	Manufacturing only
1	✓		ANOVA	2		No	Yes	No
1		✓	VCA	3		No	No	No
2		✓	VCA	3	4	No	Yes	Yes
3		✓	VCA	10	4 segments	No	Yes	No
4		✓	VCA	1	1	No	No	No
5		✓	HLM	2		Yes	Yes	No
6		✓	VCA	1	2	No	No	No
7		✓	VCA	3	Average	No	No	Yes
8		✓	VCA	10	3 segments	No	Yes	No
9		✓	VCA	2	1	No	No	No
10		✓	HLM	3		Yes	Yes	No
11		✓	HLM	5	1	Yes	Yes	No
12		✓	VCA	2	1	No	No	No
13		✓	HLM	3		Yes	No	No
14	✓		ANOVA	2	ANOVA uncorrected	Yes	Yes	No
14		✓	HLM	2	Multilevel	Yes	Yes	No
15		✓	VCA	2	4	No	Yes	No
16		✓	HLM	1	Sample (1978–1994)	Yes	Yes	Yes
17		✓	HLM	3		No	No	No
18		✓	VCA	3		Yes	No	Yes
19	✓		ANOVA	5A	Canada	Yes	Yes	No
20	✓		ANOVA	5	Panel B (R^2)	Yes	Yes	No
21	✓		ANOVA	5	Panel B (R^2)	Yes	Yes	No
22	✓		ANOVA	5	Panel B (R^2)	Yes	Yes	No
23	✓		ANOVA	5A	Australia	Yes	Yes	No
24	✓		ANOVA	5	Panel B (R^2)	Yes	Yes	No
25	✓		ANOVA	5	Panel B (R^2)	Yes	Yes	No
26	✓		ANOVA	5	Panel B (R^2)	Yes	Yes	No
27	✓		ANOVA	5A	USA	Yes	Yes	No
28	✓		ANOVA	5	Panel B (R^2)	Yes	Yes	No
29	✓		ANOVA	5A	UK	Yes	Yes	No
30	✓		ANOVA	2	Bottom (Sample B)	No	Yes	Yes
31	✓		ANOVA	3		Yes	Yes	No
32	✓		ANOVA	5	Panel B (R^2)	Yes	Yes	No
33	✓		ANOVA	5	Panel B (R^2)	Yes	Yes	No
34	✓		ANOVA	5	Panel B (R^2)	Yes	Yes	No
35	✓		ANOVA	5	B	Yes	No	No
36	✓		ANOVA	5	Panel B (R^2)	Yes	Yes	No
37	✓		ANOVA	4	Segment ROA	Yes	No	No
38	✓		ANOVA	5	Panel B (R^2)	Yes	Yes	No
39	✓		ANOVA	5	Panel B (R^2)	Yes	Yes	No
40	✓		ANOVA	2	Downsizing last	Yes	Yes	No
41	✓		ANOVA	5	Panel B (R^2)	Yes	Yes	No

Continued

Sample		Sum of squares				Variance				Standard deviation				Note
ID	n	Y	I	C	B	Y	I	C	B	Y	I	C	B	
1	747	0.010	0.210	0.240	0.310	0.011	0.179	0.100	0.409	0.103	0.423	0.316	0.639	a
2	20,161					0.003	0.175	0.110	0.487	0.055	0.418	0.332	0.698	
3	3,447					0.008	0.153	0.145	0.251	0.088	0.391	0.381	0.501	e, l
4	16,277					0.002	0.136	0.192	0.175	0.045	0.369	0.438	0.418	
5	1,564					—	0.105	0.143	0.463	—	0.324	0.379	0.680	i
6	13,051					0.022	0.105	0.208	0.158	0.148	0.324	0.456	0.397	
7	16,596					0.005	0.102	0.179	0.371	0.071	0.319	0.423	0.609	f
8	7,994					0.011	0.097	0.051	0.480	0.107	0.311	0.225	0.693	e, l
9	14,575					0.025	0.076	0.094	0.208	0.158	0.276	0.307	0.456	f
10	10,633					0.008	0.076	0.072	0.366	0.089	0.276	0.268	0.605	
11	10,776					0.005	0.070	0.180	0.361	0.071	0.265	0.424	0.601	
12	28,809					0.010	0.069	0.108	0.314	0.100	0.263	0.329	0.560	
13	7,197					0.010	0.066	0.109	0.361	0.100	0.258	0.330	0.601	
14	19,405	0.005	0.139	0.147	0.438	0.005	0.053	0.202	0.401	0.071	0.230	0.449	0.633	a, g, l
15	24,808					0.003	0.053	0.087	0.526	0.055	0.230	0.295	0.725	
16	17,773					—	0.042	0.155	0.385	—	0.205	0.394	0.620	i
17	6,821					0.002	0.037	0.302	0.327	0.045	0.192	0.550	0.572	f, j
18	4,549					0.000	0.031	0.007	0.362	0.000	0.177	0.084	0.601	f, h
19	1,142	0.004	0.303	0.090	0.168									a
20	281	0.010	0.265	0.108	0.358									a
21	86	0.124	0.261	0.145	0.242									a
22	129	0.113	0.222	0.108	0.258									a
23	690	0.006	0.191	0.098	0.488									a
24	339	0.006	0.186	0.311	0.243									a
25	1,780	0.008	0.160	0.054	0.457									a
26	344	0.021	0.150	0.042	0.466									a
27	12,390	0.001	0.145	0.135	0.400									a
28	572	0.025	0.119	0.139	0.517									a
29	6,096	0.001	0.114	0.229	0.245									a
30	10,866	0.001	0.098	0.116	0.414									b, k
31	72,742	0.008	0.096	0.120	0.377									a
32	273	0.054	0.081	0.061	0.426									a
33	99	0.110	0.078	0.073	0.421									a
34	2,107	0.014	0.077	0.129	0.439									a
35	58,132	0.003	0.068	0.119	0.349									c, k
36	629	0.083	0.064	0.112	0.178									a
37	8,522	0.000	0.046	0.078	0.344									d
38	1,071	0.002	0.036	0.048	0.835									a
39	1,329	0.084	0.023	0.200	0.331									a
40	1,810	0.013	0.021	0.027	0.194									a
41	10,531	0.006	0.017	0.100	0.458									a
Mean (wei.)		0.006	0.091	0.122	0.377	0.008	0.084	0.138	0.358	0.082	0.283	0.363	0.590	
Mean (unw.)		0.028	0.127	0.121	0.374	0.008	0.090	0.136	0.356	0.082	0.292	0.354	0.589	
Median		0.008	0.114	0.112	0.349	0.007	0.076	0.126	0.364	0.079	0.276	0.356	0.603	

Note to Table 4: (a) Sequential method: YICB (sum of squares). (b) Sequential method: YCIB (sum of squares). (c) YCIB (sum of squares) listed because overlapping sample 31 is YICB (sum of squares). (d) Partial method (sum of squares). (e) n not provided so estimated as # of businesses × # of years × 0.623, which is the average of $n/(\#$ of businesses × # of years) for the other samples to account for the fact that not all businesses are observed all years. (f) Model with industry × year (variance). (g) Year sum of squares and variance reported as < 0.010; here, the midpoint is taken. (h) Year variance estimated as -0.003; here, 0 is taken. (i) Year variance accounted for but unreported. (j) Corporate variance is the sum of the business-invariant and business-variant corporate effects. (k) Variances provided but only from a model with covariance. (l) Standard deviation provided but not relative to performance.

Table 5 Sample dimensions correlate strongly with sum of squares but not with variance

	SS	Var		
Sample dimensions:	$d.f.$	$d.f.$	n_k	$ln(n_k)$
Year	0.84	0.16	0.18	0.23
Industry	0.60	0.10	0.11	−0.18
Corporate	0.80	0.12	−0.02	0.09
Business	0.51	0.43	0.34	0.11

Note: Correlations for standard deviation are within 0.06 of those reported for variance.

Table 6 Meta-analytic results for variance and standard deviation for $k = 18$ samples

	Variance	Standard deviation
Year	0.01 (0.00, 0.01)	0.08 (0.06, 0.10)
Industry	0.08 (0.06, 0.10)	0.28 (0.25, 0.31)
Corporate	0.14 (0.11, 0.16)	0.36 (0.33, 0.40)
Business	0.36 (0.30, 0.42)	0.59 (0.54, 0.65)
$I - Y$	0.08 (0.05, 0.10)	0.21 (0.16, 0.24)
$C - I$	0.05 (0.02, 0.09)	0.08 (0.03, 0.13)
$B - C$	0.22 (0.15, 0.30)	0.23 (0.15, 0.31)

Note: Weighted mean and 95% confidence interval indicated.

Table 7 Meta-analytic results for standard deviation by subgroup

Samples		Effect size			
		Year	Industry	Corporate	Business
A1 Sample	USA	0.07 (0.06, 0.08)	0.30 (0.25, 0.35)	0.39 (0.35, 0.43)	0.60 (0.56, 0.66)
A2	non-USA	0.10 (0.06, 0.13)	0.26 (0.23, 0.29)	0.32 (0.26, 0.38)	0.57 (0.46, 0.69)
B1 Sample	Manuf. only	0.06 (0.04, 0.11)	0.31 (0.22, 0.42)	0.36 (0.31, 0.45)	0.64 (0.60, 0.68)
B2	Other	0.09 (0.07, 0.11)	0.27 (0.24, 0.30)	0.36 (0.31, 0.41)	0.57 (0.51, 0.64)
C1 Method	VCA	0.08 (0.06, 0.11)	0.31 (0.26, 0.35)	0.34 (0.30, 0.39)	0.58 (0.51, 0.66)
C2	HLM	0.08 (0.06, 0.09)	0.24 (0.21, 0.26)	0.40 (0.35, 0.47)	0.61 (0.60, 0.63)
D1 Model	$YICB$ only	0.07 (0.05, 0.08)	0.28 (0.21, 0.32)	0.35 (0.30, 0.40)	0.66 (0.62, 0.70)
D2	Other	0.09 (0.06, 0.12)	0.29 (0.25, 0.32)	0.38 (0.32, 0.43)	0.52 (0.46, 0.58)
		Difference in effect size			
k	N		$I-Y$	$C-I$	$B-C$
A1 12	137,827		0.24 (0.19, 0.30)	0.09 (0.02, 0.17)	0.22 (0.14, 0.30)
A2 6	87,356		0.16 (0.15, 0.18)	0.06 (0.03, 0.10)	0.25 (0.11, 0.42)
B1 4	59,079		0.30 (0.23, 0.42)	0.05 (-0.07, 0.19)	0.28 (0.18, 0.36)
B2 14	166,104		0.19 (0.15, 0.21)	0.09 (0.04, 0.13)	0.21 (0.11, 0.31)
C1 11	151,014		0.22 (0.16, 0.27)	0.04 (0.00, 0.09)	0.24 (0.13, 0.35)
C2 7	74,169		0.17 (0.15, 0.18)	0.17 (0.10, 0.25)	0.21 (0.15, 0.27)
D1 9	116,561		0.22 (0.15, 0.27)	0.07 (-0.01, 0.16)	0.31 (0.23, 0.39)
D2 9	108,622		0.20 (0.14, 0.24)	0.09 (0.03, 0.13)	0.14 (0.06, 0.24)

Note: Weighted mean and 95% confidence interval indicated.

Figure 1 Examples of industry, corporate, and business effects

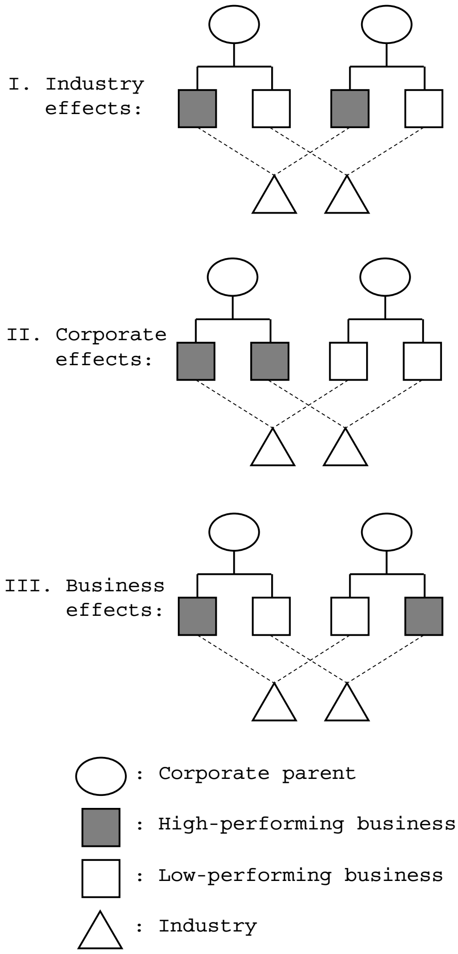

Figure 2 **The industry and business explained sum of squares depend on sample dimensions**

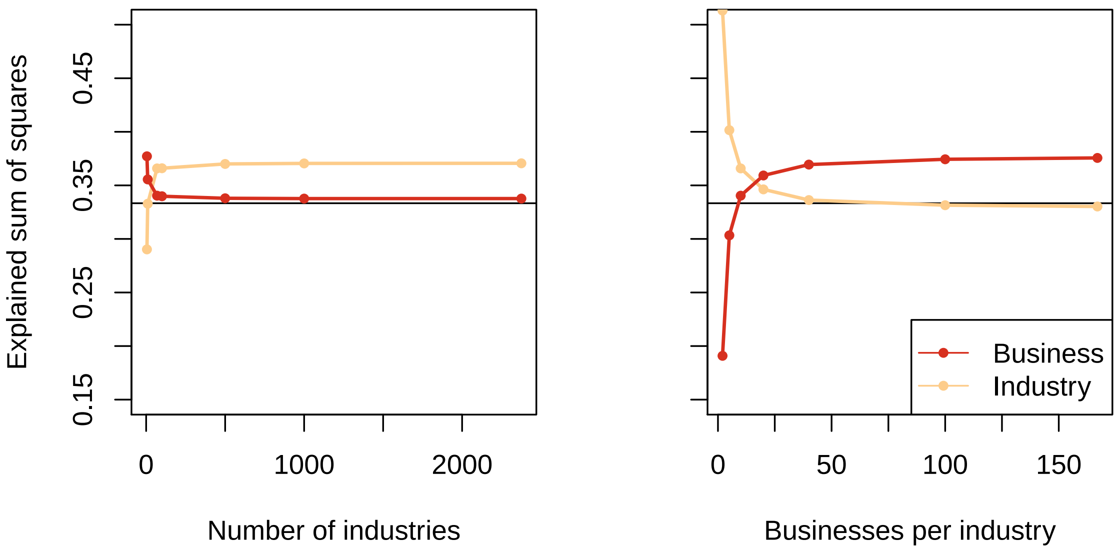

Figure 3 **The explained sum of squares depend on sample dimensions even with adjusted R^2**

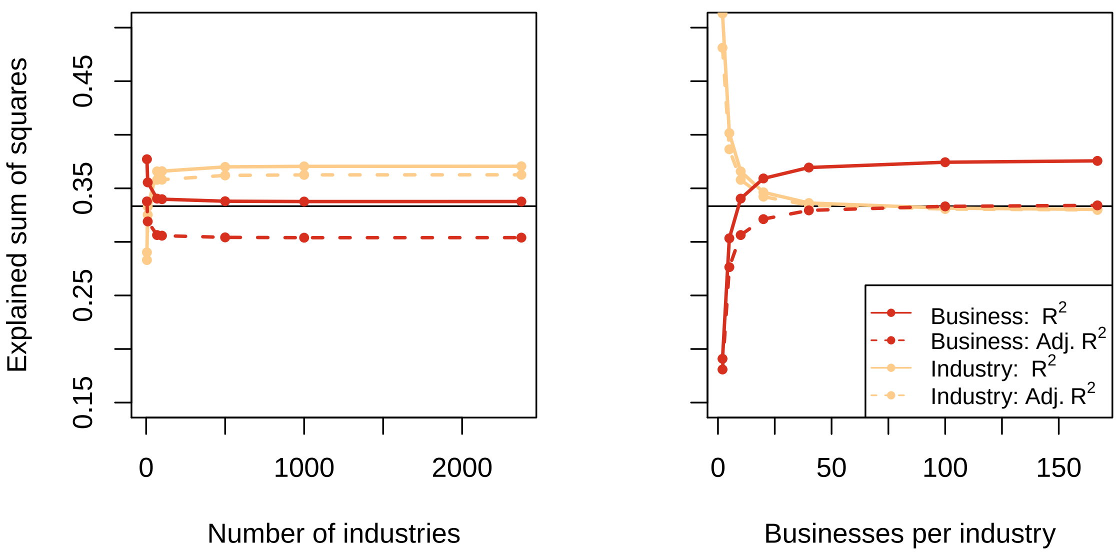

Figure 4 **The industry and business explained variances are mostly insensitive to sample dimensions**

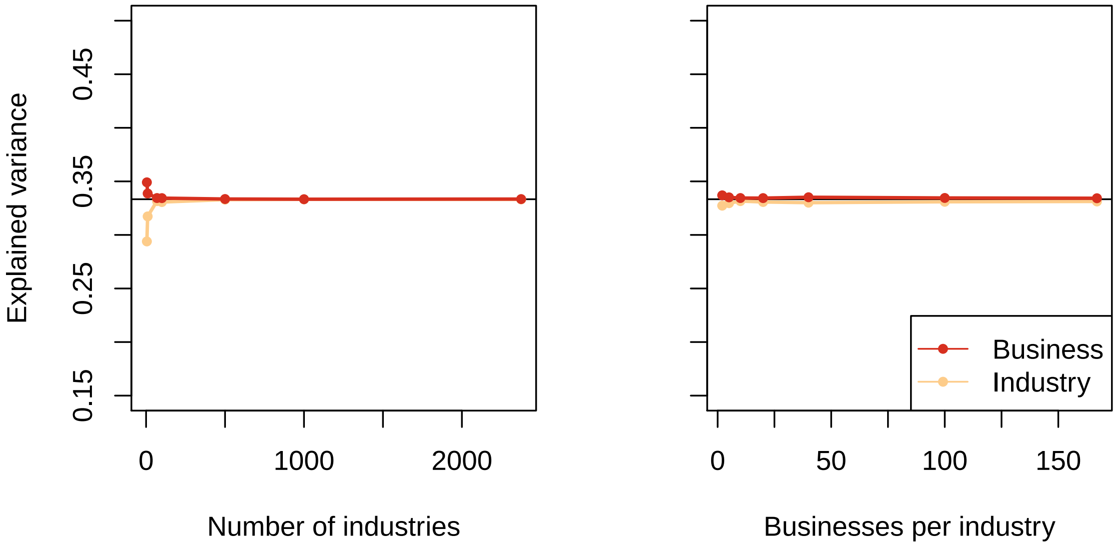

Figure 5 **The variance measure attributes equal importance to industry and business but the sum of squares measure does not**

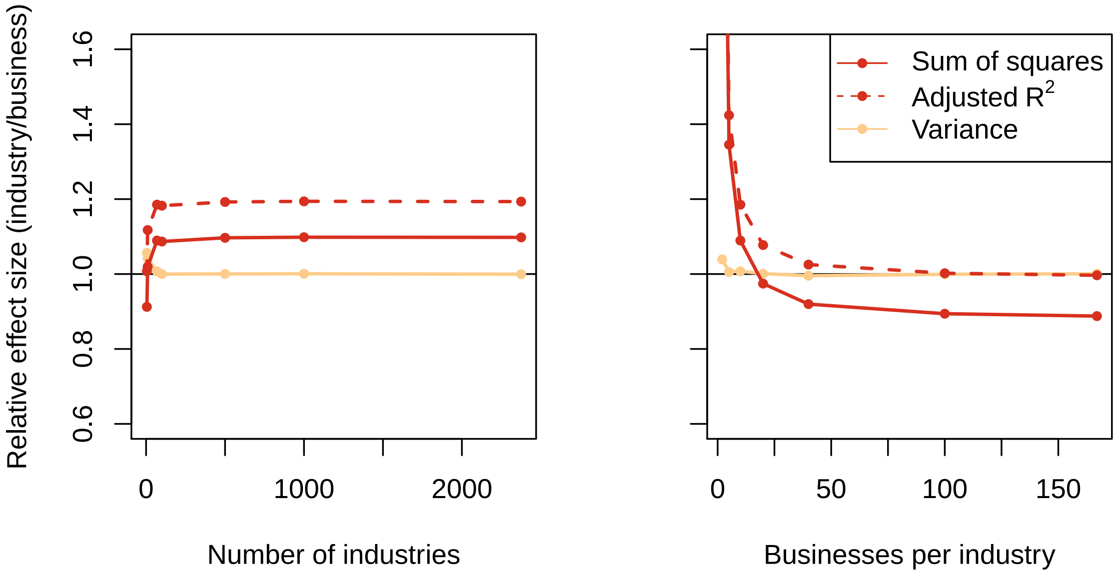

Figure 6 The variance measure amplifies differences between business and industry

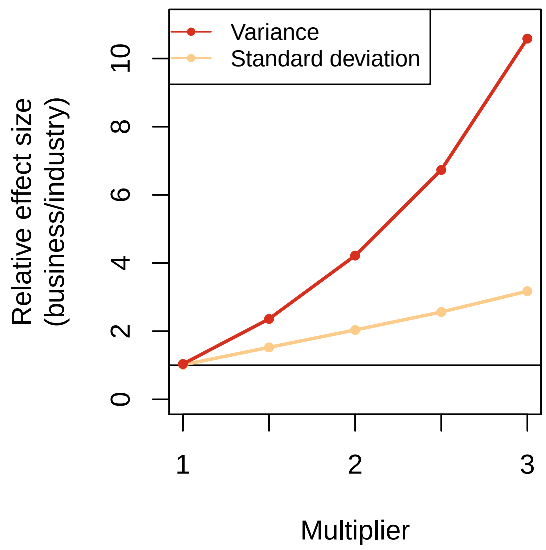

Figure 7 Sample dimensions predict explained sum of squares

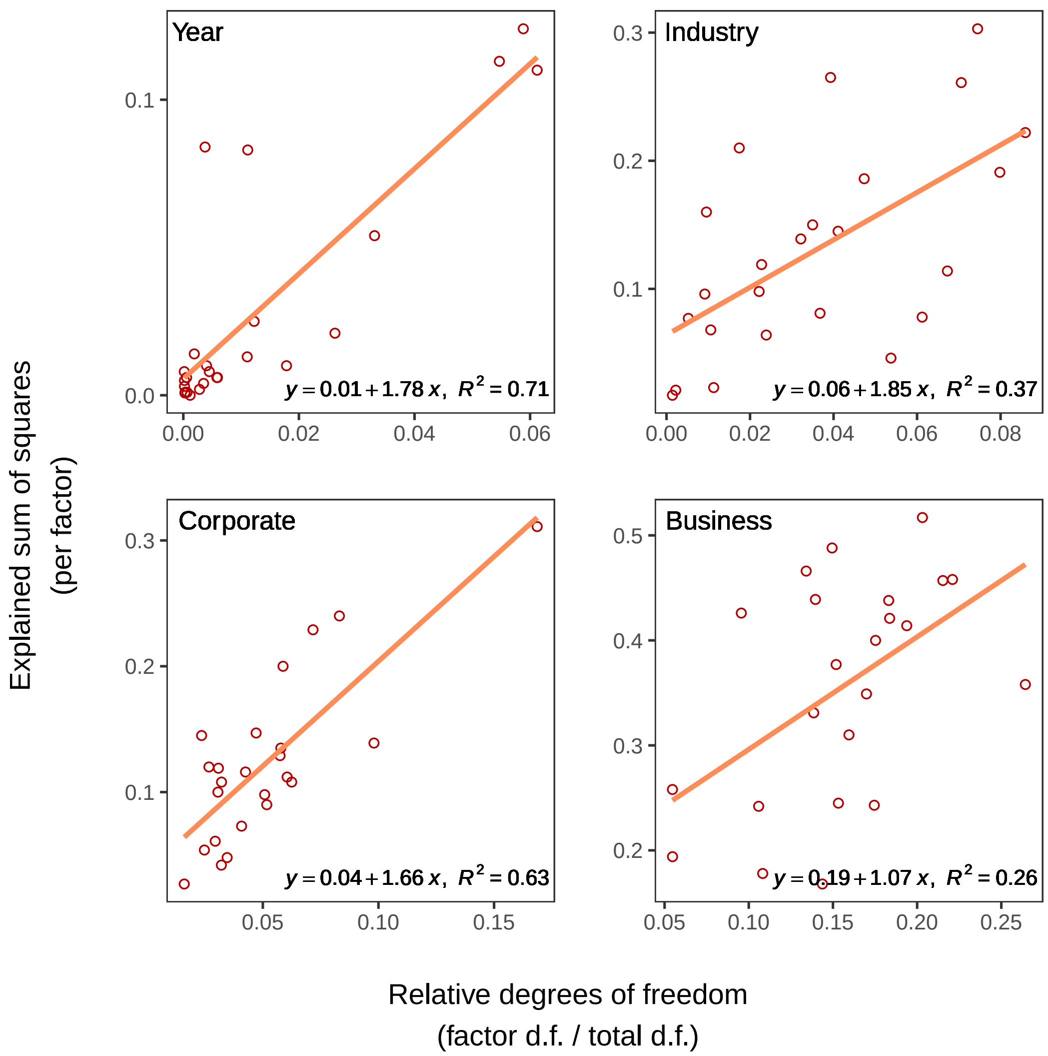

Figure 8 **Results for sum of squares and variance differ for the same sample**

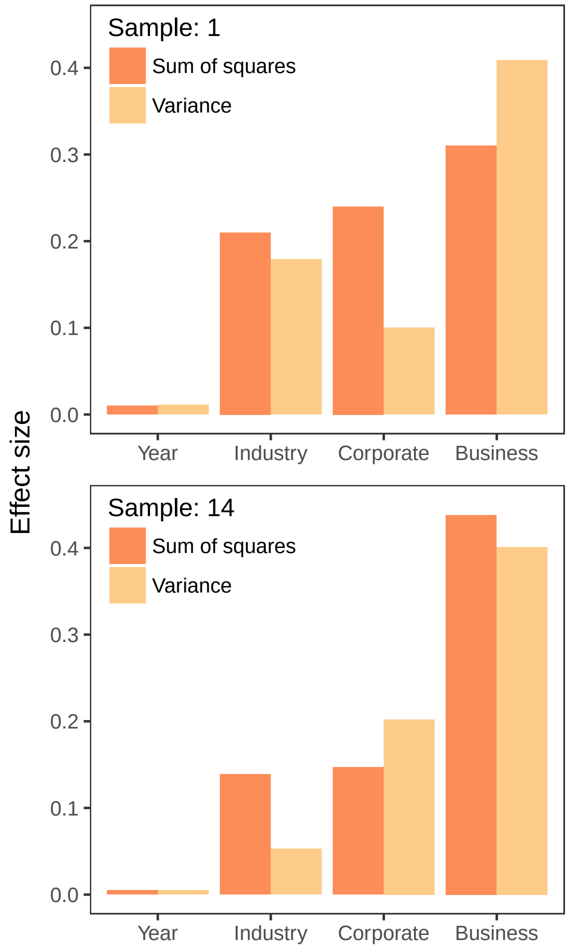

Figure 9 **Meta-analytic results with 95% CI for $k = 18$ samples**

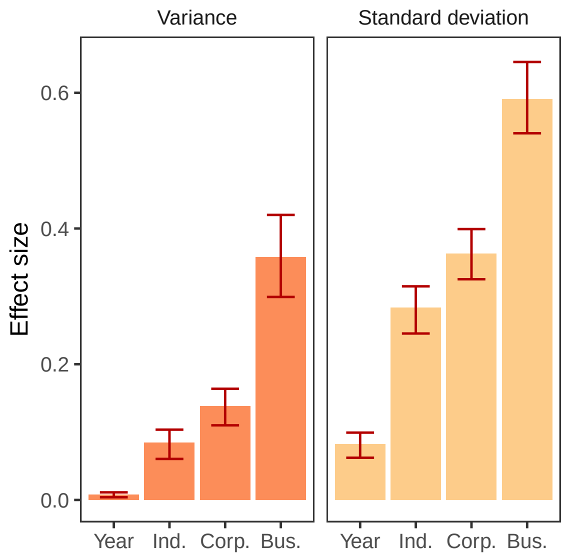

Figure 10 Difference between factors for variance (left) and standard deviation (right) with 95% CI

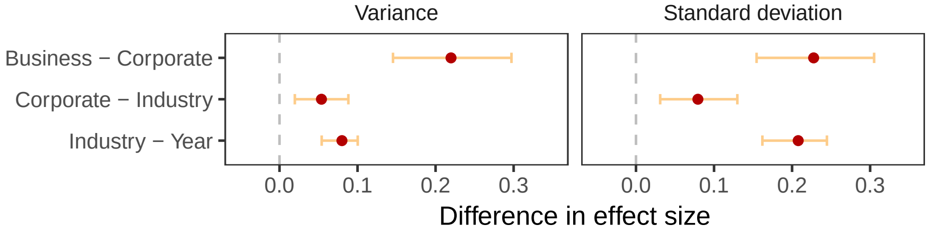

Figure 11 Meta-analytic results with 95% CI by subgroup