RESEARCH NOTES AND COMMENTARIES

IS PERFORMANCE DRIVEN BY INDUSTRY- OR FIRM-SPECIFIC FACTORS? A RESPONSE TO HAWAWINI, SUBRAMANIAN, AND VERDIN

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Hawawini, Subramanian, and Verdin (2003) examined the relative impact of industry- vs. firm-level factors shaping firm performance. They demonstrated that variance in firm performance attributable to industry-level factors increases, while variance attributable to firm-level factors decreases when 'exceptionally' higher- and lower-performing 'outlier' firms in each industry are excluded. They concluded that previous research underestimated the relative impact of industry-level factors for 'average' firms that make up the bulk of an industry. We take issue with their methods used to identify and exclude outliers as well as their conclusions drawn from such analyses. Rather than excluding true 'outlier' firms, we argue that they incorporated an artificial restriction of within-industry sample variance that almost deterministically led to lower firm and higher industry variance component estimates. We demonstrate this point with a comparable sample of data to which we apply progressively greater restrictions on within-industry sample variance leading to similar results. Finally, we show that exclusion of firms from a data sample based on commonly understood standards of outlier identification leads to little change in industry and firm variance component estimates compared to full-sample estimates. Copyright © 2005 John Wiley & Sons, Ltd.

Recently, Hawawini, Subramanian, and Verdin (2003) asked whether findings from past research on determinants of variability in firm performance (e.g., Rumelt, 1991; McGahan and Porter, 1997) are generalizable across all firms in an industry or whether they are, instead, driven by a few exceptional, outlier firms.¹ These results are important since they shed light on a fundamental issue in strategy research: the relative importance of industry vs. firm factors on firm profitability. In this commentary, we discuss concerns regarding

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¹ In their study, they also examined whether or not the results of prior research held when using market-based measures of firm performance, rather than accounting measures. They found consistent results across these measures. This finding may be interesting to strategy scholars on its own. Our commentary does not address this aspect of their study.

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methods used and conclusions drawn with their examination of this issue.

Hawawini et al. began their inquiry by partitioning variance in firm performance using a sample of 5620 annual observations for 562 large corporations from 1987 to 1996. Their initial results were consistent with prior studies. With both accounting measures and two economic measures not previously analyzed in this literature (i.e., economic profit and total market value), their results indicated that variance components (‘VC’) related to firm effects were largest with industry effects of secondary importance. Consistent with prior studies, their initial VC results suggested that intra-industry strategy perspectives had the greatest explanatory power in any analysis of performance differences among firms.2

Hawawini et al. then questioned this conclusion, arguing that these findings may be driven by a subset of firms described as ‘exceptional firms’ (e.g., pp. 1, 2), ‘value leaders and losers’ (e.g., 10, 12, 13, 14), and quite often as ‘outliers’ (e.g., 2, 10, 12, 13, 14). To test this proposition, Hawawini et al. repeated their VC analysis, but this time with a modified sample excluding the top and bottom two performing firms within each industry. This analysis yielded a new set of VC estimates with different strategy research implications. Stable industry and firm effects became roughly equivalent. Hawawini et al. concluded that previous studies underestimated the importance of industry-level factors in shaping firm performance. A few ‘outlier’ firms in each industry skewed VC estimates in favor of firm effects.

We disagree. VC results using the modified sample excluding ‘outlier’ firms potentially misinform scholarship on this fundamental strategy question. As we show below, their methods were inconsistent with the commonly understood conceptual definition, identification, and methodological treatment of outlier firms in management research. We empirically demonstrate that this artificial restriction of within-industry variance leads, by construction, to lower firm and higher industry VC estimates.

CONCEPTUAL ANALYSIS

Outlier identification and exclusion

Our criticism focuses primarily on the criteria Hawawini et al. used to select their modified sample. In establishing sample selection boundaries, methodologists commonly cite two justifications for restricting sample ranges (Cohen et al., 2003). First, researchers may argue for restricting the sample range if initial sample analyses reveal the presence of outliers that skew results and their interpretation. Second, researchers may argue for restricting the sample range if the potential range of data to be sampled extends outside the intended range of interest in the current study.

At first glance, it seems that Hawawini et al. opted for the first justification for sample restriction. They argued for excluding ‘outlier’ observations from the full sample so that they could focus on the vast majority of the firms that are not ‘notable leaders or losers in their industry’ (p. 1). The key question becomes whether they appropriately identified outliers. Outliers are ‘one or more atypical data points that do not fit with the rest of the data’ (Cohen et al., 2003: 390), even though those data points were sampled from the population of interest. They are extreme rarities in most samples. Texts dealing with outlier identification typically note heuristic guides of at least ±3.0 standard deviations (S.D.) away from the mean as appropriate for preliminary identification in large samples (Cohen et al., 2003).3 Researchers may consider outlier exclusion from the sample followed by reanalysis of the remaining data (Chatterjee and Wiseman, 1983). Hawawini et al.’s definition of outliers is much broader than this. If the observations within an industry are roughly normally distributed, standard rules for outlier identification (±3 S.D. rule) would identify approximately 1 percent of the observations as outliers. In removing the top and bottom two firms per industry, Hawawini et al. reduced their sample from 5620

2 As Hawawini et al. note (pp. 8–9), corporate variance components are omitted from their model. This omission follows primarily from their decision to use economic performance measures available only at the corporate level. This meant that ‘firms’ in their sample that might have several business units operating in different industries—what we would describe as multi-business corporations—could not be broken down into segments for separate analysis. They aggregated multi-business corporations into individual ‘firms’ with membership in a combination of 2- and 3-digit SIC delimited industries based on their primary SIC.

3 However, researchers should not employ these heuristics mindlessly. It is not advisable to drop these extreme values without having an underlying rationale (e.g., possibly miscoded data) as to why these data should not be included.
to 3420 observations, a reduction of 39.1 percent. Exclusion of nearly 40 percent of the observations as ‘outliers’ certainly violates commonly understood heuristics for identifying outliers in empirical research.

Sample range restriction and VC analyses

If their outlier exclusion cannot be justified, what about the other common justification? Were Hawawini et al.’s actions in creating their modified sample an appropriate restriction in range for their VC analyses? Sample range issues derive from understanding how an empirical research issue implicates a population to be studied. Researchers restrict the range of observations drawn from a population for any number of reasons, but the focal purpose of any sample restriction should be to ensure that the most relevant subjects for a given topic of inquiry are included, while subjects outside the range of the research topic are excluded. For example, an empirical researcher examining issues related to management succession in entrepreneurial firms may decide to restrict the size of firms sampled. Failure to impose the range restriction could result in a sample with observations that go beyond the population of interest and could distort observed results.

However, the range restriction employed in this study was not appropriate for a number of reasons. First, Hawawini et al. applied a restriction on the variance in firm performance, the primary criterion of interest in this study. Thus, they were restricting the range of the criterion they were trying to explain. Second, and more importantly, the range restriction was tied directly to one of the right-hand side terms they sought to estimate: the VC estimate for intra-industry firm effects. Since they restricted the range for only one of the dimensions for which they were decomposing variance, they directly influenced the results. This rendered firm effects less substantial relative to the others in the model. Also, because of the nested nature of their VC model—firm effects are nested within industry effects—the range restriction on firm variance was indirectly tied to the industry component. As a result, the range restriction on intra-industry variance in firm performance almost certainly raised the relative value of the VC estimate for stable industry effects. The only question is how much it would raise industry effects. With a 40 percent range restriction, the answer was, not surprisingly, a lot. As we will show in our analyses, the degree to which a researcher can alter the relative importance of such VC estimates is directly related to the degree to which he or she restricts the range on any one dimension.

EMPIRICAL ANALYSES

We illustrate this point with our own set of VC estimates using a comparable sample. To start, we follow other previous VC studies (e.g., McGahan and Porter, 1997) by drawing our sample of firm accounting returns from the Compustat Industry Segment database. Our sample includes all U.S.-based corporations in the database from 1987 to 1996 that have at least $100 million in sales and assets from non-financial and non-governmental industries. Our resulting database comprises 19,926 annual business unit observations from 2686 businesses operating in 84 industries (defined at the 3-digit SIC level). The dependent variable in our model is, thus, business unit (‘firm’) return on assets (‘ROA’).

RESULTS AND CONCLUSION

Results when increasing intra-industry range restrictions

Our full sample VC estimation (Table 1, column 1) produces results very comparable to Hawawini et al.’s full sample estimates. Our analysis attributes 9.1 percent of variance in firm ROA to stable industry effects and 4.0 percent to unstable industry effects, compared to 8.1 percent and 3.1 percent respectively in Hawawini et al. Our

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We also tried but were unsuccessful in replicating their sample. We were unable to recreate their sampling procedures as described in the article. We corresponded with the authors for additional guidance but were unsuccessful at recreating the number of observations and industries in either their full or modified sample.

We also exclude units if (a) they are described as ‘corporate’ or ‘other’ businesses since these do not appear to be active business units or (b) they report less than 4 years of data in the period studied.

We only include industries with at least 13 firms so that, with all of our analyses, we retain the same number of industries.

Hawawini et al. found consistent results across accounting- and market-based performance indicators. We focus on an accounting measure since this allows us to assess the effects at the business segment, rather than corporate level.
Table 1. Variance component estimates with ‘outlier’ firms within industries excluded from the sample

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<thead>
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<th>Column 1</th>
<th>Column 2</th>
<th>Column 3</th>
<th>Column 4</th>
<th>Column 5</th>
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</thead>
<tbody>
<tr>
<td></td>
<td>Base analysis: includes all observations</td>
<td>Top and bottom firm in each industry excluded</td>
<td>Top and bottom 3 firms per industry excluded</td>
<td>Top and bottom 6 firms per industry excluded</td>
<td>Observations with average performance ±3 S.D. excluded</td>
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<td>Variance component</td>
<td>% of total variance</td>
<td>Variance component</td>
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</tr>
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</tr>
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</tr>
<tr>
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<td>0.00320</td>
<td>45.6</td>
<td>0.00284</td>
</tr>
<tr>
<td>N</td>
<td>19,926</td>
<td>18,824</td>
<td>16,443</td>
<td>12,784</td>
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</table>
firm effects are 43.8 percent, while their firm effects were 35.8 percent. Our firm effects may be higher since our sample is based on individual business unit data. Hawawini et al. used corporate-level data with individual business units consolidated into a single ‘firm.’

We re-estimate the model after excluding the top and bottom one then three and finally six firms from each industry, for a total reduction of 6 percent, 18 percent, and 38 percent in sample size, respectively. We defined these extreme firms based on their average ROA within each industry from 1987 to 1996. Exclusion of the top and bottom six (12 total) eliminates 38 percent of the firms in our base sample—comparable to the 39 percent reduction in Hawawini et al. As expected, stable firm effects decrease from 43.8 percent with no intra-industry range restriction to 37.7 percent then 29.8 percent and finally 22.9 percent of total variance with the greatest intra-industry range restriction. Stable firm effects are nearly halved (43.8% to 22.9%) with the range restriction. This result is comparable to the 53 percent decline in firm effects reported in Hawawini et al., a result we expected since we replicated their inappropriate sample selection methodology with this analysis.

Since firms are nested within industries, an exclusion of extreme observations within industries also has a profound impact on the higher-level industry effects. The increasing intra-industry range restriction increases stable (unstable) industry effects from 9.1 percent (4.0%) to 14.7 percent (5.2%) for combined industry effects of 19.9 percent in the most restricted sample. For us, combined industry effects are slightly lower than stable firm effects of 22.9 percent, compared to slightly higher combined industry effects (20.1% industry vs. 16.7% firm effect) in Hawawini et al. However, one would be mistaken to conclude that our findings endorse their conclusions. With these analyses, we intended to show that the changes in firm vs. industry effects seen in Hawawini et al. are simply a consequence of their sample selection methodology. Thus, they concluded that this shift indicates that past research underestimated the impact of industry factors on the great body of unexceptional firms. In contrast, we conclude that it is simply an artifact of a range restriction of intra-industry sample variance. With increasing restrictions, we can obtain ever-higher industry effects at the expense of firm effects.

Results when increasing inter-industry range restrictions

To highlight this point, we conduct an additional set of VC analyses where we remove ‘outlier’ industries to demonstrate that a range restriction on any one dimension will have significant, but predictable, results. Table 2 presents results from VC estimation based on this new inter- (rather than intra-) industry range restriction approach. We re-estimate the model after excluding the top- and bottom-performing two industries (5% of all industries), seven industries (17%) and 16 industries (38%) from the base sample. We define these top (bottom) industry performers based on their average ROA over the study period.

As expected, stable industry effects decrease from 9.1 percent to 6.5 percent then 4.9 percent and finally 1.5 percent of total variance with the greatest inter-industry range restriction. This decrease in industry effects is much more dramatic than the modest halving of firm effects with a similar intra-industry range restriction. Industry effects compared to firm effects are much more sensitive to range restrictions. Hawawini et al. concluded that prior research understated industry effects for firms that were not exceptional performers. Based on VC results in Table 2, we could conclude that prior research overstated industry effects for firms in industries that were not exceptional in performance. However, such conclusions are inappropriate. These results derive from the same sort of artificial sample range restrictions we criticized earlier, only this time the range restrictions are at the industry level. We note one key difference here. Since industries are not nested in a higher-level effect (unlike with firms), most of the decrease in industry variance is reallocated to the error component, leaving the other VC estimates largely unchanged.

Results when applying commonly understood guidelines of outlier identification and exclusion

Whether it is applied at the intra- or inter-industry level, sample range restrictions are simply inappropriate with variance-based empirical models. This is especially true given the interdependence of firms in many markets—strong performance by one firm often results in other firms making less. However, it remains true that real outliers could skew the results of this type of analysis. Thus, for
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our final analysis, we follow Cohen et al.’s (2003) guidelines and re-estimate VC effects after excluding firms with average performance at least three standard deviations from their industry’s average performance. This approach excludes 1.4 percent (270) of the observations in our sample. Excluding these observations (Table 1, column 5) results in VC estimates very close to those based on the full sample (Table 1, column 1). Stable firm effects are virtually unchanged (43.8% vs. 43.6%) while the stable industry effects rise slightly (9.1% vs. 11.2%). Therefore, we conclude that if we exclude outlying firms in each industry based on well-grounded guidelines, findings from previous major empirical studies on this issue are confirmed. Firm effects are significantly larger than industry effects in understanding firm profitability, even when true outlier firms are excluded from the analysis.

With these results, we return to our discussion of outliers. Cohen et al. (2003: 390) note that researchers need to be aware of possible outliers in their data since they may ‘have a profound impact’ on statistical estimates leading to ‘misleading results.’ The robustness of findings using strict guidelines for outlier identification confirms that prior research (e.g., Rumelt, 1991; McGahan and Porter, 1997) did not report misleading results. On the other hand, we conclude that modified sample results presented by Hawawini et al. are misleading and merit substantial revision based on legitimate methods outlined above.

REFERENCES


