Industry Effects in Firm and Segment Profitability Forecasting[†]

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Abstract

Academics and practitioners have long recognized the importance of a firm's industry membership in explaining its financial performance. Yet, contrary to conventional wisdom, recent research shows that industry-specific profitability forecasting models are not better than economy-wide models. The objective of this paper is to further explore this result and to provide insights into when and why industry-specific profitability forecasting models are useful. We show that industry-specific forecasts are significantly more accurate in predicting profitability for single-segment firms and, to some extent, for business segments. For multiple-segment firms, the aggregation of segment-level data for external reporting of firm-level financials obliterates the industry effects of their segments. (*JEL* L25, G17, M21, M41, C53)

Keywords: Industry membership, Profitability forecasting, Disaggregation, Segment disclosure

Data Availability: Data are publicly available from the sources indicated in the text.

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1. Introduction

Prior research shows that the predictability of earnings is due to the mean reversion of firm profitability (Fama and French 2000). Market participants and financial analysts can therefore improve earnings forecasts by exploiting this mean reversion in profitability. While a large body of academic literature argues that the mean reversion in firm profitability should be an industry-specific phenomenon,[1] a recent empirical study by Fairfield et al. (2009) shows that industry-specific forecasting models are generally no better than economy-wide models in predicting the future profitability of firms. The objective of this paper is to further explore this surprising result and provide insights into when and why industry-specific profitability forecasting models are useful.

Unlike the prior literature, we examine the advantage of industry-specific profitability forecasts for single- and multiple-segment firms separately. This distinction is important as many firms are diversified firms operating in various industries (Berger and Ofek 1995). These different activities are usually organized in separate business segments. For such diversified multiple-segment firms, no single industry accurately represents the entire firm. A firm-level industry-specific forecasting model as used in Fairfield et al. (2009) is therefore unable to capture industry effects in profitability forecasting for multiple-segment firms. For firms with a single business segment, however, the firm-level reporting does not distort the truth – the only segment of a single-segment firm is effectively identical to the whole firm. Hence, industry effects in profitability forecasting should exist when confining the analysis to single-segment firms.

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[1] See for example Schmalensee (1985), McGahan and Porter (1997), and Bou and Satorra (2007). For a detailed review of this literature, see Fairfield et al. (2009).

Following Fairfield et al. (2009), we use a variety of out-of-sample tests to compare industry-specific and economy-wide forecasts of firm profitability for single- and multiple-segment firms. We document that industry-specific forecasting models significantly improve the profitability forecasts for firms with a single segment. In contrast, for multiple-segment firms, industry-specific forecasts are no more accurate than economy-wide forecasts. These results are robust to various industry classifications.

The existence of industry effects in profitability forecasting for single-segment firms suggests that industry effects exist at the more refined business segment level. In general, however, we find only mixed evidence for industry effects in segment profitability forecasting. To further explore this result, we carry out two additional analyses.

First, we distinguish segments of single-segment firms from segments of multiple-segment firms. The literature on corporate diversification and segment reporting shows that conglomerates do not manage their business segments on a stand-alone basis. Yet, to the extent that multiple-segment firms transfer resources or misallocate costs from one segment to another, the profitability of their segments is considerably less influenced by industry-specific factors. Second, given the changes in segment disclosure regulations in 1998, we consider the accounting regime before and after separately. While the new Statement of Financial Accounting Standards No. 131 (SFAS 131) increased the firms' transparency, segment data are less comparable across firms than before, thereby weakening the empirical linkage between segment profitability and industry membership. In line with these considerations, we find that industry effects in segment profitability forecasting are stronger for the pre- than the post-SFAS 131 era, and for the segments of single-segment firms than of multiple-segment firms.

This paper contributes to the literature by deepening the understanding of the industry effects in firm and segment profitability forecasting. Because multiple-segment firms represent a large fraction of the entire sample of firms, it is natural that Fairfield et al. (2009) do not find any overall industry effect in profitability forecasting at the firm level. More important, the results of this study show how to improve the profitability forecasts of single-segment firms. The finding that information contained in segment-level data can help to improve profitability forecasts also highlights the importance of less aggregated accounting disclosure.

2. Mean reversion of profitability

The early studies on the predictability of earnings and profitability are based on firm-specific time series models (e.g., Lev 1983).[2] A major shortcoming of these models is the requirement of a long earnings history for each firm, causing a severe survivorship bias. Additionally, even when using firms with long earnings histories (e.g., 20 annual observations), the firm-specific regression samples remain small, leading to statistically weak results.

Other studies use cross-sectional regressions instead, allowing minimal survivor requirements and the use of large samples (e.g., Freeman et al. 1982). The more powerful statistical analyses of these studies yield reliable evidence of the predictability of profitability, which follows a mean-reverting process. A drawback of this literature is that most studies do not adjust the standard errors of their tests to account for cross-sectional dependence among firm observations. To address this issue, Fama and French (2000) use the Fama and MacBeth (1973) methodology to re-examine and confirm the mean reversion of profitability. They find that the adjustment

[2] Usually earnings are normalized by a size variable, like total assets, to mitigate the scale effect. Predicting earnings is thus equivalent to predicting a profitability ratio.

toward the mean is stronger when profitability deviates more from its mean, and stronger when profitability is below the mean.

We follow this literature and use a mean reverting model to forecast profitability. Unlike Fama and French (2000), we opt for the parsimonious first-order autoregressive specification (i.e., the persistence model). This choice is based on an important insight of the recent forecasting literature (e.g., Trapani and Urga 2009). This literature finds that despite misspecification, simple models with fewer model parameters often produce more accurate forecasts than correctly specified models. While sophisticated models can achieve a better in-sample goodness of fit, they often have a worse out-of-sample forecasting performance. Furthermore, the persistence model does not require long earnings histories and therefore minimizes the survivorship bias. Finally, limited availability of segment-level data prevents us from using more sophisticated models to forecast profitability at the segment level.[3]

3. Research design and data

Research design

Following Fairfield et al. (2009), our research design involves three steps. First, we estimate two competing profitability forecasting models *in-sample*. Second, we use the estimated model parameters to predict future profitability. Third, we compare the profitability forecasts with the observed profitability in various *out-of-sample* tests.

The two competing models are:

$$\text{IS model: } x_{i,t} = \alpha_{j,t} + \beta_{j,t}\, x_{i,t-1} + \varepsilon_{i,t},$$

$$\text{EW model: } x_{i,t} = \alpha_{t} + \beta_{t}\, x_{i,t-1} + \varepsilon_{i,t},$$

[3] In additional tests we also consider more complex forecasting models, similar to those in Fairfield et al. (2009). Since the forecast accuracy of these specifications is worse than the simple AR(1) model, we do not report the results.

where $x_{i,t}$ is the profitability of firm/segment i in year t, j is the industry of the firm/segment, and $\varepsilon_{i,t}$ is the error term. The industry-specific (IS) model estimates a regression for each industry j separately, whereas the economy-wide (EW) model pools all observations into one regression.

The model coefficients are indexed by a year subscript t because they are re-estimated each year on a rolling basis using the most recent 10 years of data. For example, to estimate the coefficients of year t, we use profitability data of all firms/segments from year t back to year $t-9$ and their lagged values from year $t-1$ back to year $t-10$.

To obtain reliable parameter estimates, we require a minimum of 100 observations for each rolling regression. For equal-footing comparisons, we estimate the economy-wide model using only observations that are included to estimate the industry-specific model.

We use the estimated coefficients of the in-sample regressions and the observed profitability of the current year to forecast the firm/segment profitability of the next year. The forecasts are thus obtained as:

$$\text{IS model: } E_{IS,t}[x_{i,t+1}] = a_{j,t} + b_{j,t}\, x_{i,t},$$

$$\text{EW model: } E_{EW,t}[x_{i,t+1}] = a_t + b_t\, x_{i,t},$$

where a and b are the estimates of the model coefficients α and β.

To perform out-of-sample tests on the relative accuracy of the industry-specific and economy-wide models, we first calculate for each observation the absolute forecast error. It is defined as the absolute difference between the observed profitability and the profitability forecast:

$$AFE_{IS,t+1} = |\, x_{i,t+1} - E_{IS,t}[x_{i,t+1}] \,|,$$

$$AFE_{EW,t+1} = |\, x_{i,t+1} - E_{EW,t}[x_{i,t+1}] \,|,$$

where AFE_{IS} and AFE_{EW} are the absolute forecast errors for a firm/segment of a year based on the industry-specific and economy-wide models, respectively. Then we measure the advantage of industry-specific profitability forecasts over economy-wide forecasts by the *forecast improvement*:

$$FI = AFE_{EW} - AFE_{IS}.$$

If industry-specific models improve the accuracy of profitability forecasts relative to economy-wide models, the forecast improvement should be positive, on average.

To assess the magnitude of the firm/segment profitability forecast improvement, we perform two tests. First, we calculate the *pooled mean* forecast improvement of all firm/segment observations over all years and industries and test whether this improvement differs from zero using a t-test. We use two-way clustered standard errors by firm/segment and year to control for cross-sectional and serial correlation (Rogers 1993). Second, we report the *grand mean* forecast improvement (the mean of the yearly mean forecast improvements), and test whether this value differs from zero using a t-test. The standard errors are adjusted for serial correlation following Newey and West (1987).[4] Besides the above, we report the number of industries (or years) in which the industry (or yearly) pooled mean forecast improvements is significantly positive/negative at the 10% level.

This paper uses the broad 12-industry classification by Fama and French to define the industry to which a firm belongs. This choice is motivated by recent insights of the literature on optimal forecasting of heterogeneous panel data sets.[5] This literature suggests that industry-specific

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[4] Fairfield et al. (2009) also report the *grand median* forecast improvement (the median of the yearly median forecast improvements) and test it with a Wilcoxon (1945) signed-rank test. Both this and t-test require the independent-observations assumption, which is likely to be violated by archival data. While correction procedures for cross-sectional and serial correlation are available for regression-based t-tests, similar correction is unavailable for the Wilcoxon signed-rank test. Therefore, we do not consider the grand median in our analysis.

[5] Trapani and Urga (2009), Pesaran and Zhou (2015), and Paap, Wang, and Zhang (2015) show that there is a trade-off between bias and variance of estimators in panel data sets. These papers suggest that it is essential to balance efficiency gains from pooling more industries together and the biases caused by heterogeneity in the data across industries. The degree of heterogeneity plays an important role when determining whether or not to pool. When the bias from ignoring the heterogeneity in the data is relatively small, homogenous estimators tend to generate better forecasts. Heterogeneous estimators are preferred when the heterogeneity is substantial.

forecasting models face a trade-off between estimation reliability and estimation bias. To reliably extract industry effects from the data, industry classifications have to be sufficiently broad; otherwise industry-specific forecasts are too noisy to accurately predict future profitability.[6]

Data and descriptive statistics

The firm and business segment data come from the Compustat annual fundamentals and Compustat segments databases of the Wharton Research Data Services (WRDS). We use firm data from 1966 to 2011, and segment data from 1976 onwards. Since the estimation of the model coefficients (in-sample regressions) requires 10 years of data, the forecasts for the out-of-sample tests of the firm-level analysis are available from 1977 onward, and from 1987 in the segment-level analysis.

We compare industry-specific and economy-wide forecasts using four measures of profitability. Following Fairfield et al. (2009), we consider the return on equity (ROE) and the return on net operating assets (RNOA) as profitability measures. Their study focuses on forecasting ROE and RNOA because these are inputs to the residual income valuation model, a popular tool to appraise firms (Ohlson 1995). Since data required to compute ROE and RNOA (net income and book value of equity) are not available at the segment level, we also consider the return on assets (ROA) and the return on sales (ROS). Analyzing the predictability of these alternative profitability measures provides an additional route to understanding the predictability of the ROE. In additional analyses presented in section 6, we also consider the growth in sales (GSL), a measure that plays a prominent role in Fairfield et al. (2009). The analysis shows that all our results extend to GSL as well. Table 1 summarizes the definitions of the four profitability

[6] In section 6, we show that our results are robust to alternative broad industry classifications, including one-digit SIC, GICS industry sectors, and one-digit NAICS. Unreported robustness tests confirm that industry effects are much less pronounced when using narrow industry classifications, such as the two-digit SIC or the Fama-French 49-industry classification.

measures, the GSL, and the variables used to compute these measures.

This study distinguishes between three types of firms depending on the number of the reported business segments. To identify the type of firm, we match the firm data with the segment data. Firms reporting only one (more than one) business segment are classified as single-segment (multiple-segment) firms unless they meet the definition of change firms specified below. Note that segment reporting standards changed considerably in 1998, with SFAS 131 superseding SFAS 14. In response, many firms reporting only one segment in 1997 increased the number of reported segments to more than one by 1999.[7] This suggests that they might not have reported genuinely prior to the introduction of SFAS 131. Owing to the doubt in correctly classifying these firms, they are excluded from the sub-samples of single- and multiple-segment firms but form a category on their own. We define this group of "change firms" as those that have changed the number of reported segments from one in 1997 to more than one in 1999.

To construct the time series of a segment, we rely on the segment ID (SID) provided by Compustat. Firms sometimes change the internal structure, leading to changes in the number of disclosed segments, and possibly their SIC codes. Such a restructuring requires firms to restate previous segment information to make them comparable across years. We utilize the restated information in the in-sample regressions to ensure not to lose any observations because of internal restructurings. To prevent a look-ahead bias, we do not use the information in the out-of-sample tests.

Segment assets and segment sales of multiple-segment firms do not always add up to firm assets and firm sales. This is either because firm assets or sales are not fully allocated at the

[7] The change in reporting standards was partly a response to analysts' complaints about the flexibility of the old standard that was exploited by some firms to avoid segment disclosures (Botosan and Stanford 2005). The introduction of SFAS 131 in 1998 arguably has given firms less discretion in segment aggregation. Berger and Hann (2003) show that the introduction of SFAS 131 has increased the number of reported segments and provided more disaggregated information.

segment level, or because of missing data. To alleviate the data quality concern, we follow Berger and Ofek (1995) and Berger and Hann (2007) and exclude all firm and segment observations with the aggregated segment assets deviating from the firm assets by more than 25%. Similarly, we exclude those with a deviation of more than 5% for segment sales.[8] The remaining discrepancies can still lead to measurement errors in segment ROA and ROS. To mitigate the problem, we allocate the deviation proportionally to each segment based on the segment assets to firm assets ratio (and its counterpart for sales).

We allocate all observations with SIC codes to the Fama-French 12 industries as defined by their classification.[9] To avoid distortions caused by regulated industries, we exclude all firms and segments in the financial service and utilities sectors (i.e., with SIC between 6000 and 7000, or between 4900 and 4950). In addition, the U.S. postal service (SIC 4311) and non-classifiable establishments (SIC above 9900) are excluded. Since the Fama-French industry number 12 (*other*) does not represent a genuine industry but merely combines all remaining non-allocated observations together, we also exclude it from the sample.

Occasionally, some firm/segment has two observations per calendar year. We drop identical duplicate entries. If the data of duplicate observations are diverging, e.g., due to reasons like shortened fiscal years, we exclude them from the sample.[10]

To mitigate the impact of small denominators on the profitability measures, we exclude firm observations with total assets, net operating assets, and sales below USD 10mn and book value of equity below USD 1mn. For segment data, we exclude observations with total identifiable

[8] We apply these exclusion criteria only before the out-of-sample tests. Excluding these observations before the in-sample regressions would reduce the available data set by 38%. Excluding these observations leads to qualitatively similar results, but at a lower level of statistical significance. These results are available upon request.

[9] The mapping of SIC codes into the Fama-French 12 industries is available on Kenneth French's website.

[10] The deletion of double observations per calendar year reduces the sample size by 6 observations in the firm-level analysis and by 2,114 observations in the segment-level analysis.

assets and sales below USD 1mn. To avoid the influence by outliers, observations with the absolute value of firm/segment profitability exceeding one are excluded. To reduce the influence by mergers and acquisitions, we remove observations with growth in operating assets, net operating assets, book value of equity, or sales above 100%.

Before the in-sample regressions, we further exclude observations with the profitability measure in concern falling in the top or bottom one percentile. However, we do not apply such an extreme-value exclusion criterion before the out-of-sample tests to avoid any look-ahead bias in the analysis. [11]

Panel A of Table 2 summarizes the number of observations after applying the exclusion criteria described above. For consistency, only observations with all profitability and sales growth measures available are used in the out-of-sample tests of the firm-level analysis. Similarly, only those with the ROA, ROS and GSL measures available are used in out-of-sample tests of the segment-level analysis. Nearly half of the observations come from single-segment firms, while another 36% can be traced back to multiple-segment firms. The remaining 15% of the observations belong to the category of change firms.

Panels B and C of Table 2 give an overview of the firm and segment data used to compute the average forecast improvements reported in the main analysis. The firm-level analysis uses 58,708 firm-year observations of 7,377 firms; the segment-level analysis is based on 80,127 segment-year observations of 15,540 different segments. For firms, the mean ROE is 8.2%. While the average ROS and ROA are of similar magnitude, the mean RNOA is 15.3%, considerably higher. These statistics are close to those in prior studies, such as Fama and French (2000) and Fairfield et al. (2009). The average levels of segment profitability are somewhat

[11] All the exclusion criteria are similar to those in Fairfield et al. (2009).

lower than their firm profitability counterparts. The mean segment ROA and ROS are 7.8% and 6.0%, respectively.

Panel C of Table 2 reports for each industry the number of observations, as well as average profitability. With 13,685 firm-year and 18,309 segment-year observations, *manufacturing* (FF 3) constitutes the largest industry in the sample. Other important industries are *business equipment* (FF 6), and *wholesale, retail & some services* (FF 9). There is substantial variation in average profitability across industries, ranging from 2.6% to 20.2%. *Telephone & television* (FF 7) is the industry with the highest levels of profitability, while *business equipment* (FF 6) exhibits the lowest levels of profitability, on average.

4. Firm-level analysis

This section compares the forecast accuracy of industry-specific and economy-wide profitability forecasting models at the firm level. Unlike Fairfield et al. (2009), we partition all firms into subsamples of single-segment firms, multiple-segment firms and change firms.

Table 3 reports the forecast improvements for each subsample, as well as the tests of the difference in forecast improvements between single- and multiple-segment firms. We find strong evidence for industry effects when forecasting firm profitability of single-segment firms. The forecast improvement of single-segment firms is significant at high levels, regardless of the test statistics.

However, there is no industry effect for multiple-segment firms. In none of the profitability measures considered is there a significantly positive forecast improvement of the industry-specific forecasting model. As a result, the difference in forecast improvement between single-segment and multiple-segment firms is highly significant. In other words, the industry-specific forecasting model is significantly better for single-segment firms relative to multiple-segment firms.

Taken together, the results suggest that aggregated reporting of various business activities of multiple-segment firms is an important factor contributing to the lack of industry effects in profitability forecasting documented in the prior literature.[12]

The table also highlights another interesting finding regarding change firms, i.e., the firms that changed from single-segment firms to multiple-segment firms after the introduction of SFAS 131. In all cases, the forecast improvements are indistinguishable from zero, very similar to those of multiple-segment firms.[13] This suggests that change firms were indeed disguised multiple-segment firms before SFAS 131, i.e., they used the greater discretion allowed under SFAS 14 to avoid reporting their segments separately. This is in line with Berger and Hann's (2003) finding that the introduction of SFAS 131 induced firms to reveal previously hidden information on their diversified activities.

All in all, this section shows that there is considerable heterogeneity in the mean-reverting pattern of profitability across industries, which can be exploited to improve the profitability forecasts of single-segment firms. In contrast, for multiple-segment firms, no industry represents the whole firm precisely enough to make industry-specific profitability forecasts more accurate than economy-wide forecasts.

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[12] In unreported robustness tests, we can replicate Fairfield, Ramnath, and Yohn's (2009) no-industry-effect result for our data sample.

[13] Untabulated additional tests show that the difference in forecast improvements of single-segment firms relative to change firms is significantly positive. Furthermore, there is little difference in forecast improvements between multiple-segment firms and change firms.

5. Segment-level analysis

Segment profitability forecast improvement

If the absence of industry effects in profitability forecasting for multiple-segment firms documented in Table 3 is due to the aggregation of segment data for external reporting of firm-level financials only, industry effects should exist at the business segment level. In this section, we therefore directly analyse industry effects in profitability forecasting at the segment level. We confine the analysis to ROA and ROS because it is not possible to compute ROE and RNOA for business segments.

Panel A of Table 4 presents the segment profitability forecast improvement of industry-specific over economic-wide models when pooling all segments together. The results only partially support the existence of industry effects in profitability forecasting at the segment level. Although the segment profitability forecast improvement for ROS is significantly positive, the industry effect in terms of ROA is insignificant. To some extent, the difference between the ROS and ROA results may be attributed to the better data quality of sales data relative to asset data at the segment level.[14] Nevertheless, these results suggest that the aggregation of business segment data alone cannot fully explain the lack of industry effects in profitability forecasting for multiple-segment firms. We explore other contributing factors in the following subsections.

Segment profitability forecast improvement by firm type

The segment-level analysis so far does not distinguish between segments of single-segment firms and segments of multiple-segment firms. There are two concerns with this approach. First, the reportable single segments of single-segment firms are effectively very similar to the single-

[14] Compared to sales recognition, the accounting practice in asset valuation usually varies more across firms owing to more alternative choices of accounting estimates and accounting methods.

segment firms themselves. We have shown strong industry effects in firm profitability forecasting for single-segment firms. Thus, the segment profitability forecast improvement for ROS might be driven entirely by the segments of single-segment firms rather than by the segments of multiple-segment firms as well. In that case, the finding cannot constitute further evidence for the aggregation explanation to the lack of industry effects for multiple-segment firms.

Second, the segments of multiple-segment firms are implicitly treated as if they are operating completely independently, like the segments of single-segment firms. However, the literature on corporate diversification suggests that conglomerates do not manage their business segments on a stand-alone basis. Rather they reallocate resources or costs from one business segment to another for potentially various reasons.[15] To the extent that multiple-segment firms shift resources or costs from one segment to another, the profitability of their segments is influenced by such strategic moves and hence is less exposed to industry-specific factors. Thus, it is plausible that the industry effect in segment profitability forecasting is considerably smaller for multiple-segment firms.

To better understand industry effects at the segment level, panel B of Table 4 partitions the segment profitability forecast improvements into three subsamples for single-segment firms, multiple-segment firms, and change firms. For single-segment firms, there are significant industry effects at the segment level for both ROS and ROA, as expected.[16] In contrast, these effects are less pronounced for the segments of multiple-segment firms. Yet, in terms of ROS,

[15] For example, the internal capital market literature argues that large firms tend to allocate resources across divisions over the business cycle (Maksimovic and Phillips 2002). The co-insurance literature suggests that coinsurance among a firm's business units can reduce systematic risk, thereby decreasing the firms' overall cost of equity capital (Hann, Ogneva, and Ozbas 2013).

[16] The number of segment-year observations of single-segment firms differs from the number of firm-year observations of single-segment firms owing to different data requirement criteria, as explained in section 3.

they are still statistically significant. This confirms that the aggregation of business segment data is indeed an explanation for the lack of industry effects for multiple-segment firms at the firm level.

The last column of the panel presents the difference in the segment profitability forecast improvements between single- and multiple-segment firms. While the difference is not significant for ROA, it is highly significant for ROS. Had there been no reallocation across the segments of multiple-segment firms, all segments in the sample should have similar exposure to industry-specific factors. The lower exposure to industry-specific factors of multiple-segment firms relative to single-segment firms is therefore consistent with the existence of cross-allocations among the business segments of multiple-segment firms.

The different improvement in ROS versus ROA between single and multiple segment firms is due to two effects. First, worse segment data quality for asset relative to sales data creates a substantially lower level of forecast improvements for ROA than ROS for the segments of single-segment firms. For the segments of multiple-segment firms, there is an additional second effect due to cross allocation between segments that can only appear in these firms. Under the influence of the first effect, the second effect is enough to drive the forecast improvement for ROA for multiple-segment firms down to an insignificant level. The similarly low forecast improvements for ROA for both firm types have resulted in their insignificant difference. This is unlike the case of ROS where the improvements for single-segment firms are more than double those for multiple-segment firms.

Panel B also shows that for change firms, the segment profitability forecast improvements are significantly negative.[17] Negative forecast improvements mean that the absolute forecast errors

[17] Untabulated tests show that the segment forecast improvements of both single- and multiple-segment firms are significantly larger than the segment forecast improvements of change firms.

of economy-wide forecasts are lower than those of industry-specific forecasts. This happens if the gain from using industry-specific forecasting models (no estimation bias) is smaller than the loss from using a small sample size (noisy parameter estimates).

A question remains as to why the exposure to industry-specific factors is weaker for the segments of change firms than for the segments of multiple-segment firms. Change firms are those having increased the number of reported segments from one to more than one following the introduction of SFAS 131. In fact, Botosan and Stanford (2005) suggest that one of the firms' main reasons to avoid detailed disclosure prior to SFAS 131 was to conceal information on highly profitable segments which cross-subsidize other business units. Against this backdrop, it seems that change firms were not only multiple-segment firms in disguise prior to SFAS 131, but also those with the largest internal transfers between their business segments. Considerable cross-subsidization within change firms thus eliminates the relation between segment profitability and industry membership altogether.

Change in segment reporting standards

In 1998, segment disclosure requirements were changed following the introduction of SFAS 131. The stated purpose of the new standard was to increase the transparency of firm segment structure. Under the previous standard SFAS 14, firms were asked to disclose segment information according to the industry classification of their segments. Besides, reported segment profits must conform to the US generally accepted accounting principles (GAAP). This guarantees a certain level of comparability across firms. With the implementation of SFAS 131, firms are only required to align the segment reporting with the internal structure and accounting.

Hence, segment profit data are not as comparable across firms as before due to non-standard definitions adopted by different firms.[18]

The introduction of SFAS 131 had two important implications for industry-specific segment profitability forecasting models. First, the data to calculate segment profitability is less comparable across firms. As a result, the accuracy of profitability forecasts might deteriorate in the post-SFAS 131 period. Second, business segment data no longer needs to be primarily organized by their industry affiliation. Industry-specific profitability forecasting models may lose some of their advantage after the introduction of SFAS 131. Since the change in disclosure requirements had little impact on single-segment firms, such an effect would be most visible for the segments of multiple-segment and change firms.

Panel C of Table 4 shows the impact of SFAS 131 on industry-specific segment profitability forecasting by dividing the data into two subsamples by reporting regime. The panel indicates that the estimates of the segment profitability forecast improvements are lower under SFAS 131 for the segments of multiple-segment and change firms.

Unsurprisingly, the pre-SFAS 131 forecast improvements are insignificant for the segments of change firms, which are reported as single-segment firms in that period. As disguised multiple-segment firms with the strongest incentives to conceal segment information, change firms have negatively significant improvements in the post-SFAS 131 period in three of the four cases. This is in line with similar results in panel B. Like multiple-segment firms, change firms have a significant reduction in the segment profitability forecast improvements for ROS. That for ROA, however, is insignificant.

For single-segment firms, the reduction in the segment profitability forecast improvements is

[18] For more details on the change of segment disclosure regulations from SFAS 14 to SFAS 131, see Berger and Hann (2003, 2007) and Hund, Monk, and Tice (2010).

always insignificant. This is consistent with the fact that the introduction of SFAS 131 had little impact for single-segment firms.

Overall, the results in panel C are consistent with the view that changes in segment data under SFAS 131 can explain the weaker segment profitability forecast improvements for multiple-segment or change firms, as well as the insignificant reduction in the improvements for single-segment firms. Since multiple-segment firms constitute a substantial fraction of the entire data sample, the results also help to explain the weak industry effects at the segment level in terms of ROA for the entire sample documented in panel A.

6. Additional analyses

Sales growth forecasting

Fairfield et al. (2009) present evidence for industry effects in sales growth forecasting. In this section, we examine whether industry effects in sales growth forecasting are also stronger for single-segment firms and for business segments.

When dividing all firms into single-segment, multiple-segment and change firms (see panel A of Table 5), the forecast improvements for sales growth are significantly positive for single-segment firms, but not for multiple-segment or change firms. The pattern is very similar to the analysis of profitability forecasting.

Panel B shows a strong industry effect in sales growth forecasting at the segment level. Yet, and in accordance with the analysis of segment profitability, panel C shows that this industry effect is mainly driven by the segments of single-segment firms.[19]

[19] We do not replicate the segment sales growth forecast improvements for the pre- and post-SFAS 131 sub-periods because we have no clear prediction about how the change in the reporting standards would impact the forecast improvements for the growth in sales.

Alternative industry classifications

Differences across industry classifications can drive the results of industry-specific analyses, depending on the application (Bhojraj et al. 2003). Furthermore, firms can actively select their industry classification by manipulating sales data to increase the relative importance of the largest industry segment, which is important to determine the primary industry (Chen et al. 2016). This section explores to what extent our results are affected by the choice of the Fama-French 12-industry classification. The robustness check covers only the firm-level analysis because alternative industry classifications are often unavailable for segment-level data.

We replicate the firm-level analysis using three alternative industry definitions that allow for broad industry classifications, namely the one-digit SIC codes, the (two-digit) GICS industry sectors, and the one-digit NAICS codes. As before, we exclude firms in regulated industries based on their SIC codes. Yet, the number of observations is different for each industry classification, since not all classifications are available for all firms.

Table 6 compares the out-of-sample test results for all the profitability measures using the alternative industry classifications. The results show that the firm-level findings are robust across the industry classifications. Industry-specific forecasting models generate more precise predictions for firm profitability for single-segment firms, but not for multiple-segment firms and change firms, with a few exceptions. Among the three alternative classifications, the GICS industry sector classification yields the strongest results, closely similar to those reported earlier based on the Fama-French 12-industry classification. This is in line with Bhojraj et al.'s (2003) finding that the firms’ industry profitability and industry growth measures have a higher correlation under GICS relative to other industry classifications.

7. Conclusion

This paper examines industry effects in profitability forecasting for firms and business segments. We measure these industry effects by comparing the accuracy of industry-specific forecasting models relative to economy-wide models. Using a variety of out-of-sample tests, this study reveals considerable industry effects in profitability forecasting for single-segment firms and, to some extent, for business segments. In contrast, there are no industry effects in firm profitability forecasting for multiple-segment firms.

This evidence is consistent with the view that the aggregation of business segment data for external reporting at the firm level is an important factor to explain the lack of industry effects for multiple-segment firms. Further analyses suggest that the reallocation of resources or costs across business segments and the deteriorated segment data under SFAS 131 are reasons for not observing industry effects at the segment level for multiple-segment firms. These results help to understand the reasons behind the lack of industry effect in firm profitability forecasting documented by Fairfield et al. (2009).

Our results are also relevant to the accounting disclosure literature. The finding that information contained in segment-level data can help to improve a firm’s profitability forecasts underlines the usefulness of less aggregated accounting disclosure. Yet, following the introduction of SFAS 131, the segment data is less comparable across firms (Hund et al. 2010). We find evidence consistent with deteriorated segment data quality being a factor contributing to the lack of industry effects in forecasting segment profitability after SFAS 131. This limits the usefulness of industry-specific profitability forecasting models to investors. Our finding highlights the importance of ensuring a certain level of comparability of the reported business segment data across firms.

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TABLE 1
Variable definitions

Variable name	Description	Computation	
		Firm-level analysis (Compustat fundamentals annual)	Segment-level analysis (Compustat segments)
(USD million)			
NI_t	Income before extraordinary items – available for common equity	Compustat item 237 WRDS mnemonic: IBCOM	
BV_t	Common/ordinary shareholder's equity	Compustat item 60 WRDS mnemonic: CEQ	
$OPINC_t$	Operating income after depreciation	Compustat item: 178 WRDS mnemonic: OIADP	WRDS mnemonic: OPS
TA_t	Identifiable/total assets	Compustat item 6 WRDS mnemonic: AT	WRDS mnemonic: IAS
$SALES_t$	Total sales	Compustat item: 12 WRDS mnemonic: SALE	WRDS mnemonic: SALES
NOA_t [†]	Net operating assets	Common stock (60/CEQ) + preferred stock (130/PSTK) + long-term debt (9/DLTT) + debt in current liabilities (34/DLC) + minority interest (38/MIB) – cash and short-term investments (1/CHE)	
ROA_t	Return on assets	$OPINC_t/(0.5*(TA_t + TA_{t-1}))$	$OPINC_t/(0.5*(TA_t + TA_{t-1}))$
ROS_t	Return on sales	$OPINC_t/SALES_t$	$OPINC_t/SALES_t$
$RNOA_t$	Return on net operating assets	$OPINC_t/(0.5*(NOA_t + NOA_{t-1}))$	
ROE_t	Return on equity	$NI_t/(0.5*(BV_t + BV_{t-1}))$	
GSL_t	Sales growth	$(SALES_t - SALES_{t-1})/SALES_{t-1}$	$(SALES_t - SALES_{t-1})/SALES_{t-1}$

[†] If the data items for preferred stock, long-term debt, debt in current liabilities, minority interest and cash and short-term investments are not available, they are assumed to equal zero.

TABLE 2

Sample selection and descriptive statistics

Panel A: Sample selection

Adjustments to data sample	Firm-level data (firm-year observations)					Segment-level data (segment-year observations)		
	ROE	*RNOA*	*ROA*	*ROS*	*GSL*	*ROA*	*ROS*	*GSL*
Observations for in-sample regressions								
Total observations, excluding utilities and financial firms/segments	209,935	209,859	210,905	222,274	205,915	194,517	251,072	228,654
Less observations with small denominators	133,550	133,504	134,436	140,068	134,314	181,035	232,250	214,429
Less observations with an absolute value larger than 1	130,676	131,010	134,403	138,818	134,314	178,213	223,303	214,429
Less observations with more than 100% growth	117,396	117,936	119,416	118,687	119,433	154,059	151,160	163,319
Less upper and lower centiles observations	115,050	115,578	117,028	116,315	117,045	150,979	148,138	160,053
Observations for out-of-sample tests, out of which			58,708				80,127	
Single-segment firms			28,234				39,446	
Multiple-segment firms			21,172				29,293	
Change firms			9,302				11,388	

This panel summarizes the sample selection procedure and the number of observations available after each filter. Besides utilities and financials, we also exclude the U.S. postal service (SIC 43), non-classifiable establishments (SIC 99) and observations without SIC code. We distinguish between three types of firms. Firms reporting only one (more than one) business segment are classified as single-segment (multiple-segment) firms unless they meet the definition of change firms. Change firms are firms that have changed the number of reported segments from one in 1997 to more than one in 1999, suggesting that they might not have reported genuinely prior to the introduction of SFAS 131 in 1998. Firms with missing segment data or where the aggregate segment data deviate substantially from firm data are excluded in the out-of-sample tests. For more details, see section 3. Variable definitions are provided in Table 1.

TABLE 2 (continued)
Sample selection and descriptive statistics

Panel B: Descriptive statistics

Variable	Mean	Std. deviation	First quartile	Median	Third Quartile
Firm-level: 7,377 firms (58,708 firm-year observations)					
NI	121.496	728.795	1.174	8.407	46.585
OPINC	237.865	1,090.917	4.183	19.899	99.538
TA	2,644.961	11,752.020	74.127	247.945	1,075.695
NOA	1,566.608	7,056.863	47.073	155.304	679.027
BV	1,030.031	4,609.057	36.366	118.189	478.273
SALES	2,564.632	10,368.740	98.439	312.056	1,236.404
ROE	8.17%	14.57%	3.25%	10.66%	16.46%
RNOA	15.26%	14.14%	7.35%	14.52%	22.77%
ROA	9.45%	8.04%	4.84%	9.52%	14.29%
ROS	8.02%	8.58%	3.29%	7.16%	11.85%
GSL	6.96%	16.49%	-0.34%	7.91%	16.91%
Segment-level: 15,540 segments (80,127 segment-year observations)					
OPINC	123.411	570.485	0.485	9.322	59.614
TA	1,244.238	5,134.817	31.117	143.089	643.236
SALES	1,246.573	6,646.675	39.997	176.192	736.192
ROA	7.84%	13.86%	2.04%	8.70%	15.24%
ROS	6.00%	13.18%	1.42%	6.56%	12.42%
GSL	7.33%	19.77%	-0.03%	6.26%	17.20%

This panel gives an overview on the firm and segment data used to compute the average forecast improvements in the out-of-sample tests for the period from 1977 to 2011 in the firm-level analysis, and from 1987 to 2011 in the segment-level analysis. OPINC (operating income), NI (income before extraordinary items), TA (total assets), SALES (total sales), BV (common shareholder's equity), and NOA (net operating assets) are reported in USD million. Variable definitions are provided in Table 1.

TABLE 2 (continued)
Sample selection and descriptive statistics

Panel C: Descriptive statistics by industry

Fama-French 12-industry classification	Description	Firm-level data						Segment-level data			
		Obs.	*ROE*	*RNOA*	*ROA*	*ROS*	*GSL*	Obs.	*ROA*	*ROS*	*GSL*
1	Consumer non-durables	6,926	9.12%	16.27%	10.56%	7.60%	6.83%	7,925	9.58%	7.07%	5.35%
2	Consumer durables	3,187	8.16%	15.42%	9.70%	6.89%	7.84%	3,804	8.71%	5.74%	5.25%
3	Manufacturing	13,685	8.50%	15.34%	9.80%	7.58%	7.60%	18,309	9.87%	6.96%	6.21%
4	Oil, gas & coal extraction and products	2,711	7.23%	11.74%	7.56%	11.30%	10.53%	3,740	6.66%	9.65%	9.69%
5	Chemicals	2,686	11.25%	17.97%	11.14%	9.18%	7.32%	3,850	11.11%	8.72%	6.25%
6	Business equipment	10,087	5.25%	13.72%	7.43%	6.38%	9.81%	17,553	4.19%	2.63%	7.54%
7	Telephone & television	3,346	11.20%	15.50%	10.47%	20.23%	8.90%	3,958	8.38%	15.84%	8.66%
9	Wholesale, retail & some services	11,854	8.08%	15.24%	9.34%	4.93%	9.18%	14,201	7.94%	3.91%	7.86%
10	Healthcare & medical equipement	4,226	8.99%	17.22%	10.81%	11.07%	11.50%	6,787	7.56%	6.16%	10.73%
Total		58,708	8.17%	15.26%	9.45%	8.02%	6.96%	80,127	7.84%	6.00%	7.33%

This panel reports the number of observations and the average firm and segment profitability and sales growth by industry. Industries are defined using the Fama-French 12-industry classification. Note that the industries 8 (*utilities*), 11 (*finance*) and 12 (*other*) have been excluded from the analysis. Variable definitions are provided in Table 1.

TABLE 3
Firm profitability forecast improvements by firm type

Firm type	Single-segment (SS) firms			Multiple-segment (MS) firms		Change firms		Difference SS-MS firms		
Observations	28,234			21,172		9,302				
	Value		*p*-Value	Value	*p*-Value	Value	*p*-Value	Value		*p*-Value
ROE										
Pooled mean	0.0481%	***	0.009	-0.0212%	0.192	-0.0141%	0.572	0.0693%	***	0.001
Grand mean	0.0431%	***	0.004	-0.0207%	0.132	-0.0142%	0.241	0.0638%	***	<0.001
No. industries	4 / 3			5 / 3		4 / 2				
No. years	10 / 2			2 / 8		3 / 1				
RNOA										
Pooled mean	0.0474%	***	0.001	-0.0074%	0.555	-0.0186%	0.487	0.0548%	***	<0.001
Grand mean	0.0443%	***	<0.001	-0.0040%	0.686	-0.0144%	0.401	0.0483%	***	<0.001
No. industries	4 / 2			3 / 3		4 / 2				
No. years	10 / 0			8 / 4		7 / 3				
ROA										
Pooled mean	0.0346%	***	<0.001	-0.0032%	0.657	-0.0015%	0.911	0.0378%	***	<0.001
Grand mean	0.0328%	***	<0.001	-0.0021%	0.699	0.0014%	0.863	0.0350%	***	<0.001
No. industries	5 / 2			4 / 2		4 / 2				
No. years	14 / 0			3 / 4		2 / 3				
ROS										
Pooled mean	0.0923%	***	<0.001	0.0075%	0.510	-0.0098%	0.601	0.0848%	***	<0.001
Grand mean	0.0943%	***	<0.001	0.0108%	0.208	-0.0129%	0.272	0.0836%	***	<0.001
No. industries	5 / 2			4 / 3		3 / 4				
No. years	26 / 0			6 / 3		2 / 3				

This table summarizes the firm profitability forecast improvement of industry-specific analysis over economy-wide analysis by firm type. We distinguish between three types of firms. Firms reporting only one (more than one) business segment are classified as single-segment (multiple-segment) firms unless they meet the definition of change firms. Change firms are firms that have changed the number of reported segments from one in 1997 to more than one in 1999, suggesting that they might not have reported genuinely prior to the introduction of SFAS 131 in 1998 (see section 3 for details). Industries are defined using the Fama-French 12-industry classification. The out-of-sample period is from 1977 to 2011. See Table 1 for variable definitions.

The pooled mean is the mean forecast improvement pooling all firm-year forecast improvements together. The grand mean is the mean of the yearly mean forecast improvements for the firms in a year. For the pooled mean, the p-values are based on standard errors corrected for two-way clustering by segment and year following Rogers (1993). For the grand mean, the standard errors are adjusted following Newey and West (1987). “No. industries” is the number of industries (out of 9) for which the pooled mean forecast improvement from using the industry-specific model is significantly positive / negative (at the 10% significance level). “No. years” is the number of years (out of 35) that the yearly mean improvement is significantly positive / negative (at the 10% significance level). *, **, and *** represent significance levels of 0.10, 0.05, and 0.01, respectively.

The column on the right presents the differences in forecast improvements between single-segment and multiple-segment firms. For the pooled mean, the p-values of the differences are based on standard errors corrected for two-way clustering by firm and year following Rogers (1993) using a regression on a constant and a firm-type dummy. For the grand mean, the p-values of the differences are based on standard errors adjusted following Newey and West (1987).

TABLE 4
Segment-level analysis

Panel A: Segment profitability forecast improvements (segment-year observations: 80,127)

	Value		*p* -Value
ROA			
Pooled mean	0.0084%		0.392
Grand mean	0.0057%		0.520
No. industries	7 / 0		
No. years	6 / 5		
ROS			
Pooled mean	0.0547%	***	<0.001
Grand mean	0.0504%	***	<0.001
No. industries	5 / 2		
No. years	14 / 1		

This panel summarizes the segment profitability forecast improvement of industry-specific over economy wide analysis. Industries are defined using the Fama-French 12-industry classification. The out-of-sample period is from 1987 to 2011. For more details on the out-of-sample tests, see section 3. See also the footnote to Table 3 for the details on the tests performed. *, **, and *** represent significance levels of 0.10, 0.05, and 0.01, respectively. Variable definitions are provided in Table 1.

TABLE 4 (continued)
Segment-level analysis

Panel B: Segment profitability forecast improvements by firm type

Firm type	Single-segment (SS) firms		Multiple-segment (MS) firms		Change firms		Difference SS-MS firms	
Segment-year observations	39,446		29,293		11,388			
	Value	*p* -Value	Value	*p* -Value	Value	*p* -Value	Value	*p* -Value
ROA								
Pooled mean	0.0182% *	0.075	0.0161%	0.351	-0.0453% **	0.022	0.0021%	0.908
Grand mean	0.0158% *	0.061	0.0130%	0.396	-0.0411% **	0.029	0.0029%	0.850
No. industries	5 / 1		7 / 0		6 / 2			
No. years	4 / 1		7 / 5		2 / 6			
ROS								
Pooled mean	0.0951% ***	<0.001	0.0427% *	0.054	-0.0545% **	0.024	0.0523% **	0.043
Grand mean	0.0932% ***	<0.001	0.0361% *	0.060	-0.0475% **	0.013	0.0571% ***	0.008
No. industries	6 / 1		4 / 2		4 / 1			
No. years	18 / 0		9 / 3		1 / 7			

This panel summarizes the segment profitability forecast improvement of industry-specific analysis over economy-wide analysis. We distinguish between three types of firms. Firms reporting only one (more than one) business segment are classified as single-segment (multiple-segment) firms unless they meet the definition of change firms. Change firms are firms that have changed the number of reported segments from one in 1997 to more than one in 1999, suggesting that they might not have reported genuinely prior to the introduction of SFAS 131 in 1998 (see section 3 for details). Industries are defined using the Fama-French 12-industry classification. The column on the right presents the differences in forecast improvements between the segments of single-segment firms and those of multiple-segment firms. For the pooled mean, the p-values of the differences are based on standard errors corrected for two-way clustering by firm and year following Rogers (1993) using a regression on a constant and a firm-type dummy. For the grand mean, the p-values of the differences are based on standard errors adjusted following Newey and West (1987). *, **, and *** represent significance levels of 0.10, 0.05, and 0.01, respectively. Variable definitions are provided in Table 1.

TABLE 4 (continued)
Segment-level analysis

Panel C: Segment profitability forecast improvements by reporting regime and firm type							
Period		Pre-SFAS 131 (1987-1997)		Post-SFAS 131 (1999-2011)		Change from SFAS 14 to SFAS 131	
		Value	*p* -Value	Value	*p* -Value	Value	*p* -Value
Single-segment firms:	Segment-year observations	20,198		17,437			
	ROA						
	Pooled mean	0.0281% *	0.071	0.0065%	0.590	-0.0217%	0.240
	Grand mean	0.0279% *	0.067	0.0053%	0.604	-0.0227%	0.191
	ROS						
	Pooled mean	0.1125% ***	<0.001	0.0764% ***	<0.001	-0.0361%	0.213
	Grand mean	0.1133% ***	<0.001	0.0772% ***	0.001	-0.0362%	0.138
Multiple-segment firms:	Segment-year observations	14,544		13,869			
	ROA						
	Pooled mean	0.0481% **	0.044	-0.0158%	0.487	-0.0639% **	0.046
	Grand mean	0.0477% **	0.045	-0.0147%	0.480	-0.0624% **	0.043
	ROS						
	Pooled mean	0.1049% ***	<0.001	-0.0267%	0.300	-0.1315% ***	<0.001
	Grand mean	0.1035% ***	<0.001	-0.0266%	0.208	-0.1301% ***	<0.001
Change firms:	Segment-year observations	5,597		5,480			
	ROA						
	Pooled mean	-0.0228%	0.279	-0.0628% *	0.063	-0.0400%	0.305
	Grand mean	-0.0183%	0.187	-0.0526%	0.117	-0.0342%	0.322
	ROS						
	Pooled mean	-0.0157%	0.648	-0.0942% ***	0.003	-0.0785% *	0.088
	Grand mean	-0.0081%	0.700	-0.0802% **	0.011	-0.0720% **	0.044

This panel compares the segment profitability forecast improvement of industry-specific analysis over economy-wide analysis before and after the introduction of SFAS 131 in 1998, as well as the difference between the two periods for the three types of firms. The observations of 1998 are excluded from the out-of-sample tests to account for the transition year. Industries are defined using the Fama-French 12-industry classification.

The p-values for the change in forecast improvements for the two periods are calculated as follows. For the pooled mean, the p-values are based on the standard errors corrected for two-way clustering by segment and year following Rogers (1993) using a regression on a constant and a post-SFAS 131 period dummy. For the grand mean, the p-values of the change are based on robust standard errors following Newey and West (1987). *, **, and *** represent significance levels of 0.10, 0.05, and 0.01, respectively. Variable definitions are provided in Table 1.

TABLE 5
Growth in sales

Panel A: Firm-level analysis by firm type

Firm type	Single-segment (SS) firms		Multiple-segment (MS) firms		Change firms		Difference SS-MS firms	
Observations	28,234		21,172		9,302			
	Value	*p* -Value	Value	*p* -Value	Value	*p* -Value	Value	*p* -Value
Pooled mean	0.1040% ***	<0.001	0.0103%	0.797	0.0048%	0.884	0.0937% ***	0.004
Grand mean	0.1064% ***	<0.001	0.0186%	0.628	-0.0191%	0.547	0.0878% ***	0.005
No. industries	3 / 0		2 / 1		1 / 1			
No. years	17 / 2		9 / 7		7 / 6			

This panel summarizes the firm forecast improvement of industry-specific analysis over economy-wide analysis for growth in sales (GSL) by firm type. We distinguish between three types of firms. Firms reporting only one (more than one) business segment are classified as single-segment (multiple-segment) firms unless they meet the definition of change firms. Change firms are firms that have changed the number of reported segments from one in 1997 to more than one in 1999, suggesting that they might not have reported genuinely prior to the introduction of SFAS 131 in 1998 (see section 3 for details). Industries are defined using the Fama-French 12-industry classification. The out-of-sample period is from 1977 to 2011. For more details on the out-of-sample tests, see section 3. *, **, and *** represent significance levels of 0.10, 0.05, and 0.01, respectively. For more details on the statistics presented in the table, see Table 3. Variable definitions are provided in Table 1.

Panel B: Segment-level analysis (segment-year observations: 80,127)

	Value	*p* -Value
Pooled mean	0.0807% ***	<0.001
Grand mean	0.0826% ***	0.002
No. industries	3 / 0	
No. years	13 / 1	

This panel summarizes the segment forecast improvement of industry-specific analysis over economy-wide analysis for growth in sales (GSL). Industries are defined using the Fama-French 12-industry classification. The out-of-sample period is from 1987 to 2011. For more details on the out-of-sample tests, see section 3. *, **, and *** represent significance levels of 0.10, 0.05, and 0.01, respectively. For more details on the statistics presented in the table, see Table 4 (panel A). Variable definitions are provided in Table

Panel C: Segment-level analysis by firm type

Firm type	Single-segment (SS) firms		Multiple-segment (MS) firms		Change firms		Difference SS-MS firms	
Segment-year observations	39,446		29,293		11,388			
	Value	*p* -Value	Value	*p* -Value	Value	*p* -Value	Value	*p* -Value
Pooled mean	0.1263% ***	<0.001	0.0292%	0.382	0.0552% *	0.092	0.0971% ***	<0.001
Grand mean	0.1333% ***	<0.001	0.0354%	0.294	0.0515% *	0.098	0.0979% ***	0.001
No. industries	3 / 0		1 / 0		2 / 0			
No. years	15 / 0		8 / 4		4 / 1			

This panel summarizes the segment forecast improvement of industry-specific analysis over economy-wide analysis for growth in sales (GSL) for the three sub-samples of firms. Industries are defined using the Fama-French 12-industry classification. The out-of-sample period is from 1987 to 2011. For more details on the out-of-sample tests, see section 3. *, **, and *** represent significance levels of 0.10, 0.05, and 0.01, respectively. For more details on the statistics presented in the table, see Table 4 (panel B). Variable definitions are provided in Table 1.

TABLE 6
Firm-level analysis with alternative industry classifications

Panel A: One-digit SIC

Firm type	Single-segment (SS) firms		Multiple-segment (MS) firms		Change firms		Difference SS-MS firms	
Observations	33,949		24,973		10,648			
	Value	*p*-Value	Value	*p*-Value	Value	*p*-Value	Value	*p*-Value
ROE								
Pooled mean	0.0175%	0.134	-0.0148%	0.332	0.0056%	0.779	0.0323% *	0.053
Grand mean	0.0157% *	0.063	-0.0160%	0.223	0.0075%	0.530	0.0317% **	0.015
RNOA								
Pooled mean	0.0337% ***	<0.001	-0.0069%	0.514	0.0086%	0.499	0.0407% ***	0.002
Grand mean	0.0328% ***	<0.001	-0.0062%	0.475	0.0128%	0.138	0.0390% ***	0.001
ROA								
Pooled mean	0.0218% ***	<0.001	-0.0063%	0.346	0.0172% **	0.031	0.0281% ***	<0.001
Grand mean	0.0219% ***	<0.001	-0.0066%	0.234	0.0200% ***	<0.001	0.0285% ***	<0.001
ROS								
Pooled mean	0.0616% ***	<0.001	0.0044%	0.637	0.0095%	0.511	0.0572% ***	<0.001
Grand mean	0.0652% ***	<0.001	0.0057%	0.406	0.0063%	0.541	0.0595% ***	<0.001

Panel B: GICS Industry sectors

Firm type	Single-segment (SS) firms		Multiple-segment (MS) firms		Change firms		Difference SS-MS firms	
Observations	32,822		23,459		10,685			
	Value	*p*-Value	Value	*p*-Value	Value	*p*-Value	Value	*p*-Value
ROE								
Pooled mean	0.0493% ***	0.009	-0.0085%	0.587	-0.0563% **	0.035	0.0578% ***	0.006
Grand mean	0.0414% ***	0.006	-0.0066%	0.594	-0.0608% ***	0.001	0.0480% ***	0.002
RNOA								
Pooled mean	0.0538% ***	<0.001	0.0010%	0.940	-0.0334%	0.208	0.0528% ***	0.001
Grand mean	0.0463% ***	<0.001	0.0036%	0.742	-0.0384% **	0.045	0.0427% ***	0.001
ROA								
Pooled mean	0.0339% ***	<0.001	0.0002%	0.978	-0.0151%	0.251	0.0337% ***	<0.001
Grand mean	0.0299% ***	<0.001	0.0014%	0.824	-0.0166% *	0.059	0.0285% ***	<0.001
ROS								
Pooled mean	0.0764% ***	<0.001	0.0050%	0.588	-0.0269%	0.147	0.0714% ***	<0.001
Grand mean	0.0791% ***	<0.001	0.0075%	0.282	-0.0283% **	0.012	0.0716% ***	<0.001

TABLE 6 (continued)
Firm-level analysis with alternative industry classifications

Panel C: One-digit NAICS

Firm type	Single-segment (SS) firms		Multiple-segment (MS) firms		Change firms		Difference SS-MS firms	
Observations	32,851		23,532		10,660			
	Value	*p* -Value	Value	*p* -Value	Value	*p* -Value	Value	*p* -Value
ROE								
Pooled mean	0.0137%	0.170	-0.0082%	0.379	0.0075%	0.486	0.0219% *	0.059
Grand mean	0.0141% **	0.070	-0.0083%	0.281	0.0031%	0.686	0.0224% ***	0.011
RNOA								
Pooled mean	0.0306% ***	<0.001	-0.0080%	0.310	0.0023%	0.779	0.0386% ***	<0.001
Grand mean	0.0299% ***	<0.001	-0.0081%	0.190	0.0030%	0.685	0.0380% ***	<0.001
ROA								
Pooled mean	0.0233% ***	<0.001	-0.0030%	0.560	0.0088%	0.114	0.0262% ***	<0.001
Grand mean	0.0233% ***	<0.001	-0.0032%	0.420	0.0096% **	0.035	0.0265% ***	<0.001
ROS								
Pooled mean	0.0595% ***	<0.001	0.0093%	0.245	0.0190% *	0.087	0.0502% ***	<0.001
Grand mean	0.0656% ***	<0.001	0.0103% *	0.083	0.0146% **	0.029	0.0552% ***	<0.001

This table reports the pooled mean and grand mean forecast improvement of industry-specific analysis over economy-wide analysis for the three sub-samples of firms using alternative industry classifications. Panel A reports the results when using the one-digit SIC; panel B reports the results when using the GICS industry sector classification, and panel C reports the results when using the one-digit NAICS. *, **, and *** represent significance levels of 0.10, 0.05, and 0.01, respectively. For more details on the statistics reported in the table, see Table 3. Variable definitions are provided in Table 1.