Industry Effects on Firm and Segment Profitability Forecasting: Do Aggregation and Diversity Matter?

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Abstract. This paper analyzes the incremental advantage of industry-specific models of profitability forecasting, over economy-wide models, for business segments and firms. Some prior research suggests that industry-specific analysis has no advantage over economy-wide analysis in forecasting firm profitability. This seems puzzling because many studies in economics and strategic management have documented the importance of industry effects in explaining firm profitability. We reconcile this apparent inconsistency by showing that industry effects on profitability forecasting exist at the more refined business segment level, but can be obscured by aggregated reporting at the firm level. Industry-specific forecasts are significantly more accurate in predicting profitability for segments and undiversified firms. The limited usefulness of industry-specific forecasting models at the firm level can be explained by the existence of multiple business segments in firms. (*JEL* L25, G17, M21, M41)

Key words: Segment profitability, Earnings predictability, Earnings persistence, Aggregation, Diversity, Industry membership

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1. Introduction

Accurate forecasts of profitability, earnings or growth are essential ingredients in company valuation. For example, valuation models such as those based on residual income (Edwards and Bell 1961 and Ohlson 1990) often require precise estimates of a firm's expected earnings or profitability for different time horizons. Some prior research has suggested that equity analyst forecasts are the best source for a firm's expected earnings (Brown et al. 1987). However, more recent studies conclude that model-based forecasts significantly outperform analysts' predictions (Hou, van Dijk, and Zhang 2012).

In general, the future of a firm may depend on economy-wide or industry-specific factors. Several studies in the economics and strategic management literatures have documented the importance of industry effects in future changes in profitability and earnings (e.g., Schmalensee 1985, McGahan and Porter 1997, and Bou and Satorra 2007). Against the backdrop of these studies, recent research often favors industry-specific more than economy-wide forecasting models. For example, Gebhardt, Lee, and Swaminathan (2001) propose a residual income model that explicitly incorporates industry-specific paths of expected long-term profitability.[1]

Yet, the preference for industry-specific forecasting models does not go unchallenged. Fairfield, Ramnath, and Yohn (2009) find that there is no significant

[1] Although firm-specific factors might be useful for forecasting, a firm-specific forecasting model is undesirable because of the survivor bias resulting from the long-history data requirement (see Fama and French 2000, p. 162, for more discussion). Indeed, Esplin (2012) shows that long-term growth forecasts obtained from industry-specific prediction models are more accurate than firm-specific forecasts.

forecast improvement of industry-specific over economy-wide analysis in predicting firm profitability. The finding questions the suitability of the valuation model by Gebhardt et al. (2001), which has enjoyed great popularity in the finance literature.[2]

This paper proposes an intuitive reconciliation of the seemingly inconsistent findings of the economics and strategic management literatures and the Fairfield et al. (2009) study. Many firms are conglomerates that operate in different industries. They often have various lines of business organized into units reported as business segments. When the segments of such diversified firms are associated with different industries, there is no single industry accurately representing the whole firm. A firm-level industry-specific forecasting model therefore cannot capture the firm's inherent complexity – and consequently fails to generate accurate predictions of future profitability. In contrast, the individual business segments of a firm are by definition more homogenous than the firm itself, and often operate mainly in one industry. Hence, for the firm's business segments, industry-specific forecasting models should generate more accurate profitability and growth forecasts. In sum, we conjecture that industry effects on profitability forecasting exist and are clearer at the segment level, but can be obscured when data are aggregated to the firm level.

Using both firm and segment data from 1967 to 2011, this study finds strong empirical support for the conjecture. In line with the literature, we employ various versions of the persistence model to predict future profitability and growth. We show that compared to economy-wide predictions, industry-specific forecasts are significantly more accurate in predicting profitability and growth for individual business segments as well as undiversified firms (with only one business segment). With regard to economic

[2] The residual income model by Gebhardt et al. (2001) has been used extensively in the finance literature to calculate a firm's implied cost of capital, see e.g., Pastor, Sinha, and Swaminathan (2008), Chava and Purnanandam (2010), Lee, Ng, and Swaminathan (2009), and Chen, Da, and Zhao (2013).

significance, the forecast improvements (in terms of absolute forecast error) for large industry sectors can be as high as around 10% of the actual profitability to be forecast.

We also address the effect of a significant change in the segment reporting standard during our sample period. Starting from 1998, the Statement of Financial Accounting Standards No. 131 (SFAS 131) superseded SFAS 14 to become the new standard. In line with other studies that express concerns about segment data quality from 1998 onward, we examine the implications of our conjecture using data from the SFAS 14 period only.[3] We find stronger supporting evidence for the years prior to 1998.

Our analysis also reveals that industry-specific models are more accurate in predicting a firm's return on sales (ROS) or net profit margin, even at the firm level. Consistent with our conjecture, the ROS forecast improvement is even larger when considering individual business segments and undiversified firms. Taken together, our results show that aggregation and diversity matter in revealing the industry effects on profitability forecasting.

This study builds on the extensive literature on predicting earnings or profitability. In practice, these tasks are equivalent to each other because earnings often are deflated by total assets in regression analysis to mitigate the scale effect (Dechow, Ge, and Schrand 2010, p. 352). Researchers from different fields have contributed to this literature. Accounting and finance scholars have examined the time-series properties and

[3] Under SFAS 14, firms were asked to disclose segment information according to the industry classification of the segments. Most important, reported segment profits must conform to the US generally accepted accounting principles (GAAP). This guarantees 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 concerns like this, other studies focus their analysis on the SFAS 14 period (e.g., Hund, Monk, and Tice 2010).

predictability of earnings.[4] Economists and strategic management researchers have studied the persistence and variability of profitability.[5] Among the many models used to forecast profitability, the first-order autoregressive model is a parsimonious choice with the slope coefficient measuring the persistence of profitability. Therefore, it is sometimes referred to as the persistence model. Fama and French (2000) modify such a model to analyze non-linearities of firm profitability. They find that mean reversion is faster when profitability is below its mean and when it is further from its mean in either direction. Fairfield et al. (2009) obtain their findings using a similar modified model. Unlike higher-order autoregressive models, the persistence model does not require long earnings histories and therefore minimizes the survivor bias. The model is particularly useful when non-earnings accounting variables are not available for use as predictors. In this paper, the limited availability of segment-level data prevents the use of sophisticated models to forecast profitability at the segment level.

Our study is also related to the growing literature that examines the usefulness of providing less aggregated segment-level data to the public. Several studies find that segment data allows stakeholders such as analysts, investors, and researchers to anticipate future earnings more accurately (e.g., Ettredge et al. 2005, Berger and Hann 2003, Baldwin 1984, and Collins 1976). In fact, it was analysts' strong desire to have more detailed segment data to supplement consolidated company data for use in forecasting company performance that led to a change in the segment reporting standard in 1997

[4] These studies include Dichev and Tang (2009), Frankel and Litov (2009), Penman and Zhang (2002), Baginski et al. (1999), Ali, Klein, and Rosenfeld (1992), Bar-Yosef, Callen, and Livnat (1987), Conroy and Harris (1987), Penman (1983), Brandon, Jarrett, and Khumawala (1983), Chant (1980), Albrecht, Lookabill, and McKeown (1977), and Watts and Leftwich (1977).

[5] Examples are Goddard et al. (2011), Bou and Satorra (2007), Glen, Lee, and Singh (2003), Ruefli and Wiggins (2003), McGahan and Porter (2002, 1999, 1997), Waring (1996), Rumelt (1991), Cubbin and Geroski (1987), and Mueller (1977).

(Botosan and Stanford 2005).

Finally, this study is related to research in the accounting and finance literature that makes use of business segment data to analyze and explain important patterns that are observable at the firm level. For example, the diversification discount has been investigated in more detail using segment data (Berger and Ofek 1995, Lamont and Polk 2002, and Hund, Monk, and Tice 2010). Moreover, disaggregated segment-level data are found to be more useful in predicting firm performance because they allow better monitoring of agency problems such as overinvestment and cross-subsidization (Berger and Hann 2007).

By using segment-level data to analyze the incremental advantage of industry-specific profitability forecasting models over economy-wide models, this paper contributes to the above-mentioned streams of research. Most of all, our results provide an intuitive explanation to Fairfield, Ramnath, and Yohn's (2009) no industry effect finding. Thereby we reconcile the apparent inconsistency between their study and others that observe industry effects in various contexts.

The paper is organized as follows. In the next section, we explain the two hypotheses developed from our conjecture and the research design used to test the hypotheses. Section 3 describes the data used and the sample construction procedure. Section 4 discusses the evidence from the firm- and segment-level analysis for the whole data period and for the SFAS 14 period. Concluding remarks are given in section 5.

2. Hypotheses and Research Design

Our hypotheses are stated in terms of forecast improvement of industry-specific (IS) over economy-wide (EW) analysis. To be concrete about the meaning of forecast improvement, we outline below the research design before introducing the hypotheses.

Details of the research design are provided after we have explained the two hypotheses.

2.1 Hypotheses

We use the standard persistence model (i.e., first-order autoregressive), as well as two other augmented specifications, to forecast profitability. The segment/firm profitability *forecast improvement* (of IS over EW analysis) is defined as the absolute forecast error from the EW analysis minus its IS counterpart. For the standard persistence model, the forecast used to define the forecast error is computed using the following regression:

$$x_t = \alpha_t + \beta_t x_{t-1} + \varepsilon_t,$$

where x_t and x_{t-1} denote the profitability of the current and the previous year, respectively. The model coefficients, α_t and β_t, are indexed by a year subscript t because they are re-estimated each year based on the most recent 10 years of data. The estimated coefficients from these *in-sample regressions* (Step 1) are used to compute the profitability forecasts and the forecast errors used for *out-of-sample tests* (Step 2). Further details of this two-step procedure are given in section 2.2.

Inspired by studies in the diversification and segment reporting literatures (e.g., Berger and Ofek 1995, Campa and Kedia 2002, Berger and Hann 2007, and Hund, Monk, and Tice 2010), we conjecture that industry effects on profitability forecasting exist and are clearer at the segment level but can be obscured when segment-level data capturing the effects are aggregated to the firm level. To verify the conjecture, we examine two implications of the conjecture elaborated below.

First, to the extent that single-segment firms on average are less diversified (more homogenous) than multiple-segment firms, we can find industry effects at the firm level for single-segment firms but not for multiple-segment firms.

H1: The firm profitability forecast improvement is positive for single-segment firms but not for multiple-segment firms.

However, there is an opposing effect against this prediction. Prior studies suggest that some firms lump together several segments to report as one segment externally (e.g., Botosan and Stanford 2005). Hence, a firm reporting to have a single segment cannot be taken literally as a firm with only one relatively homogeneous internal unit. If many firms lump together all segments to report as a single segment, such single-segment firms need not be on average less diversified than multiple-segment firms. In such circumstances, we may not be able to find significant industry effects at the firm level for single-segment firms.

Therefore, the first hypothesis is a joint test of our conjecture and the maintained assumption that not too many genuinely multiple-segment firms have reported as single-segment firms. Confirming the hypothesis is a strong support to our conjecture. Failing to confirm it could be due to the violation of the maintained assumption.

By definition a segment of a firm is more homogeneous in activities than the firm itself. If as conjectured it is only because of aggregated reporting at the firm level that obscures the industry effects on profitability forecasting, then we should see the effects re-appearing at the segment level. This gives our second hypothesis for testing:

H2: The segment profitability forecast improvement is positive.

2.2 Research Design

Like Fairfield, Ramnath, and Yohn (2009), our procedure to construct forecast improvements involves two steps. First, we estimate an IS and an EW model of firm/segment profitability. Three specifications are considered, ranging from the basic first-order autoregressive specification stated below to two augmented versions to be detailed shortly:

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

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

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 IS model estimates a regression for each industry j separately, whereas the EW model pools all observations into one regression. We estimate the year-indexed coefficients on a rolling basis using the most recent 10 years of data. For example, to estimate α_t and β_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 reasonably reliable estimates, we require a minimum of 100 observations for each rolling regression. Some industries are excluded from the analysis owing to too few observations. For equal-footing comparisons, we estimate the EW model using only observations that are included to estimate the IS model.

Besides the basic specification, we consider augmented versions of the model by adding first a dummy variable to capture nonlinear mean reversion of profitability and then in the third specification also the predicted value of sales growth. This last version of the in-sample regression that contains all the variables is as follows:

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

$$\text{EW model: } x_{i,t} = \alpha_t + \beta_t x_{i,t-1} + \gamma_t D_{i,t} x_{i,t-1} + \lambda_t\, \text{PREDGSL}_{i,t} + \varepsilon_{i,t},$$

where $D_{j,i,t}$ in the IS model is a dummy variable equal to 1 if in year $t - 1$ the profitability of firm/segment i is below the mean profitability of all firms/segments in the same industry j, and zero otherwise. The dummy variable $D_{i,t}$ in the EW model is the counterpart of $D_{j,i,t}$ for all firms/segments in any industry. These dummy variables allow the mean reversion of profitability to differ for firms/segments with above- and below-average profitability. Fama and French (2000), among others, have documented a non-linear pattern of the mean reversion of profitability.

Penman (2003) and Lundholm and Sloan (2007) suggest that predicted sales growth should be important to profitability forecasting. Therefore, in the third specification we also include the predicted sales growth of a firm/segment, $\text{PREDGSL}_{i,t}$. This is the fitted value of a first-order autoregressive regression of sales growth: $g_{i,t} = \eta_{j,t} + \theta_{j,t}\, g_{i,t-1} + \varepsilon_{i,t}$, where $g_{i,t}$ is the percentage change in sales of firm/segment i from year $t-1$ to year t and $\eta_{j,t}$ and $\theta_{j,t}$ are coefficients of the model. The regression is carried out for each industry j separately because Fairfield, Ramnath, and Yohn (2009) have documented a significant industry effect on sales growth forecasting.

In the second step of the procedure to construct forecast improvements, we use the estimated coefficients of the in-sample regressions and the observed profitability of last year to forecast the firm/segment profitability of the current year. For the basic first-order autoregressive specification, this means

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

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

where a and b denote the estimated coefficients. The counterparts of the two augmented specifications are defined analogously.

To perform an out-of-sample test on the relative accuracy of the two models, we first calculate for each observation the absolute forecast error (AFE) defined as the absolute difference between the profitability actually observed and the profitability forecast:

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

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

where AFE_{IS} and AFE_{EW} are the absolute forecast errors for a firm/segment of a year based on the IS and EW models, respectively. Next, we calculate the forecast improvement (FI) of the IS over EW model by deducting AFE_{IS} from AFE_{EW}:

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

If IS analysis can improve the accuracy of profitability forecasting compared to EW analysis, the FI measure should be positive on average.

To assess the average magnitude of the firm/segment profitability forecast improvement, we calculate the overall average across all firm/segment observations, respectively. This is referred to as the *pooled mean* in the result tables. Following Fairfield, Ramnath, and Yohn (2009), we also calculate another measure of average forecast improvement by taking the mean of the yearly average forecast improvements. This is referred to as the *grand mean*. Most of the results are robust to the two measures. In our view, the pooled mean uses information more efficiently than the grand mean. Thus, the latter is a more conservative measure for proving significant forecast improvements. The p-values reported in the result tables are obtained from t-tests based on robust standard errors.[6]

[6] For the pooled mean, standard errors are clustered by firm and year following Rogers (1993); for the grand mean, standard errors are adjusted following Newey and West (1987).

3. Data and Sample Selection

In this section, we give an overview of the data used and the sample constructed, followed by a discussion of the summary statistics.

The firm and business segment data used in the analysis come from the Compustat annual fundamentals and Compustat segments databases of the Wharton Research Data Services (WRDS). Most of the analysis uses segment data, which are available from as early as 1976. Because the data coverage in the initial year is not good, we use data from 1977 onward. Our in-sample regressions require 10 years of data to estimate the coefficients of the models. So the earliest forecasts for the out-of-sample tests for business segments are from 1987. In some of the analysis involving firm data, the in-sample regressions require 20 years of data. Therefore, we use firm data from 1967 onward. This allows the earliest forecasts for the out-of-sample tests for firms to be available from 1987 as well, facilitating comparing the results of the firm- and segment-level analyses.

We use the two-digit primary Standard Industry Classification (SIC) code to define the industry to which a firm or business segment belongs.[7] Observations with missing SIC codes are excluded from the sample. To avoid distortions caused by regulated industries, we also 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). Besides the financial and utilities sector, we also exclude the U.S. postal service (SIC 4311) and non-classifiable establishments (SIC above 9900).

[7] Some studies (e.g., Fairfield, Ramnath, and Yohn 2009) use the Global Industry Classification Standard (GICS) to classify industries. However, GICS codes are often unavailable for segment-level data.

Some firms in the sample change their internal structure from time to time, which leads to changes in the number of the disclosed segments and possibly their SIC codes. Such a restructuring requires firms to restate previous segment information to make them comparable across years. We use the restated information in the in-sample regressions, but not in the out-of-sample analysis to prevent look-ahead bias.

In some of the analysis, we distinguish between single- and multiple-segment firms. Multiple-segment firms are firms that report more than one segment; single-segment firms are those reporting only one segment. Following SFAS 131, some firms have changed the number of reported segments from one in 1997 to more than one by 1999, suggesting that they might not be genuinely single-segment firms prior to 1997. Owing to the doubt in correctly classifying these firms, we exclude them from analyses that require a differentiation between single- and multiple-segment firms.

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.[8] To mitigate the impact of small denominators on firm 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 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

[8] The deletion of double observations per calendar year reduces the sample size by 4 observations in the firm-level analysis and by 807 observations in the segment-level analysis.

mergers and acquisitions, we remove observations with growth in operating assets, net operating assets, book value of equity, and sales above 100%. Recall that our analysis has an in-sample regression step and an out-of-sample test step. 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 again before the out-of-sample tests to avoid any look-ahead bias in the analysis.

We focus on return on assets (ROA) and return on sales (ROS) as profitability measures. Return on net operating assets (RNOA) and return on equity (ROE) are also used as alternative measures in the firm-level analysis to be comparable to Fairfield, Ramnath, and Yohn (2009). Due to data limitations, these measures cannot be constructed at the segment level. Table 1 summarizes the definitions of the four profitability measures and the variables used to compute the measures.

Panel A of table 2 summarizes the number of observations after applying each exclusion criterion described above. The exclusion criteria are similar to those in Fairfield, Ramnath, and Yohn (2009). For consistency, only observations with all four profitability measures available are used in the firm-level analysis and only those with both ROA and ROS measures available are used in the segment-level analysis.

Profitability forecasts are constructed from the estimated coefficients of in-sample regressions based on the most recent 10 years of data (for segment-level analysis) or up to 20 years (for firm-level analysis). So forecasts are available for out-of-sample tests only from 1987 onward. Because segment data are required to classify firms into single- or multiple-segment, firm-year observations before 1977 are unclassified owing to no segment data in early years.

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 section 4. The firm-level analysis uses 51,869 observations of 7,169 unique firms, whereas the segment-level analysis is based on 90,422 observations of 17,151 unique segments.

For firms, the ROA on average is 8.50%, while the mean ROS is slightly higher, reaching 8.66%. With 14.21%, the mean RNOA is considerably higher. In contrast, the average ROE is much lower: only 7.49%. These statistics are similar to those in prior studies, such as Fama and French (2000) and Fairfield, Ramnath, and Yohn (2009). In terms of ROA, the segment profitability is 8.68% on average, very similar to the firm profitability. However, the segment ROS is somewhat lower, with an average equal to 7.25%.

Panel C reports for each industry the number of observations, as well as average profitability. With 4,747 firm-year and 7,824 segment-year observations, *electronic & other electric equipment* (SIC 36) constitutes the largest industry in the sample. Other large industries are *chemicals & allied products* (SIC 28), *industrial machinery & equipment* (SIC 35), *instruments & related products* (SIC 38), and *business services* (SIC 73).

There is substantial variation in profitability across industries. For firms, *chemicals & allied products* is the sector with the highest ROA (10.7%), whereas *communications* has the highest ROS (19.7%). The lowest ROA is from *auto repair, services & parking* (4.9%), and the lowest ROS is from *food stores* (3.4%). Apart from industries with only a few observations, the highest segment ROA is from *educational services* (13.0%) and the highest and second highest segment ROS are from *pipelines, except natural gas* (25.1%) and *communications* (19.0%), respectively. *Metal mining* has the lowest segment ROA (4.2%), and *food stores* has the lowest segment ROS (2.9%).

4. Results on Forecast Improvement of IS over EW Model

The results of our firm- and segment-level analyses for the whole data period and the SFAS 14 period are discussed in this section. We conclude the section with an extension of the analysis to sales growth forecast improvement of IS over EW model.

4.1 Firm-level Analysis

We begin with panel A of table 3 that verifies whether Fairfield, Ramnath, and Yohn's (2009) *no industry effect* result for profitability forecasting continues to hold for our sample covering 1987-2011. As expected, firm profitability forecast improvements (of IS over EW analysis) are not significantly different from zero for the two profitability measures, namely ROE and RNOA, analyzed by Fairfield, Ramnath, and Yohn's (2009). The result holds regardless of the specifications considered or the way the mean forecast improvements are computed. The *no industry effect* finding is further confirmed when using ROA as the profitability measure. The use of this measure facilitates comparison with the results based on segment-level analysis (where ROE and RNOA cannot be computed owing to data limitations).

Interestingly, we also obtain a new finding: In terms of ROS, the firm profitability forecast improvement is highly significantly positive, regardless of the specifications or forecast improvement measures. This suggests that Fairfield, Ramnath, and Yohn's (2009) *no industry effect* result for profitability forecasting may be sensitive to the profitability measure used. Notwithstanding this, the new finding can be completely consistent with our conjecture that industry effects on profitability forecasting are stronger at the segment level than at the firm level. The results of our two tests presented below provide evidence supporting the conjecture as well as the consistency with the new finding based on ROS.

We argue that the lack of (or weaker) industry effect at the firm level is due to aggregated reporting that obscures the relation between profitability and industry-specific characteristics. Many firms do not operate in a single industry. Often they have different lines of business organized into units reported as business segments. When the segments of a multiple-segment firm are associated with different industries, there is no one single industry that can accurately represent the whole firm. Describing a multiple-segment firm with a primary industry ignores the relation between its profitability and the other industries to which its segments belong. In contrast, for firms with a single business segment, the firm-level reporting does not distort the truth – the only segment of a single-segment firm is effectively identical to the whole firm. If industry effects on profitability forecasting exist at the segment level, they should also be observed at the firm level when confining to single-segment firms. However, for multiple-segment firms, the effects can still be insignificantly different from zero.

To test this hypothesis (H1), we match the sample of firm profitability forecast improvements with the business segment data. This allows partitioning the forecast improvements into subsamples for single- and multiple-segment firms. The results are presented in panel B of table 3. The reduction in the total sample size to 34,733 in the panel is mainly due to the unavailability of segment data for matching. Moreover, we exclude observations with the firm sales deviated more than 1% from the aggregated segment sales to mitigate data quality concerns. Owing to the doubt in correctly classifying firms that might not be genuinely single-segment, as suggested by the increase in the reported number of segments to more than one immediately after SFAS 131, we also exclude such firms from the analysis.

By partitioning the sample, we find evidence strongly supporting H1. First of all, except for one case (namely, ROA with the second specification), all the forecast improvements for multiple-segment firms are statistically indistinguishable from zero. So EW analysis remains as good as IS analysis in forecasting firm profitability for multiple-segment firms, as predicted by the hypothesis.

In contrast, the forecast improvements for single-segment firms generally are significantly positive. Many are at the 5% or even 1% significance level. Although in terms of ROE the forecast improvements for single-segment firms are insignificant in the first two specifications, they become significantly positive at the 10% level when predicted sales growth (PREDGSL) is included in the third specification. Overall, the evidence provides solid support for the prediction that IS analysis is useful for profitability forecasting even at the *firm* level when confining to single-segment firms.

Consistent with our conjecture, the point estimates of the forecast improvements for single-segment firms in panel B of table 3 are all markedly greater than their counterparts in the full sample in panel A. This holds even for ROS, which unlike the other profitability measures shows strong industry effects on profitability forecasting at the firm level even for the full sample that contains both single- and multiple-segment firms. The fact that for ROS the industry effects appear only in the subsample of single-segment firms but not in the other at all is a very clean support to the first hypothesis. Therefore, we conclude that the findings above broadly confirm H1.

Although the forecast improvement for single-segment firms on average is not large, the economic significance of the improvement is material for certain industries. For example, one of the largest industry sectors is *communications* (SIC 48). This industry sector has an ROE forecast improvement of 1.3%. Given that the single-segment firms in this sector on average have an ROE of about 13.8%, the forecast improvement of 1.3% means IS forecasts on average being 9.4% (= 1.3% / 13.8%) closer to the actual ROE than EW forecasts. Other industries with material forecast improvements for single-segment firms include *chemicals & allied products* (SIC 28), *railroad transportation* (SIC40), and *transportation services* (SIC 47).

As already explained, we have doubt in correctly classifying firms that might not be genuinely single-segment firms prior to 1997 and thus exclude them in the analysis above. To verify that the nature of these "non-classified" firms is consistent with our suspicion, we also analyze the forecast improvements for this group of firms. Since we suspect that they are disguised multiple-segment firms, we expect no significant forecast improvements for these firms. The results tabulated in appendix table 1 (available upon request) confirm the expectation. None of the forecast improvements is significant, regardless of the profitability measure and the regression specification used. As such, the finding also provides further indirect evidence for the hypothesis that under SFAS 14, managers hid important segment information from analysts and investors (Botosan and Stanford 2005).

In the next subsection, we turn to the segment-level analysis to obtain more direct evidence to support our conjecture.

4.2 Segment-level Analysis

If what drives our results of H1 is the existence of industry effects on profitability forecasting at the segment level, we should also observe forecast improvements of IS over EW analysis for segment profitability. Table 4 shows the results of this hypothesis (H2). Only the first two specifications of in-sample regression are considered here because the segment predicted sales growth (PREDGSL) of the third specification requires 20 years of data to construct. Given that our segment data start from 1977, this would leave too few years in the out-of-sample test period for the results to be reliable. Moreover, even if considered, the results of the third specification would not be directly comparable to other results based on the 1987-2011 out-of-sample test period.

The results in table 4 provide some support for H2. When profitability is measured in terms of ROS, the segment profitability forecast improvements are significantly positive at the 5% or even 1% level, regardless of the two specifications or the way the mean forecast improvements are measured. In terms of the magnitude, the point estimates are also in line with those of the firm profitability forecast improvements for single-segment firms in panel B of table 3. Note that the segment-level analysis includes all segments, whether they belong to single- or multiple-segment firms. The similar magnitude of the point estimates of the forecast improvements suggests that a segment, regardless of where it is from, behaves like a single-segment firm. This is consistent with the belief that what drives our results of H1 is the existence of industry effects on profitability forecasting at the segment level.

However, in terms of ROA, the forecast improvements are not strong enough to be regarded as significant at the conventional level. This difference between the results for ROS and ROA highlights an issue about segment data in the SFAS 131 period already recognized in the literature. Arguably, ROS is more reliable than ROA as a profitability measure in the sense that sales unlike identifiable assets can be correctly assigned to segments without ambiguity. The reliability of ROA decreases in the SFAS 131 period because firms are only required to align the segment reporting with the internal structure and accounting. Consequently, segment profits become less comparable across firms owing to non-uniform definitions adopted by different entities (Berger and Hann 2003 and Berger and Hann 2007). In contrast, SFAS 14 asked firms to report segment information according to industry classification. Most important, the segment profits reported must conform to the US generally accepted accounting principles (GAAP), ensuring certain level of comparability across firms.

Although the issue above also affects ROS, the impact is unlikely to be as severe because the denominator, namely segment sales, can be more reliably measured than its counterpart in ROA, namely the identifiable assets of a segment. Thus, the results in table 4 are consistent with the well-recognized problem of segment profit data in the SFAS 131 period. To provide further support of this explanation of the results in table 4 and for robustness checking, we re-examine the two hypotheses using only data from the SFAS 14 period. The results are discussed in the next subsection.

4.3 Analysis for the SFAS 14 Period

Table 5 shows the results of H2 using data from the SFAS 14 period. The sample size decreases considerably to 46,917 segment-year observations, only about half of the size of the full sample. By excluding observations with problematic segment profit data from the SFAS 131 period, we find clear support to H2. Apart from one exception, all the segment profitability forecast improvements are significantly positive at the 5% level, regardless of the profitability measures, the two specifications, or the way the mean forecast improvements are measured. The exception is also significantly positive, though at the 10% level. For ROS, which arguably is the more reliable profitability measure, the significance levels of the forecast improvements are uniformly at 1%. All of the previously insignificant results for ROA now become significantly positive. Overall, we conclude that the evidence in table 5 strongly supports H2.

As in the analysis for single-segment firms, *communications* (SIC 48) is the industry sector with the largest forecast improvements. For instance, the segment ROS and ROA forecast improvements are 1.5% and 0.7%, respectively. The segments in this sector on average have an ROS of about 19% and an ROA of about 10%. Therefore, IS forecasts on average are around 8% and 7% closer to the actual ROS and ROA, respectively, than EW forecasts. Other industries with material forecast improvements are *food & kindred products* (SIC 20), *chemicals & allied products* (SIC 28), *rubber & plastic products* (SIC 30), and *railroad transportation* (SIC40).

For completeness and robustness checking, we also revisit H1 using data from the SFAS 14 period. To be more comparable with the results in table 5, we restrict to the same in-sample and out-of-sample periods in table 6 and consequently only consider the same two specifications. Excluding the observations from the SFAS 131 period reduces the total size of the sample to 16,546 firm-year observations. Among these, 10,242 observations are from single-segment firms, with the remaining 6,304 from multiple-segment firms.

Again, table 6 strongly supports the prediction in H1 that IS analysis is useful for profitability forecasting even at the *firm* level when confining to single-segment firms. All the forecast improvements for single-segment firms are highly significantly positive at the 5% level. Most of the forecast improvements are also significant at the 1% level.

The results for multiple-segment firms also broadly support the prediction that EW analysis remains as good as IS analysis in forecasting firm profitability for such firms. Apart from a few exceptional cases (namely, ROE and ROS), all other forecast improvements for multiple-segment firms are statistically indistinguishable from zero. Taken together, the evidence in table 6 provides solid support for H1.

The difference in the results between the two accounting regimes highlights a potential drawback of the new accounting standard SFAS 131. The new standard has clearly brought many benefits, such as an increase in the number of reported segments and a higher informative value of the segment data. On the other hand, under SFAS 131 the segment data are less comparable across firms. The increased noise in the segment data limits the usefulness of the data in predicting profitability and hence reduces the accuracy of industry-specific forecasting models at the segment level.

4.4 Extension: Sales Growth Forecasting

One of the in-sample regression specifications of the firm-level analysis in section 4.1 uses a firm's predicted sales growth (PREDGSL) as an explanatory variable. As explained in section 2.2, this variable is itself constructed from an IS forecasting model because Fairfield et al. (2009) has documented a significant industry effect on sales growth forecasting. However, it is a priori not clear that such an effect also exists in the sample of this study. Moreover, it is interesting to know whether our conjecture on profitability forecasting also applies to sales growth forecasting, i.e., industry effects on sales growth forecasting exist and are clearer at the segment level, but can be obscured when data are aggregated to the firm level. To examine these issues, we repeat the firm- and segment-level analysis on sales growth forecasting using exactly the same empirical approach and dataset as in the analysis on profitability forecasting.

The results presented in table 7 underline the importance of using IS models to forecast firm and segment sales growth. Panel A of the table summarizes the results from the firm-level analysis. Similar to Fairfield et al. (2009), we find a significant forecast improvement of IS over EW model for the period from 1987 to 2011. This justifies the inclusion of PREDSGL as an additional explanatory variable in forecasting firm profitability in section 4.1.

Next, we partition the sample of firms into single- and multiple-segment firms. Panel B of table 7 shows the forecast improvements for these two subsamples. While for single-segment firms, the forecast improvement of IS over EW model is highly significant at the 1% level, sales growth forecasts for multiple-segment firms cannot be significantly improved using IS analysis. The finding supports the extension of H1 to sales growth forecasting. Finally, panel C of the table shows that at the segment level the sales growth forecast improvement of IS over EW model is significantly positive. This last result supports the extension of H2 to sales growth forecasting.

5. Concluding Remarks

Fairfield, Ramnath, and Yohn (2009) have shown that there is no incremental advantage of using IS analysis for predicting firm profitability, compared to EW analysis. Yet, several studies have presented evidence that firm profitability is at least partly governed by industry effects (e.g., Bou and Satorra 2007 and McGahan and Porter 1997). This paper proposes an intuitive reconciliation of these seemingly conflicting findings, based on the fact that many firms have multiple business segments operating in different industries. We argue that when segment-level data are aggregated to the firm level for external reporting, industry effects on forecasting profitability are obscured at the firm level.

Our empirical analysis shows that IS models are indeed significantly more accurate than EW models in predicting profitability and growth at the segment level. We even find higher accuracy in predicting profitability at the *firm* level when confining to single-segment firms, which operate in one industry only. Taken together, the findings underline that industry factors have an impact on profitability and growth forecasting. It is merely because of the aggregated nature of firm-level data that prevents the industry effects from standing out in firm-level analysis.

Besides the results above, we document that when profitability is measured in terms of ROS, industry effects on profitability forecasting can be clearly seen at the firm level even without focusing on single-segment firms. This interesting new finding strengthens the conclusion that industry characteristics are indeed important to profitability forecasting. The finding also serves as a support for the conventional wisdom that sales convey valuable information about a firm's future prospect.

The results of this study are relevant to the accounting disclosure literature as well. Since we find that segment-level data can provide more accurate information about a firm's future profitability, this can be taken as evidence for the usefulness of less aggregated accounting disclosure. The complication due to segment data under SFAS 131 however highlights the importance of ensuring comparability of the reported business segment data.

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Table 1
Variable definitions

Variable name	*Description*	*Computation Firm-level analysis (Compustat fundamentals annual)*	*Computation Segment-level analysis (Compustat segments)*
NI_t *(in mn)*	Income before extraordinary items – available for common equity	Compustat item 237 WRDS mnemonic: IBCOM	
BV_t *(in mn)*	Common/ordinary shareholder's equity	Compustat item 60 WRDS mnemonic: CEQ	
$OPINC_t$ *(in mn)*	Operating income after depreciation	Compustat item: 178 WRDS mnemonic: OIADP	WRDS mnemonic: OPS
TA_t *(in mn)*	Identifiable/total assets	Compustat item 6 WRDS mnemonic: AT	WRDS mnemonic: IAS
$SALES_t$ *(in mn)*	Total sales	Compustat item: 12 WRDS mnemonic: SALE	WRDS mnemonic: SALES
NOA_t *(in mn)*	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	$OPINC_t/(0.5*(SALES_t + SALES_{t-1}))$	$OPINC_t/(0.5*(SALES_t + SALES_{t-1}))$
$RNOA_t$	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	$(SALES_t - SALES_{t-1})/ SALES_{t-1}$	$(SALES_t - SALES_{t-1})/ SALES_{t-1}$

NI (income before extraordinary items), *BV* (common shareholder's equity), *OPINC* (operating income), *TA* (total assets), *SALES* (total sales), and *NOA* (net operating assets) are reported in USD million. If the data items *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
Time period: 1987-2011

Panel A: Sample selection						
Adjustments to data sample	Firm-level data (firm-year observations)				Segment-level data (segment-year observations)	
	ROA	*ROS*	*RNOA*	*ROE*	*ROA*	*ROS*
Observations for in-sample regressions:						
Total observations, excluding utilities and financial firms/segments	254,248	246,176	253,354	253,419	254,126	267,918
Less observations with small denominators	159,188	158,737	158,346	158,381	236,060	249,298
Less observations with an absolute value larger than 1	159,150	157,494	155,469	154,808	232,878	239,991
Less observations with more than 100% growth	140,882	140,153	139,165	138,352	210,962	207,997
Less upper and lower centiles observations	138,066	137,351	136,383	135,586	206,744	203,839
Observations for out-of-sample tests, out of which:	51,869				90,422	
single-segment firms	20,362					
multiple-segment firms	14,371					
unclassified	17,145					

Panel A 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) and non-classifiable establishments (SIC 99). For variable definitions, see table 1. Single-segment firms are firms that report only one segment; multiple-segment firms are those reporting more than one segment. Following SFAS 131, some firms have changed the number of reported segments from one in 1997 to more than one in 1999, suggesting that they might not be genuinely single-segment firms prior to 1997. Owing to the doubt in correctly classifying these firms, they are excluded from the sub-samples of single- and multiple-segment firms.

Table 2
Sample selection and descriptive statistics (*Continued*)

Panel B: Summary statistics					
Variable	Mean	Std. Deviation	First Quartile	Median	Third Quartile
Firm-level: 7,169 firms (51,869 firm-year obs.)					
NI	192.412	1,107.492	1.244	12.682	76.000
OPINC	363.225	1,617.542	5.540	30.589	159.889
TA	4,080.182	15,838.560	114.167	421.375	1,912.887
NOA	2,394.291	9,496.890	69.625	261.324	1,165.151
BV	1,581.442	6,485.568	57.038	198.206	813.700
SALES	3,714.045	14,669.310	134.677	475.051	1,890.907
ROA	8.50%	7.53%	4.26%	8.52%	12.98%
ROS	8.66%	9.23%	3.30%	7.51%	12.99%
RNOA	14.21%	13.89%	6.55%	13.22%	21.16%
ROE	7.49%	15.08%	2.39%	9.71%	15.93%
Segment-level: 17,151 segments (90,422 segment-year obs.)					
TA	1,281.919	5,094.477	31.743	149.180	669.580
OPINC	125.045	556.830	0.667	10.175	63.268
SALES	1,432.484	6,362.375	41.967	185.551	765.200
ROA	8.68%	13.99%	2.52%	8.95%	15.78%
ROS	7.25%	12.86%	1.79%	6.99%	13.41%

Panel B gives an overview of the firm and segment data used to compute the average forecast improvements in the out-of-sample tests. Because profitability forecasts are constructed from the estimated coefficients of in-sample regressions based on the most recent 20 years of data, forecasts are not available for out-of-sample tests until 1987 onward.

Table 2
Sample selection and descriptive statistics (*Continued*)

Panel C: Descriptive statistics by industry									
Two-digit SIC	Description	Firm-level					Segment-level		
		Obs.	*ROA*	*ROS*	*RNOA*	*ROE*	Obs.	*ROA*	*ROS*
01	Agricultural production-crops	10	5.15%	9.00%	7.08%	6.37%	279	6.93%	9.89%
02	Agricultural production-livestock	0	-	-	-	-	3	8.93%	6.54%
07	Agricultural services	0	-	-	-	-	3	15.89%	13.48%
10	Metal mining	592	5.10%	10.26%	8.03%	4.84%	521	4.15%	7.07%
12	Coal mining	0	-	-	-	-	289	8.39%	10.77%
13	Oil & gas extraction	1,619	6.50%	14.59%	9.67%	6.11%	2,810	6.87%	13.78%
14	Nonmetallic minerals	11	10.12%	9.55%	15.64%	11.28%	311	11.95%	12.90%
15	General building	473	7.16%	6.74%	9.92%	7.62%	699	5.51%	4.08%
16	Heavy construction	74	8.03%	6.30%	16.28%	9.47%	391	6.83%	3.28%
17	Special trade contractors	0	-	-	-	-	367	7.00%	3.72%
20	Food & kindred products	2,299	10.00%	8.24%	15.84%	10.99%	2,846	11.79%	8.08%
21	Tobacco products	0	-	-	-	-	1	-0.58%	-0.70%
22	Textile mill products	555	8.35%	6.36%	11.85%	4.00%	896	7.85%	5.27%
23	Apparel & other textile	734	9.71%	7.47%	15.11%	7.40%	963	10.51%	6.69%
24	Lumber & wood	579	6.63%	6.59%	10.50%	5.03%	917	9.77%	6.50%
25	Furniture & fixtures	551	9.47%	6.33%	14.78%	8.32%	803	9.03%	5.41%
26	Paper & allied products	1,173	8.29%	8.57%	12.22%	7.77%	1,790	10.55%	8.99%
27	Printing & publishing	1,060	10.03%	10.00%	15.73%	9.25%	1,834	12.12%	9.77%
28	Chemicals & allied products	3,354	10.65%	11.56%	18.25%	11.08%	5,797	12.16%	10.02%
29	Petroleum & coal	765	10.04%	10.20%	17.07%	12.38%	878	8.83%	5.13%
30	Rubber & plastic products	851	10.06%	7.70%	15.73%	7.76%	1,838	12.37%	8.08%
31	Leather	253	9.63%	5.94%	16.39%	5.99%	443	7.01%	4.22%
32	Stone, clay & glass	554	9.02%	9.65%	13.41%	9.09%	1,193	11.22%	9.57%
33	Primary metal products	1,401	7.79%	7.03%	11.91%	5.77%	2,175	9.12%	6.49%
34	Fabricated metal products	1,360	9.50%	7.98%	15.08%	8.66%	2,653	11.93%	7.80%
35	Industrial machinery & equipment	3,672	7.74%	6.96%	13.58%	6.54%	7,508	7.58%	5.06%
36	Electronic & other electric equipment	4,747	6.81%	6.44%	12.22%	4.44%	7,824	6.90%	4.79%
37	Transportation equipment	1,909	8.38%	7.32%	15.00%	8.62%	3,136	10.70%	7.03%
38	Instruments & related products	3,244	8.94%	9.38%	15.13%	7.42%	6,045	7.45%	6.22%
39	Misc. manufacturing industries	676	8.08%	6.83%	13.71%	4.94%	1,079	8.03%	5.83%

40	Railroad transportation	401	7.08%	17.07%	11.53%	8.73%	424	6.93%	15.89%
42	Trucking & warehouse	669	9.18%	6.66%	15.03%	8.60%	953	8.65%	5.72%
44	Water transportation	307	6.42%	13.70%	8.80%	6.02%	644	6.95%	14.05%
45	Transportation by air	553	6.29%	7.84%	11.91%	5.60%	906	4.95%	4.92%
46	Pipelines, except natural gas	0	-	-	-	-	59	8.38%	25.08%
47	Transportation services	78	9.72%	9.12%	19.07%	8.76%	456	9.65%	8.61%
48	Communications	2,746	10.22%	19.74%	15.49%	11.41%	3,716	10.27%	18.95%
49	Electric, gas & sanitary services	280	5.99%	12.58%	8.69%	4.64%	785	6.27%	9.27%
50	Wholesale trade-durable products	2,002	8.01%	4.86%	12.74%	7.28%	3,302	7.97%	3.73%
51	Wholesale trade-nondurable goods	1,105	7.79%	5.20%	13.51%	8.27%	1,910	8.73%	4.56%
52	Building materials	133	7.97%	4.03%	12.08%	3.36%	285	6.99%	3.60%
53	General merchandise stores	723	8.80%	4.78%	14.58%	8.09%	901	7.28%	3.74%
54	Food stores	794	9.14%	3.36%	15.55%	9.04%	822	9.02%	2.90%
55	Automotive dealers & services	173	8.03%	4.18%	11.55%	8.10%	377	6.99%	3.76%
56	Apparel & accessory stores	776	9.83%	5.06%	19.81%	8.08%	1,088	11.74%	5.39%
57	Furniture stores	413	8.60%	4.60%	17.53%	5.92%	619	6.40%	3.49%
58	Eating & drinking places	1,100	10.31%	7.62%	15.10%	7.75%	1,795	8.27%	5.42%
59	Miscellaneous retail	1,155	8.48%	5.16%	14.23%	6.23%	1,786	8.31%	4.45%
70	Hotels & other lodging places	284	5.07%	9.69%	7.07%	2.46%	594	6.38%	10.68%
72	Personal services	27	5.74%	9.15%	9.56%	5.83%	245	10.84%	10.23%
73	Business services	3,281	7.53%	8.43%	15.65%	5.76%	6,982	5.98%	5.54%
75	Auto repair, services & parking	17	4.88%	6.99%	6.71%	3.33%	247	5.31%	6.56%
76	Misc. repair services	0	-	-	-	-	4	16.70%	8.57%
78	Motion pictures	206	5.54%	6.58%	8.71%	-1.47%	627	4.10%	4.18%
79	Amusement & recreation services	577	8.22%	12.58%	11.85%	3.56%	1,129	7.34%	9.39%
80	Health services	766	10.51%	10.27%	15.30%	7.66%	1,490	9.43%	8.00%
82	Educational services	0	-	-	-	-	265	13.02%	10.48%
83	Social services	0	-	-	-	-	75	12,31%	10.21%
86	Membership organizations	0	-	-	-	-	1	13.16%	8.89%
87	Engineering & management services	787	8.33%	7.00%	16.25%	6.67%	1,643	9.35%	6.27%
Total		51,869	8.50%	8.66%	14.21%	7.49%	90,422	8.68%	7.25%

Panel C reports the number of observations and the average firm and segment profitability in each industry classified by the two-digit SIC.

Table 3
Firm profitability forecast improvements of industry-specific analysis over economy-wide analysis
Time period: 1967-2011 (out-of-sample: 1987-2011)

Panel A: Total sample, firm observations: 51,869

In-sample regression model	AR(1)		AR(1) + NL dummy		AR(1) + NL dummy + PREDGSL	
	mean	p-value	mean	p-value	mean	p-value
ROE						
Pooled mean	-0.005%	0.805	-0.005%	0.747	0.060%	0.259
Grand mean	-0.004%	0.828	-0.006%	0.692	0.072%	0.229
RNOA						
Pooled mean	0.017%	0.248	0.004%	0.754	0.000%	0.992
Grand mean	0.017%	0.207	0.005%	0.693	0.002%	0.940
ROA						
Pooled mean	0.012%	0.162	0.000%	0.966	0.007%	0.630
Grand mean	0.013%	0.114	0.001%	0.903	0.009%	0.550
ROS						
Pooled mean	0.052%	<0.001	0.035%	0.001	0.045%	0.001
Grand mean	0.053%	<0.001	0.036%	0.001	0.046%	0.002

Table 3 (*Continued*)

Firm profitability forecast improvements of industry-specific analysis over economy-wide analysis

Time period: 1967-2011 (out-of-sample: 1987-2011)

Panel B: Sample partitioned into single- and multiple-segment firms

In-sample regression model	AR(1)				AR(1) + NL dummy				AR(1) + NL dummy + PREDGSL			
Firm type	Single-segment firms		Multiple-segment firms		Single-segment firms		Multiple-segment firms		Single-segment firms		Multiple-segment firms	
Firm observations	20,362		14,371		20,362		14,371		20,362		14,371	
	mean	p-value	mean	p-value	mean	p-value	mean	p-value	mean	p-value	mean	p-value
ROE												
Pooled mean	0.031%	0.229	-0.015%	0.623	0.013%	0.581	-0.020%	0.445	0.095%	0.063	0.066%	0.378
Grand mean	0.029%	0.152	-0.012%	0.623	0.012%	0.486	-0.018%	0.407	0.092%	0.089	0.072%	0.331
RNOA												
Pooled mean	0.050%	0.003	-0.001%	0.977	0.037%	0.031	-0.012%	0.564	0.043%	0.044	-0.003%	0.940
Grand mean	0.048%	0.002	0.001%	0.945	0.036%	0.016	-0.010%	0.578	0.040%	0.050	-0.001%	0.971
ROA												
Pooled mean	0.037%	<0.001	-0.009%	0.528	0.023%	0.023	-0.022%	0.100	0.032%	0.007	-0.005%	0.827
Grand mean	0.037%	<0.001	-0.008%	0.494	0.022%	0.015	-0.020%	0.073	0.030%	0.011	-0.004%	0.852
ROS												
Pooled mean	0.089%	<0.001	0.007%	0.616	0.072%	<0.001	0.006%	0.671	0.092%	<0.001	0.020%	0.353
Grand mean	0.089%	<0.001	0.008%	0.445	0.071%	<0.001	0.007%	0.535	0.090%	<0.001	0.021%	0.310

The panels of this table report the average firm profitability forecast improvement of industry-specific analysis over economy-wide analysis. The firm profitability forecast is based on the fitted value from the first-order autoregressive model estimated on a rolling basis using the most recent 10 years of data. We use three different in-sample regression models, a simple AR(1), an AR(1) augmented with a dummy variable (NL dummy) for observations with below average firm profitability, and an AR(1) that includes both the dummy variable and predicted sales growth (PREDGSL). Predicted sales growth is similarly the fitted value from the first-order autoregressive model estimated on a rolling basis using the most recent 10 years of data. (for more details, see section 4.1). The pooled mean is the average forecast improvement when pooling the observations of all years together. The grand means is the mean of the yearly average forecast improvements. The p-values reported in the result tables are obtained from t-tests based on robust standard errors. For the pooled mean, standard errors are clustered by firm and year following Rogers (1993); for the grand mean, standard errors are adjusted following Newey and West (1987). Panel A is based on the total sample of firm profitability forecast improvements. Panel B is based on the single- and multiple-segment firm subsamples. To utilize segment-level information to categorize single- and multiple-segment firms, firm-level data are matched to segment-level data to construct the subsamples. Observations with firm sales deviated from aggregated segment sales by more than 1% are excluded. In addition, firms that have changed the number of reported segments from one in 1997 to more than one in 1999 are also excluded from the single- and multiple-segment firm subsamples (see section 4.2 for details).

Table 4
Segment profitability forecast improvements of industry-specific analysis over economy-wide analysis
Time period: 1977-2011 (out-of-sample: 1987-2011)

Segment observations: 90,422				
In-sample regression model	AR(1)		AR(1) + NL dummy	
	Mean	p-value	Mean	p-value
ROA				
Pooled mean	0.021%	0.233	0.015%	0.556
Grand mean	0.015%	0.382	0.006%	0.799
ROS				
Pooled mean	0.082%	<0.001	0.060%	0.016
Grand mean	0.073%	0.001	0.050%	0.046

The table reports the average segment profitability forecast improvement of industry-specific analysis over economy-wide analysis. The segment profitability forecast is based on the fitted value from the first-order autoregressive model estimated on a rolling basis using the most recent 10 years of data. We use two different in-sample regression models, a simple AR(1), and an AR(1) augmented with a dummy variable (NL dummy) for observations with below average firm profitability (see section 4.1 for details). The pooled mean is the average forecast improvement when pooling the observations of all years together. The grand means is the mean of the yearly average forecast improvements. The p-values reported in the result tables are obtained from t-tests based on robust standard errors. For the pooled mean, standard errors are clustered by firm and year following Rogers (1993); for the grand mean, standard errors are adjusted following Newey and West (1987).

Table 5
Analysis of the SFAS 14 Period -
Segment profitability forecast improvements of industry-specific analysis over economy-wide analysis
Time period: 1977-1997 (out-of-sample: 1987-1997)

Segment observations: 46,917.				
In-sample regression model	AR(1)		AR(1) + NL dummy	
	Mean	p-value	Mean	p-value
ROA				
Pooled mean	0.062%	0.011	0.077%	0.030
Grand mean	0.064%	0.028	0.082%	0.054
ROS				
Pooled mean	0.134%	<0.001	0.122%	<0.001
Grand mean	0.137%	<0.001	0.126%	0.002

This table reports the segment profitability forecast improvements of industry-specific analysis over economy-wide analysis for the SFAS 14 period. For more details, see table 4.

Table 6
Analysis of the SFAS 14 Period -
Firm profitability forecast improvements of industry-specific analysis over economy-wide analysis
Time period: 1977-1997 (out-of-sample: 1987-1997)

Sample partitioned into single- and multiple-segment firms

In-sample regression model	AR(1)				AR(1) + NL dummy			
Firm type	Single-segment firms		Multiple-segment firms		Single-segment firms		Multiple-segment firms	
Firm observations	10,242		6,304		10,242		6,304	
	mean	p-value	mean	p-value	mean	p-value	mean	p-value
ROE								
Pooled mean	0.147%	0.007	0.087%	0.278	0.237%	0.003	0.250%	0.051
Grand mean	0.164%	0.012	0.089%	0.249	0.261%	0.011	0.252%	0.070
RNOA								
Pooled mean	0.070%	0.006	0.050%	0.153	0.072%	0.005	0.057%	0.193
Grand mean	0.070%	0.013	0.051%	0.114	0.074%	0.009	0.058%	0.176
ROA								
Pooled mean	0.046%	0.005	0.025%	0.313	0.039%	0.007	0.022%	0.410
Grand mean	0.047%	0.009	0.025%	0.263	0.040%	0.009	0.022%	0.378
ROS								
Pooled mean	0.108%	<0.001	0.040%	0.130	0.100%	<0.001	0.060%	0.039
Grand mean	0.109%	<0.001	0.041%	0.095	0.101%	<0.001	0.061%	0.043

This table reports the firm profitability forecast improvements of industry-specific analysis over economy-wide analysis for the SFAS 14 period. The table is based on the single- and multiple-segment firm subsamples. For more details, see table 3.

Table 7
Sales growth forecast improvements of industry-specific analysis over economy-wide analysis
Time period: 1967-2011 (out-of-sample: 1987-2011)

Panel A: Firm-level analysis. Total sample, firm observations: 51,869		
In-sample regression model	AR(1)	
	mean	p-value
Pooled mean	0.061%	0.019
Grand mean	0.060%	0.032

Panel B: Firm-level analysis. Sample partitioned into single- and multiple-segment firms				
In-sample regression model	AR(1)			
Firm type	Single-segment firms		Multiple-segment firms	
Firm observations	20,362		14,371	
	mean	p-value	mean	p-value
Pooled mean	0.091%	0.001	0.026%	0.407
Grand mean	0.092%	0.003	0.023%	0.468

Panel C: Segment-level analysis. Segment observations: 90,422		
In-sample regression model	AR(1)	
	mean	p-value
Pooled mean	0.110%	0.003
Grand mean	0.114%	0.003

The panels of this table report the average sales growth forecast improvement of industry-specific analysis over economy-wide analysis. Panel A and B report the sales growth forecast improvement for the firms, panel C reports the sales growth forecast improvement for the segments. For more details, please refer to tables 3 and 4.

Appendix Table 1 (not for publication)
Firm profitability forecast improvements of industry-specific analysis over economy-wide analysis (non-classified firms)
Time period: 1967-2011 (out-of-sample: 1987-2011).

In-sample regression model	AR(1)		AR(1) + NL dummy		AR(1) + NL dummy + PREDGSL	
Firm observations	7,980		7,980		7,980	
	mean	p-value	mean	p-value	mean	p-value
ROE						
Pooled mean	-0.006%	0.859	0.007%	0.805	0.048%	0.369
Grand mean	-0.011%	0.610	-0.004%	0.857	0.086%	0.197
RNOA						
Pooled mean	-0.002%	0.951	-0.015%	0.520	0.006%	0.799
Grand mean	-0.005%	0.801	-0.017%	0.371	0.017%	0.538
ROA						
Pooled mean	0.004%	0.756	-0.004%	0.764	0.014%	0.457
Grand mean	0.005%	0.587	-0.003%	0.794	0.024%	0.300
ROS						
Pooled mean	0.003%	0.872	-0.010%	0.621	0.023%	0.300
Grand mean	0.006%	0.682	-0.005%	0.782	0.034%	0.151

The table report the average firm profitability forecast improvement of industry-specific analysis over economy-wide analysis for firms that have changed the number of reported segments from one in 1997 to more than one in 1999, and are therefore neither classified as single segment-firms, nor as multiple-segment firms. For more details, see table 3.