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

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Abstract. A recent study shows that industry-specific analysis has no incremental advantage over economy-wide analysis in forecasting firm profitability. This result seems puzzling because some earlier studies have documented the importance of industry effects in explaining firm profitability. We reconcile the apparent inconsistency by showing that industry effects on profitability forecasting exist at the more refined business segment level, but are obscured by aggregated reporting at the firm level. Using segment-level analysis as well as firm-level analysis that also utilizes segment-level information, we provide consistent evidence supporting that industry-specific analysis is more accurate than economy-wide analysis in predicting the profitability of business segments and the profitability of single-segment firms. (*JEL* L25, G17, M21, M41)

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

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1. Introduction

Economists and business researchers, especially in accounting and finance, are interested in predicting earnings or forecasting profitability.[1] These tasks in practice 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). Consequently, predicting earnings is the same as forecasting return on assets (ROA), a frequently used measure for profitability.[2]

Among the many models used to forecast profitability or earnings, the first-order autoregressive model is a parsimonious choice with the slope coefficient measuring the persistence of profitability or earnings. The model, sometimes referred to as the *persistence* model, is particularly useful when

[1] Researchers from different fields have contributed to the literature on predicting earnings or forecasting profitability. Accounting and finance scholars have examined the time-series properties and predictability of earnings. These studies include Dichev and Tang (2009), Frankel and Litov (2009), Penman and Zhang (2002), Fama and French (2000), 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). Economists and strategic management researchers have studied the persistence and variability of profitability. 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).

[2] Other common measures of profitability include return on net operating assets (RNOA) and return on equity (ROE).

non-earnings accounting variables are not available for use as predictors. For example, the limited availability of segment-level data prevents the use of sophisticated models to forecast profitability at the segment level. Unlike higher-order autoregressive models, the persistence model does not require long earnings histories and therefore minimizes the survivor bias.

In estimating the persistence model for forecasting profitability or earnings, one can use either an industry-specific (IS) or an economy-wide (EW) formulation.[3] Prior studies in economics and strategic management have documented the importance of industry effects in explaining firm profitability (e.g., Bou and Satorra 2007 and McGahan and Porter 1997). In the light of these studies, one would expect an IS analysis to deliver more accurate profitability forecasts than its EW counterpart. Interestingly, Fairfield, Ramnath, and Yohn (2009) find no significant forecast improvement of IS over EW analysis in predicting firm profitability. The objective of this paper is to reconcile the apparent inconsistency between their *no industry effect* finding and the industry effects often observed in other contexts.

Some studies find that when more disaggregated segment-level data are made available to the public, analysts, investors, and researchers are able 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 the change in the accounting standard on segment reporting in 1997 (Botosan and Stanford 2005). Disaggregated segment-level data are more useful in predicting firm performance because they allow better monitoring of agency problems such as overinvestment and cross-subsidization (Berger and Hann 2007 and Berger and Ofek 1995).

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[3] A firm-specific formulation is undesirable because of the survivor bias resulting from the long-history data requirement. See Fama and French (2000), p. 162, for a discussion.

We conjecture that industry effects on profitability forecasting exist at the segment level but are obscured when data are aggregated to the firm level. To support the conjecture, we provide evidence in line with its implications for single- and multiple-segment firms and also for segments as the unit of analysis. In addition, we find that the observed effects at the segment level are weaker when a segment is larger and hence likely to be more diverse (less homogenous) in its activities. Finally, our *difference in forecast improvement* analysis to verify the implied difference between segment and firm profitability forecast improvements also supports the conjecture. Overall, we show that aggregation and diversity matter in revealing the industry effects on profitability forecasting.

Our main analysis is based on data from 1978-1997 under the segment disclosure regulation SFAS 14. To validate the robustness of the findings, we expand the analysis to include post-1998 years, up to 2010, under the more recent regulation SFAS 131.[4] The additional results (reported in an appendix available upon request) are broadly consistent with the findings based on the pre-1998 sample. Taken together, our results provide an 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. Besides this major contribution, our results may also be taken as evidence for the usefulness of more disaggregated accounting disclosure.

The rest of the paper is organized as follows. In the next section, we explain the four hypotheses developed from our conjecture and give an overview of the persistence model used to test the

[4] Superseding SFAS 14, the segment disclosure regulation SFAS 131 was aimed to increase the transparency of reported business segments. The regulation became effective for fiscal years beginning after December 15, 1997. Previously, firms were asked to disclose segments according to their industry classification. Following SFAS 131, firms have to report segment information consistent with the internal structure of the firm. This requirement led to an increase in the reported segments (Berger and Hann 2003).

hypotheses. Section 3 describes the data used and the sample construction procedure. Section 4 gives the details of the methodology, followed by the results of the firm- and segment-level analyses and the *difference in forecast improvement* analysis. Concluding remarks are given in section 5.

2. Empirical Model and Hypotheses

We use the standard persistence model (i.e., first-order autoregressive) 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. 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 4.1.

We focus on return on assets (ROA) as the profitability measure. 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 three profitability measures and the variables used to compute the measures.

Inspired by studies in the diversification and segment reporting literatures (e.g., Hund, Monk, and Tice 2010, Berger and Hann 2007, Campa and Kedia 2002, and Berger and Ofek 1995), we conjecture that industry effects on profitability forecasting exist but are obscured when segment-level data capturing the effects are aggregated to the firm level. To verify the conjecture, we examine four 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. However, there is a competing hypothesis 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). Therefore, 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.

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

In sum, this first hypothesis for testing 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.

Understandably, an externally reported segment of a firm cannot be as refined as the most basic unit of the firm, which ideally is completely homogeneous in activities. Nonetheless, it is reasonable to expect that other things being equal, the smaller a segment, the more homogeneous it is likely to be. We therefore predict that the industry effects on segment profitability forecasting are stronger the smaller the size of a segment.

H3: The segment profitability forecast improvement is more positive for smaller segments than larger segments.

Given that the segment of a single-segment firm cannot be too much different from the firm itself, there is no reason to believe that for single-segment firms, the segment profitability forecast improvement is significantly different from its firm profitability counterpart. In contrast, for a firm reporting to have multiple segments, while each of the segments may not be so refined to capture a homogeneous basic unit, a segment of the multiple-segment firm should be more homogeneous in activities than the multiple-segment firm itself. Therefore, we expect the segment profitability forecast improvement to be higher than its firm profitability counterpart for multiple-segment firms.

The predictions above for the single- and multiple-segments firms are tested by examining the *difference in forecast improvement* (DFI) measure defined as the segment profitability forecast improvement minus its firm profitability counterpart (see section 4.4 for details on this measure). Below is the last hypothesis for testing:

H4: The difference between segment and firm profitability forecast improvements is insignificant for single-segment firms but positive for multiple-segment firms.

The key difference between examining the segment profitability forecast improvement and the DFI measure is that in the latter case, a significance result is established by comparing to the firm profitability forecast improvement as the benchmark. This benchmark choice is tougher than using zero as the benchmark, which is implicitly assumed when examining the segment profitability forecast improvement. Unlike zero, the firm profitability forecast improvement is itself subject to variation, making it harder to show a significantly positive DFI measure.

3. Data and Descriptive Statistics

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

3.1 Data and Sample

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 is based on segment data, which are available from as early as 1976. Because the data coverage in the initial years is not good, we use data from 1978 onward. Our in-sample regressions require 10 years of data to estimate the coefficients of the models. Therefore, the earliest forecasts for the out-of-sample tests are from 1988. Owing to significant changes in the business segment disclosure requirements following the implementation of SFAS 131, our main analysis uses data up to 1997 only. Additional analyses based on data until 2010 are reported in an appendix available upon request.

We use the two-digit primary Standard Industry Classification (SIC) code to define the industry to which a firm or business segment belongs.[5] 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).

Although firms can be uniquely identified by the gvkey variable, Compustat does not provide a business segment identifier. We construct a unique identifier for segments using the reported segment name (snms). In many cases, the reported segment name changes slightly from year to year,

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[5] 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.

despite that the business segment appears to remain the same. We therefore standardize the segment name as follows to reduce the chance of breaking a segment data series unnecessarily.

First, all letters are converted to upper cases. Next, we omit all "AND" and punctuations in a segment name. Then we replace any recognized abbreviations (e.g., SOFTWR) by their full expressions (e.g., SOFTWARE). Finally, we remove all extra space characters to obtain the standardized segment name. The segment identifier is defined by assigning a unique number to each combination of the standardized segment name and the firm identifier (gvkey).

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 due to reasons like shortened fiscal years. Such observations are excluded from the sample.[6] We also remove firm and segment observations with negative sales, which raise data quality concerns. To mitigate the impact of small denominators on firm profitability measures, we exclude firm observations with total assets or net operating assets below USD 10mn or book value of equity below USD 1mn in the analysis using the firm ROA, RNOA, or ROE measure, respectively. For segment data, we exclude observations with total identifiable assets 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

[6] The deletion of double observations per calendar year reduces the sample size by 4 observations in the firm-level analysis and by 1,010 observations in the segment-level analysis.

remove observations with the growth in operating assets, net operating assets, or book value of equity 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.

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 three profitability measures available are used in the firm-level analysis.

3.2 Descriptive Statistics

Panels B and C of table 3 give an overview of the firm and segment data used to compute the average forecast improvements reported in sections 4.2 and 4.3. Because profitability forecasts are constructed from the estimated coefficients of in-sample regressions based on the most recent 10 years of data, forecasts are not available for out-of-sample tests until 1988 onward. The firm-level analysis uses 27,361 observations of 5,527 unique firms, whereas the segment-level analysis is based on 54,814 observations of 13,187 unique segments.

For firms, the ROA on average is 8.28%, while the mean RNOA is considerably higher, reaching 13.44%. In contrast, the average ROE is much lower: only 6.61%. These statistics are similar to those in prior studies, such as Fama and French (2000) and Fairfield, Ramnath, and Yohn (2009). Segment profitability is considerably lower, with the average ROA equal to 7.09%.

Panel C reports the number of observations, as well as the average profitability, for each industry. In the firm sample, *electronic & other electric equipment* (SIC 36) constitutes the largest industry sector, with 2,231 firm-year observations. In the segment sample, the largest industry is *industrial machinery & equipment* (SIC 35), with 4,532 segment-year observations. Other large industries in the samples are *chemicals & allied products* (SIC 28), *instruments & related products* (SIC 38) and *oil & gas extraction* (SIC 13).

There is substantial variation in profitability across industries. For firms, *chemicals & allied products* is the sector with the highest ROA (10.8%), whereas the lowest ROA (1.48%) is from *metal mining*. For segments, the highest ROA (39.9%) from *social services* appears to be an outlier; the second highest (22.3%) is from *personal services*. The sector with the lowest segment ROA (–18.25%) is *services, other*.

4. Segment and Firm Profitability Forecast Improvements: IS versus EW Analysis

In this section, we present the results of the analyses after explaining the details of the empirical methodology.

4.1 Methodology

Like Fairfield, Ramnath, and Yohn (2009), our tests are based on profitability forecast improvements (of IS over EW analysis). The procedure to construct forecast improvements involves two steps.

First, we estimate an IS and a EW first-order autoregressive model of firm/segment profitability:

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

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

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.

In the second step, 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:

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

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

where a and b denote the estimated coefficients. 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 or segment profitability forecast improvement, we calculate the overall average across all firm or 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 (clustered by firm) following Rogers (1993).

4.2 Firm-level Analysis

To begin, the left column in panel A of table 3 replicates Fairfield, Ramnath, and Yohn's (2009) *no industry effect* finding for our sample covering 1988-1997. As expected, the firm profitability forecast improvements (of IS over EW analysis) are not significantly different from zero for all three profitability measures. As a robustness check, we repeat the analysis for all years of data available from WRDS (i.e., 1979-2010). The results are reported in the right column of the panel. Again, none of the forecast improvements is significantly different from zero, regardless of the profitability measures or the way the mean forecast improvements are computed. In sum, panel A confirms that at the firm level, IS analysis has no significant advantage over the simpler EW analysis in forecasting profitability.[7]

The result above suggests that firm profitability is mostly governed by economy-wide factors that affect each industry in a similar way. Industry-specific analysis does not seem to add much to the accuracy of firm profitability forecasts. Why? We conjecture that the lack of an 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

[7] For simplicity, we use the most basic form of first-order autoregressive model without including any additional predictors such as the predicted sales growth and a dummy variable to account for the non-linearity in mean reversion of profitability that are used in Fairfield, Ramnath, and Yohn (2009). Including these variables does not qualitatively change the *no industry effect* benchmark results.

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 segment, aggregated reporting at the firm level does not severely distort the truth. The only segment of a single-segment firm is very much like the whole firm. If industry effects on profitability forecasting exist at the segment level, they may also be observed at the firm level when confining to single-segment firms. However, for multiple-segment firms, the effects should 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 16,301 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 that IS analysis is useful for profitability forecasting even at the *firm* level when confining to single-segment firms. Nearly all the forecast improvements for single-segment firms are significantly positive at the 5% level, with some at the 1% level, regardless of the three profitability measures. The magnitudes of the forecast improvements are all larger than their counterparts in the full sample in panel A. In contrast, EW analysis remains as good as IS analysis in predicting firm profitability for multiple-segment firms. None of the forecast improvements for such firms is significantly different from zero. Taken together, the findings consistently confirm H1.

These results provide support for the conjecture that industry effects on profitability forecasting are obscured by aggregated reporting at the firm level. To obtain more direct evidence to support the conjecture, we turn to the segment-level analysis in the next subsection.

4.3 Segment-level Analysis

If industry effects on profitability forecasting exist at the segment level, the segment profitability forecast improvement should be significantly positive, unlike its firm profitability counterpart. This hypothesis (H2) is confirmed by the results in panel A of table 4. Only ROA can be computed from segment data. The panel shows the segment profitability forecast improvements measured by the pooled mean and grand mean. Both indicate the same magnitude of mean forecast improvement at the segment level. The pooled mean is highly significant at less than 1% level, although the more conservative grand mean is significant only at the 5% level.

Under the premise that business segments are themselves aggregated entities of more basic units, the incremental advantage of using IS analysis to forecast segment profitability should be greater for smaller segments that tend to be more homogenous in activities. However, for larger segments, they are likely to be more diverse in activities. So analogous to the argument that single-segment firms are less diverse (more homogenous) in activities than multiple-segment firms, we hypothesize that the smaller a business segment, the more homogenous its activities and therefore the stronger the industry effects on segment profitability forecasting (H3). Given that more accurate proxies for the homogeneity/diversity of segment activities are unavailable, we use the size of a segment measured by its segment sales as a crude proxy.

To test H3, we partition the segment profitability forecast improvements into two subsamples based on the median of segment sales. Below- and above-median segments of a year are referred to as small and large segments of the year, respectively. The results in panel B of table 4 show that the segment profitability forecast improvement for small segments is significantly positive at the 1% level for both the pooled mean and the more conservative grand mean. In contrast, the forecast improvement for large segments is not significantly different from zero regardless of the measure in concern. This sharp difference between small and large segments is consistent with the hypothesis. The disappeared forecast improvement for large segments suggests that their activities might be too diverse for them to be very closely tied to their primary industries.

Besides this test of H3, we also run a linear regression of the forecast improvement on segment size and some control variables. This alternative test mitigates the confounding effects from the control variables. We are able to identify two relevant control variables, namely industry sales and industry concentration. We interpret industry sales as a proxy for the size of an industry and hence the likelihood of having more segments in the industry for use in IS analysis. Clearly, if the number of segments in an industry is small, it is not likely to give reliable estimates of the coefficients of the IS model. The incremental advantage of using IS analysis for profitability forecasting is small too. Therefore, we expect the segment profitability forecast improvement to increase with the industry sales.

In more concentrated industries, competition is lower. Segment profitability is therefore more persistent and predictable. IS analysis takes industry characteristics (such as industry concentration) into consideration implicitly, whereas EW analysis completely ignores industry differences. Consequently, we expect the incremental advantage of using IS analysis for profitability forecasting to increase with industry concentration.

We use the Herfindahl index (HI) to measure industry concentration. The HI of industry j is computed as follows, based on the sales of the firms reporting segments in the industry:

$$HI_j = \sum_i s_{ij},$$

where s_{ij} is the share of firm i's sales in the total sales of industry j. A low HI means a more concentrated industry; a high HI means less concentrated. The following is the linear regression used for the alterative test of H3:

$$FI_{i,t} = \alpha + \beta_1 \log(SALES_{i,t}) + \beta_2 \log(INDUSTRY\ SALES_{j,t}) + \beta_3 \log(HI_{j,t}) + \varepsilon_{i,t}.$$

Log transformation is used to reduce the skewness of the explanatory variables. Like computing the grand mean besides the pooled mean, we estimate the regression equation using two econometric approaches. First, we run a panel regression using all segment-year observations. Robust standard errors are used to account for heteroscedasticity and serial correlation (Rogers 1993). Second, we employ the Fama and MacBeth (1973) methodology to first estimate the regression equation cross-sectionally for each year and then take an average of the estimated coefficients across years.

Panel C of table 4 shows the estimation results. The control variables are significant and in the directions anticipated. As the control variables are added to the regression one after another, the estimated coefficients of the segment size variable continue to be significantly negative. That is to say, the segment profitability forecast improvement is greater, the smaller the segment size. This further confirms H3.

4.4 Difference in Forecast Improvement Analysis

We have shown that the segment profitability forecast improvement is significantly positive. Moreover, because single-segment firms cannot be too much different from the only segments they reported, we are able to show that even the firm profitability forecast improvement is significantly positive for such firms. If these findings fit together, we should also see little difference between the segment and firm profitability forecast improvements for single-segment firms. However, for multiple-segment firms, moving from the aggregated firm level to the more refined segment level should allow the industry effects on profitability forecasting to reappear clearly. We therefore expect the segment profitability forecast improvements for multiple-segment firms to be significantly above its firm profitability counterpart.

These implications for the two types of firms, stated in H4, are tested using the *difference in forecast improvement* (DFI) measure. It is defined as the segment profitability forecast improvement minus its firm profitability counterpart:

$$DFI = FI_{SEGMENT} - FI_{FIRM}.$$

To construct the measure, we match the profitability forecast improvement of each segment of a firm to the firm-level profitability forecast improvement. This of course requires firm and segment data to be available at the same time. In addition, we require the firm sales to be within 1% from the aggregated segment sales. Finally, like testing H1, we exclude firms with the doubt in correctly classifying them as genuinely single-segment (see subsection 4.2).

Table 5 shows the results for H4. For single-segment firms, there is little difference in the profitability forecast improvement when moving from the aggregated firm level to the more refined segment level. This is indicated by the insignificant pooled and grand means of the DFI measure. In contrast, both means of the measure are significantly positive for multiple-segment firms, showing that industry effects on profitability forecasting for such firms are significantly more noticeable at the segment level than at the firm level.

The last column of table 5 shows the means of the DFI measure for the whole sample. They are significantly positive as well, suggesting that the difference in forecast improvement for multiple-segment firms is quite substantial. Otherwise, the insignificance results for single-segment firms could have overshadowed the significantly positive DFI for multiple-segment firms. Overall, the results in table 5 support H4 unambiguously.

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 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. These findings underline that industry factors have an impact on profitability 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.

The results of this study are also relevant to the accounting disclosure literature. 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 more disaggregated accounting disclosure.

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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)	
ROE_t	Return on equity	$NI_t/(0.5*(BV_t + BV_{t-1}))$	
$RNOA_t$	Return on net operating assets	$OPINC_t/(0.5*(NOA_t + NOA_{t-1}))$	
ROA_t	Return on assets	$OPINC_t/(0.5*(TA_t + TA_{t-1}))$	$OPINC_t/(0.5*(TA_t + TA_{t-1}))$

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

Panel A: Sample selection				
Adjustments to data sample	Firm-level data (firm-year observations)			Segment-level data (segment-year observations)
	ROA	*RNOA*	*ROE*	*ROA*
Total observations, excluding utilities and financial firms/segments	114,505	114,319	114,362	151,583
Less observations with negative sales	114,475	114,289	114,332	151,570
Less observations with small denominators	87,588	76,366	99,085	144,125
Less observations with an absolute value larger than 1	87,465	75,257	95,343	142,532
Less observations with more than 100% growth	74,403	66,081	81,183	133,655
Less upper and lower centiles observations	72,915	64,761	79,561	130,983
Observations of absolute forecast errors	33,789	29,771	35,282	54,814
Observations in out-of-sample prediction, out of which:	27,361	27,361	27,361	54,814
single-segment firms				25,691
multiple-segment firms				22,376

Panel A summarizes the sample selection procedure and the number of observations available after each filter. 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: 5,527 firms (27,361 firm-year obs.)					
NI	82.500	361.000	0.589	6.663	36.682
OPINC	178.260	676.781	3.436	16.682	80.748
TA	2,212.168	9,349.131	70.242	229.034	958.801
NOA	1,314.782	5,510.057	45.260	147.961	614.998
BV	750.978	2,587.391	33.466	100.786	387.012
ROA	0.0828	0.0799	0.0399	0.0847	0.1300
RNOA	0.1344	0.1375	0.0600	0.1272	0.2052
ROE	0.0661	0.1630	0.0162	0.0952	0.1587
Segment-level: 13,187 segments (54,814 segment-year obs.)					
TA	847.513	3,878.513	18.439	86.324	400.634
OPINC	82.821	375.263	0.186	5.627	37.101
ROA	0.0709	0.1560	0.0119	0.0845	0.1527
Explanatory variables of regression analysis (54,270 segment-year obs.)					
SALES	941.417	4,624.95	22.488	110.300	480.428
INDUSTRY SALES	251,676	225,590	58,485	186,092	399,485
HI	0.00062	0.00553	0.00008	0.00020	0.00062

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 10 years of data, forecasts are not available for out-of-sample tests until 1988 onward. *SALES* is the segment sales used as a proxy for the segment size. *INDUSTRY SALES* is the total industry sales defined as the sum of all segment sales within a given industry. *HI* is the industry concentration measured by the Herfindahl index based on the sales of the companies that report segments within a given industry. A low Herfindahl index indicates a highly competitive industry; a high Herfindahl index indicates a highly concentrated industry.

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

Panel C: Descriptive statistics by industry

Two-digit SIC	Description	Firm-level Obs.	Firm-level *ROA*	Firm-level *RNOA*	Firm-level *ROE*	Segment-level Obs.	Segment-level *ROA*
01	Agricultural production-crops	0	-	-	-	187	0.0658
02	Agricultural production-livestock	0	-	-	-	43	0.0345
07	Agricultural services	0	-		-	2	-0.1343
10	Metal mining	551	0.0148	0.0251	0.0003	974	-0.0474
12	Coal mining	0	-	-	-	273	0.0727
13	Oil & gas extraction	1,389	0.0426	0.0627	0.0203	2,936	0.0305
14	Nonmetallic minerals	59	0.0407	0.0613	0.0179	328	0.0630
15	General building	238	0.0454	0.0633	0.0105	584	0.0346
16	Heavy construction	26	0.0640	0.1393	0.0549	235	0.0678
17	Special trade contractors	0	-	-	-	195	0.0596
20	Food & kindred products	1,050	0.1051	0.1682	0.1088	1,557	0.1130
21	Tobacco products	0	-	-	-	1	-0.0058
22	Textile mill products	385	0.0910	0.1253	0.0584	589	0.0891
23	Apparel & other textile	336	0.0964	0.1420	0.0635	569	0.0837
24	Lumber & wood	301	0.0768	0.1183	0.0649	605	0.1235
25	Furniture & fixtures	255	0.1065	0.1623	0.0948	450	0.0895
26	Paper & allied products	607	0.0976	0.1423	0.0897	1,034	0.1055
27	Printing & publishing	602	0.1033	0.1638	0.0932	1,182	0.1304
28	Chemicals & allied products	1,608	0.1082	0.1803	0.1128	3,694	0.0709
29	Petroleum & coal	424	0.0673	0.1147	0.0740	556	0.0791
30	Rubber & plastic products	464	0.1065	0.1597	0.0791	1,141	0.1246
31	Leather	124	0.0926	0.1439	0.0511	238	0.0791
32	Stone, clay & glass	323	0.0869	0.1300	0.0803	694	0.1036
33	Primary metal products	790	0.0790	0.1205	0.0603	1,287	0.0982
34	Fabricated metal products	726	0.0957	0.1506	0.0826	1,584	0.1144
35	Industrial machinery & equipment	1,865	0.0786	0.1354	0.0544	4,532	0.0636
36	Electronic & other electric equipment	2,231	0.0802	0.1367	0.0591	4,122	0.0696
37	Transportation equipment	924	0.0820	0.1355	0.0786	1,729	0.1010
38	Instruments & related products	1,500	0.0917	0.1517	0.0719	3,467	0.0532
39	Misc. manufacturing industries	350	0.0841	0.1367	0.0512	683	0.0638

40	Railroad transportation	234	0.0697	0.1181	0.0761	259	0.0678
42	Trucking & warehouse	326	0.0903	0.1448	0.0721	532	0.0809
44	Water transportation	170	0.0544	0.0818	0.0529	324	0.0620
45	Transportation by air	239	0.0612	0.1157	0.0331	461	0.0409
47	Transportation services	81	0.0901	0.1803	0.1170	197	0.0769
48	Communications	1,437	0.1067	0.1589	0.1158	2,085	0.0848
49	Electric, gas & sanitary services	244	0.0531	0.0807	0.0230	724	0.0364
50	Wholesale trade-durable products	1,000	0.0788	0.1220	0.0598	1,906	0.0686
51	Wholesale trade-nondurable goods	596	0.0737	0.1259	0.0755	1,192	0.0784
52	Building materials	115	0.0690	0.1052	0.0075	201	0.0603
53	General merchandise stores	380	0.0775	0.1224	0.0631	569	0.0647
54	Food stores	431	0.0908	0.1575	0.0821	472	0.0973
55	Automotive dealers & services	58	0.0945	0.1372	0.0674	183	0.0553
56	Apparel & accessory stores	352	0.0932	0.1670	0.0747	465	0.0987
57	Furniture stores	249	0.0836	0.1567	0.0507	404	0.0564
58	Eating & drinking places	512	0.0978	0.1356	0.0521	971	0.0667
59	Miscellaneous retail	565	0.0808	0.1284	0.0506	915	0.0711
70	Hotels & other lodging places	187	0.0550	0.0746	0.0162	392	0.0567
72	Personal services	0	-	-	-	157	0.2233
73	Business services	1,379	0.0841	0.1667	0.0591	3,473	0.0609
75	Auto repair, services & parking	85	0.0716	0.0962	0.0773	166	0.0461
76	Misc. repair services	0	-	-	-	4	0.1826
78	Motion pictures	190	0.0486	0.0729	-0.0057	503	0.0128
79	Amusement & recreation services	293	0.0802	0.1176	0.0180	635	0.0623
80	Health services	410	0.0946	0.1405	0.0601	1,039	0.0649
82	Educational services	0	-	-	-	68	0.0704
83	Social services	0	-	-	-	1	0.3991
86	Membership organizations	0	-	-	-	1	0.1314
87	Engineering & management services	379	0.0729	0.1328	0.0456	1,130	0.0385
89	Services, other	0	-	-	-	4	-0.1825
99	Non-operating establishments	231	0.0438	0.0765	-0.0003	0	-
Total		27,361	0.0828	0.1344	0.0661	54,814	0.0709

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

Table 3
Firm profitability forecast improvements of industry-specific analysis over economy-wide analysis

Panel A: Total sample				
Years	1988-1997		1979-2010	
Firm observations	27,361		88,743	
	mean	p-value	mean	p-value
ROA				
Pooled mean	-0.00002	0.798	-0.00002	0.768
Grand mean	0.00000	0.991	-0.00000	0.994
RNOA				
Pooled mean	0.00011	0.385	0.00010	0.187
Grand mean	0.00015	0.647	0.00010	0.544
ROE				
Pooled mean	0.00026	0.227	0.00003	0.789
Grand mean	0.00031	0.379	0.00005	0.803

Table 3
Firm profitability forecast improvements of industry-specific analysis over economy-wide analysis (*Continued*)

Panel B: Sample partitioned in single and multiple segment firms				
Years	1988-1997			
Firm type	Single-segment firms		Multiple-segment firms	
Firm observations	10,432		5,869	
	mean	p-value	mean	p-value
ROA				
Pooled mean	0.00035	0.021	-0.00020	0.315
Grand mean	0.00036	0.146	-0.00020	0.334
RNOA				
Pooled mean	0.00071	0.001	-0.00001	0.977
Grand mean	0.00072	0.041	0.00002	0.961
ROE				
Pooled mean	0.00096	0.009	-0.00016	0.746
Grand mean	0.00102	0.038	-0.00014	0.669

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 (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 are based on t-tests with robust standard errors (clustered by firm) following Rogers (1993). 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

Panel A: Total sample

Years	1988-1997	
Segment observations	54,814	
	mean	p-value
ROA		
Pooled mean	0.00037	<0.001
Grand mean	0.00038	0.042

Panel B: Sample partitioned in small and large segments

Years	1988-1997			
Segment size	Small segments		Large segments	
Segment observations	27,393		27,421	
	mean	p-value	mean	p-value
ROA				
Pooled mean	0.00057	<0.001	0.00017	0.200
Grand mean	0.00058	0.001	0.00018	0.511

These two panels report 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 (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 are based on t-tests with robust standard errors (clustered by firm) following Rogers (1993). Panel A is based on the total sample of segment profitability forecast improvements. Panel B is based on the small- and large-segment subsamples, where small and large segments are defined as segments with below- and above-median segments sales in a given year, respectively.

Table 4
Segment profitability forecast improvements of industry-specific analysis over economy-wide analysis (*Continued*)

Panel C: Regression tests of segment profitability forecast improvements (based on 54,291 segment-year observations from 1988 to 1997)						
	Dependent variable: Segment-level forecast improvement					
Explanatory variables:	Panel regressions			Fama-MacBeth regressions		
log(*SALES*)	-0.00016 (0.001)	-0.00018 (<0.001)	-0.00024 (<0.001)	-0.00015 (0.048)	-0.00017 (0.031)	-0.00022 (0.012)
log(*INDUSTRY SALES*)		0.00027 (<0.001)	0.00058 (<0.001)		0.00032 (0.001)	0.00062 (0.001)
log(*HI*)			0.00050 (<0.001)			0.00046 (0.031)
Adjusted R-squared	0.1%	0.1%	0.2%	0.1%	0.2%	0.4%

This panel presents the regression tests of the segment profitability forecast improvement (*FI*) of industry-specific analysis over economy-wide analysis using the model below

$$FI_{i,t} = \alpha + \beta_1 \log(SALES_{i,t}) + \beta_2 \log(INDUSTRY\ SALES_{j,t}) + \beta_3 \log(HI_{j,t}) + \varepsilon_{i,t}.$$

SALES is the segment sales used as a proxy for the segment size. *INDUSTRY SALES* is the total industry sales defined as the sum of all segment sales within a given industry. *HI* is the industry concentration measured by the Herfindahl index based on the sales of the companies that report segments within a given industry. All variables are transformed by natural log to reduce the skewness of the variables. The panel regressions pool all segment-year observations together and estimate the coefficients in one regression step. Robust standard errors are used to account for the impacts of heteroscedasticity and serial correlation (Rogers 1993). The Fama-MacBeth regressions first estimate the coefficients cross-sectionally for each year and then average the coefficients across years. The adjusted R-squared value for Fama-MacBeth regressions is the mean of the adjusted R-squared values for the yearly regressions. The p-values of the tests are reported in parentheses.

Table 5
Difference in forecast improvement analysis: segment versus firm profitability forecast improvement

Years	1988-1997					
	Single-segment firms		Multiple-segment firms		Total sample	
Segment observations	11,478		10,655		25,533	
ROA	mean	p-value	mean	p-value	mean	p-value
Pooled mean	0.00013	0.187	0.00053	0.019	0.00030	0.005
Grand mean	0.00014	0.378	0.00054	0.002	0.00030	0.008

This table presents the tests based on the difference in forecast improvement (DFI), i.e., the segment profitability forecast improvement minus its firm profitability counterpart. The pooled mean is the average difference in forecast improvement when pooling the observations of all years together. The grand means is the mean of the yearly average difference in forecast improvement. The p-values are based on t-tests with robust standard errors (clustered by firm) following Rogers (1993). To construct the difference in forecast improvement measure, segment-level observations are matched to firm-level observations before the in-sample regressions. Observations with firm sales deviated from aggregated segment sales by more than 1% are excluded. The single- and multiple-segment firm subsamples reported in the first and second columns also exclude firms that have changed the number of reported segments from one in 1997 to more than one in 1999 (see section 4.4 for details).