**Industry Effects in Firm and Segment Profitability Forecasting:**
**Corporate Diversification, Industry Classification, and Estimation Reliability**[1]

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**Abstract**

Academics and practitioners have long recognized the importance of a firm's industry membership in explaining its financial performance. Yet, contrary to conventional wisdom, recent research shows that industry-specific profitability forecasting models are not better than economy-wide models. This paper re-examines the incremental advantage of industry-specific models. We find considerable industry effects in profitability forecasting. However, the effects are only visible for focused firms. For diversified firms, aggregated reporting at the firm level prevents the effects from being observed. Furthermore, to reliably extract industry patterns from the data, industry classifications have to be sufficiently broad – otherwise industry-specific profitability forecasts are too noisy to improve forecast accuracy. Additional analysis shows that industry effects in profitability forecasting can be profitably exploited by market participants. (*JEL* L25, G17, M21, M41, C53)

*Key words: Industry membership, Profitability forecasting, Diversification, Disaggregation*

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## 1. INTRODUCTION

Academics and practitioners have long recognised the importance of a firm's industry membership in understanding its performance. A large body of economic and strategic management research stresses the importance of industry effects in firm profitability and firm performance.[2] Industry membership considerations are also important to equity investors. For example, the literature on industry momentum effects shows that stock returns are closely connected to industry membership (Moskowitz and Grinblatt 1999). Similarly, the importance of industry-specific expertise led brokerage firms to organizing equity analysts by industry (Boni and Womack 2006; Kadan et al. 2012).

Yet, the view that industry membership is important to understanding firm performance does not go unchallenged. Analysing a large sample of U.S. firms, a recent study by Fairfield, Ramnath, and Yohn (2009) shows that industry-specific models do not improve firm profitability forecasts relative to economy-wide models. They conclude that there is no industry effect in profitability forecasting.

Against the backdrop of these seemingly conflicting perspectives, the objective of this paper is to shed new light on the importance of industry membership in profitability forecasting. Our contribution is to introduce two novel aspects to the analysis, which have been overlooked in previous studies.

First, many firms are diversified into various industries. Their activities are usually organized in separate business segments. Yet, when the segments of such multiple-segment firms belong to different industries, no single industry can accurately represent the whole firm. A firm-level industry-specific forecasting model as used in Fairfield, Ramnath, and Yohn (2009) is therefore unable to capture the industry effects in profitability forecasting for multiple-segment firms. Put differently, the lack of industry effects can be explained by the aggregated reporting of multiple-segment firms at the firm level. However, industry effects in profitability forecasting should reappear when confining the analysis to single-segment firms.

Second, we resort to recent insights of the literature on optimal forecasting of heterogeneous panel data sets. The findings by Trapani and Urga (2009) suggest that there is a trade-off between the estimation reliability of economy-wide models and the ability to precisely capture industry effects with industry-specific models.[3] Economy-wide models tend to generate better forecasts than industry-specific models because of a higher efficiency (i.e., lower standard errors) in the estimation process. Yet, it can be optimal to allow for some heterogeneity across industries, especially when there are considerable industry effects in the data. Hence, the *no industry effect* finding documented in previous literature might be caused by the usual convention of using narrow industry classifications to

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

[3] The balance between the accurate measurement of industry effects and adequate estimation reliability is equivalent to the trade-off between heterogeneous and homogenous estimators discussed in the forecasting literature. See section 2 for a more detailed literature review.

categorize firms. Lacking sufficient observations for each industry, the numerous parameters of industry-specific forecasting models cannot be accurately estimated, which results in unreliable profitability forecasts. Therefore, it should be possible to improve the predictions of industry-specific forecasting models by using broader industry classifications.

In light of these new insights, we re-examine the incremental advantage of industry-specific forecasting models over economy-wide approaches in predicting firm profitability as studied by Fairfield, Ramnath, and Yohn (2009). We compare the relative accuracy of industry-specific versus economy-wide forecasts using a large variety of out-of-sample tests. Since prior research shows that the predictability of profitability is largely due to its mean reversion (Fama and French 2000), we use the parsimonious first-order autoregressive model to forecast profitability.

As expected, we find considerable heterogeneity in the mean-reverting pattern of firm profitability across industries, which can be exploited to improve the profitability forecasts. Yet, these industry effects are only observable for firms with a single segment. For multiple-segment firms, industry-specific forecasts are no more accurate than economy-wide forecasts, since no single industry can accurately represent the whole firm. Furthermore, in order to reliably extract industry patterns from the data, the industry classifications have to be sufficiently broad – otherwise industry-specific profitability forecasts are not reliable. All our results are robust to using a variety of industry classification systems.

To explore the economic relevance of our findings, we examine whether the more accurate industry-specific forecasts of firm profitability can be valuable to investors. If stock prices do not efficiently incorporate fundamental information related to the industry exposure of single-segment firms, there should be profitable investment opportunities based on the firms' industry-specific profitability forecasts. We hence propose a trading strategy that exploits the difference in expected profitability between industry-specific and economy-wide forecasts. A dollar-neutral hedge portfolio constructed with this strategy yields significant risk-adjusted returns of up to 5.6% per year. These results show that investors do not efficiently use the information related to industry memberships of single-segment firms, as exploitable by industry-specific profitability forecasting models.

The findings of the firm-level analysis suggest that industry effects in profitability forecasting exist at the more refined segment level. For multiple-segment firms, these effects are not visible owing to aggregation of segment level data for external reporting of firm-level financials. If this conjecture is true, we should observe significant forecast improvements of profitability forecasting directly at the segment level.

However, we find only weak evidence of industry effects in segment profitability forecasting. Further analyses identify two major reasons for the limited industry effects at the segment level. First, the literature on corporate diversification and segment reporting suggests that conglomerates do not manage their business segments on a stand-alone basis. They might transfer resources or allocate costs from one segment to another for various reasons, including cross-subsidization or hiding segment information (Bernardo, Luo, and Wang 2006; Berger and Hann 2007). To the extent that multiple-segment firms shift resources or misallocate costs from one segment to another, the growth and profitability of their segments are influenced by such strategic moves, weakening the linkage of segment profitability to industry-specific factors. Second, the introduction of the new segment disclosure regulation SFAS 131 in 1998 considerably changed the segment data quality. While the new standard increased the firms' transparency, segment data are not as comparable across firms as before, which weakens the empirical linkage between segment profitability and industry membership. In line with these considerations, we find that industry effects in segment profitability forecasting are much stronger for the pre- than the post-SFAS 131 era, and for the segments of single-segment firms than of multiple-segment firms.

In summary, by including the corporate diversification aspect in the analysis and using broader industry classifications to improve estimation reliability, this paper restores the importance of industry membership in profitability forecasting.

This paper develops as follows. In the next section we review the relevant literature in more detail. Section 3 presents the research design and gives an overview on the data sample. Section 4 presents the main results of the paper using firm-level data. In section 5, we look at the relation between industry membership and profitability forecasting at the business segment level. Section 6 proposes a trading strategy that shows how to profitably exploit industry effects in profitability forecasting. Additional tests are presented in section 7. Section 8 offers some concluding remarks.

## 2. LITERATURE REVIEW

### 2.1. MEAN REVERSION OF PROFITABILITY

The early studies on the predictability of earnings and profitability are based on firm-specific time series models (e.g., Lev 1983).[4] A major shortcoming of these models is the requirement of a long earnings history for each firm, causing a severe survivorship bias. When using firms with long earnings histories (e.g., 20 annual observations), the firm-specific regression samples are small, leading to statistically weak results.

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

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

We follow this literature and use a mean reverting model to forecast profitability. Unlike Fama and French (2000), we opt for the parsimonious first-order autoregressive specification. This choice is based on an important insight of the recent forecasting literature (e.g., Trapani and Urga 2009). The literature – see also section 2.3 – finds that despite misspecification, simplified models with fewer model parameters often provide more accurate forecasts than correctly specified models. Put differently, sophisticated models with high in-sample goodness of fit can have poor out-of-sample forecasting performance.

### 2.2. DISAGGREGATION APPROACH TO PROFITABILITY FORECASTING

A strand of the literature on profitability forecasting discusses whether disaggregation approaches to profitability forecasting can improve forecast accuracy. Fairfield, Sweeney, and Yohn (1996) find that the common practice of separating extraordinary items and discontinued operations from other components of earnings improves one-year-ahead return on equity (ROE) forecasts. Further disaggregation of earnings into operating earnings, non-operating earnings and taxes, and special items yields even more accurate forecasts.

Another approach is the DuPont decomposition of the return on net operating assets (RNOA) into asset turnover and profit margin. Fairfield and Yohn (2001) find that this disaggregation does not provide incremental information for forecasting the change in one-year-ahead RNOA. However, disaggregating the change in RNOA into the change in asset turnover and the change in profit margin does provide incremental information. Using a variation of the Fairfield and Yohn (2001) model, Soliman (2008) confirms that the information from the DuPont decomposition is incremental to various accounting signals examined in prior research on forecasting earnings.

Esplin et al. (2014) look at the operating/financial disaggregation and the unusual/infrequent disaggregation. Most related prior research uses the information from a disaggregation to directly forecast ROE. This is referred to as the aggregate forecasting approach. Their study uses also the components forecasting approach. That is, they first separately forecast the three components of ROE, namely RNOA, net borrowing cost and leverage, based on the Nissim and Penman (2001) decomposition. Then they obtain the forecast of ROE by combining the component forecasts. Using this approach, they show that the operating/financial disaggregation yields less accurate forecasts than the unusual/infrequent disaggregation. However, the latter can be improved upon by combining both types of disaggregation together.

Comparing the (disaggregated) industry-specific forecasting approach to its (aggregated) economy-wide counterpart, Fairfield, Ramnath, and Yohn (2009) can also be considered a study of the disaggregation strand of the profitability forecasting literature. They find that industry-specific profitability forecasts are no more accurate than economy-wide forecasts. In terms of the analysis framework, our paper is closest to their study. Our innovation is to further separate firms into single-segment and multiple-segment firms. This disaggregation shows that industry-specific forecasts are superior to their economy-wide counterparts for single-segment but not for multiple-segment firms.

### 2.3. PANEL DATA FORECASTING

Our paper also builds on the literature on optimal forecasting of heterogeneous panel data sets. When estimating panel data models, researchers have to decide whether the estimated coefficients are allowed to be heterogeneous (like in the industry-specific model), or not (like in the economy-wide model). In the econometrics literature, this question is known as “to pool or not to pool”.[5] Pesaran and Smith (1995) argue in favour of heterogeneous models, since the main assumption of homogenous estimators, their common slope coefficients, is usually rejected. Yet, in a series of papers, Baltagi shows that homogenous panel data estimates yield better out-of-sample forecasts than heterogeneous estimators.[6]

A number of recent papers by Trapani and Urga (2009), Pesaran and Zhou (2015), and Paap, Wang, and Zhang (2015) highlight that there is a trade-off between bias and variance of the estimators. When confronted with panel data, it is important to balance efficiency gains from pooling and the biases caused by heterogeneity in the data. It turns out that the degree of heterogeneity plays an important role when determining whether or not to pool. When the bias from ignoring the heterogeneity in the data is relatively small, homogenous estimators tend to generate better forecasts. But heterogeneous estimators are preferred when the heterogeneity is substantial.

Our results confirm these conclusions. The economy-wide (homogenous) model yields more accurate forecasts relative to industry-specific (heterogeneous) models when using around 50 narrowly defined industries. However, when sorting firms into fewer and broader industries, industry-specific forecasts outperform economy-wide forecasts.

## 3. RESEARCH DESIGN AND DATA

### 3.1. RESEARCH DESIGN

This study compares the forecast accuracy of industry-specific relative to economy-wide profitability forecasting models. Following Fairfield, Ramnath, and Yohn (2009), our research design involves three steps. First, we estimate a profitability forecasting model *in-sample*. Second, we use the estimated model parameters to predict future profitability. Third, we compare the profitability forecasts with the actual, observed profitability in various *out-of-sample* tests.

Among the many models that may be used to forecast profitability, the persistence model (i.e., first-order autoregressive model) is a parsimonious choice. Unlike higher-order autoregressive models, the persistence model does not require long earnings histories and therefore minimizes the survivorship bias. Furthermore, limited availability of segment-level data prevents us from using more sophisticated models to forecast profitability at the segment level.[7] The two competing models are:

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

[5] For an excellent review, Baltagi et al (2008).

[6] See Baltagi and Griffin (1997), Baltagi, Griffin, and Xiong (2000), Baltagi and Bresson (2002), and Baltagi et al. (2003).

[7] In additional tests we also consider more complex forecasting models, similar to those in Fairfield, Ramnath, and Yohn (2009). Since their forecast accuracy is worse than the simple AR(1) model, we do not present the results here.

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

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 industry-specific (IS) model estimates a regression for each industry $j$ separately, whereas the economy-wide (EW) model pools all observations into one regression. In the econometrics and forecasting literature, the industry-specific model is known as heterogeneous model, while the economy-wide model is denoted homogenous model (Baltagi and Griffin 1997).

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

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

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

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

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

where $a$ and $b$ are the estimates of the model coefficients $\alpha$ and $\beta$.

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

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

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

where $AFE_{IS}$ and $AFE_{EW}$ are the absolute forecast errors for a firm/segment of a year based on the industry-specific and economy-wide models, respectively. Finally, we measure the advantage of industry-specific profitability forecasts over economy-wide forecasts as the difference in absolute forecast errors of both predictions. More precisely, we calculate the *forecast improvement* (of industry-specific over economy-wide models) by deducting $AFE_{IS}$ from $AFE_{EW}$:

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

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

We assess the magnitude of the firm/segment profitability forecast improvement using a variety of standard tests of the forecasting literature. As a first test, we calculate the pooled mean forecast improvement of all firm/segment observations over all years and industries. Then we test whether the pooled forecast improvement is significantly different from zero using a t-test. The t-test is based on two-way clustered standard errors by firm/segment and year to correct for cross-sectional and serial correlation following (Rogers 1993).

Second, we report the grand mean forecast improvement, which is the mean of the yearly mean forecast improvements. Similar to the pooled mean, we test the significance of the grand mean using a t-test, with the standard errors adjusted for serial correlation following (Newey and West 1987).

These two tests are also known as Diebold and Mariano (1995) test, which is widely used in the forecasting literature to compare the forecast accuracy of two competing forecasting models. The grand mean corresponds to the original Diebold and Mariano (1995) test with an absolute loss function, while the pooled mean is equivalent to the panel version of the Diebold and Mariano (1995) test as proposed by Pesaran, Schuermann, and Smith (2009), again using an absolute loss function.

As a third test, we follow Fairfield, Ramnath, and Yohn (2009) and compute the grand median forecast improvement. Similar to the grand mean, the grand median is the median of the yearly median forecast improvements. Tests of the grand medians are based on a Wilcoxon (1945) signed-rank test.

Finally, we report the number of industries (or years) in which the industry (or yearly) pooled mean forecast improvements is significantly positive/negative at the 10% level.

**3.2. DATA AND DESCRIPTIVE STATISTICS**

This section gives an overview of the data used and the sample constructed, followed by a presentation of the summary statistics.

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

This paper explores whether industry-specific forecasts are more accurate than economy-wide forecasts using four measures of profitability. Following Fairfield, Ramnath, and Yohn (2009), we consider the return on equity (ROE) and the return on net operating assets (RNOA) as profitability measures. Fairfield, Ramnath, and Yohn (2009) focus on forecasting ROE and RNOA since these two profitability measures are used as inputs to the residual income valuation model, a popular tool to appraise firms Ohlson (1995).

Since data for net income and book value of equity, which are required to compute ROE and RNOA, are not available at the segment level, we also consider the return on assets (ROA) and the return on sales (ROS). Another benefit of using ROS is that it relies on income statement information only. Given that sales is more readily available and can be better assigned to segments without ambiguity, a segment's ROS should be more reliable than its ROA because of higher data quality.

Although ROS has limited purpose for valuation, it is among the main drivers of ROE. According to the Du Pont analysis, what drive the ROE are the asset-to-equity ratio (a financial leverage measure, financial leverage) and the ROA, which can be further broken down into the asset turnover ratio (ATO) and the ROS. Practitioners often use such Du Pont analysis to understand the driving forces of company performance. Analyzing the predictability of these alternative profitability measures provides an additional route to understanding the predictability of the ROE.

Most importantly, analysts generally have a need to forecast different profitability measures for other reasons than using them as inputs for valuation purposes (Pinto et al. 2010). For example, by analyzing the trends in ROS and asset turnover separately, analysts are able to better understand whether competition in the product market or asset utilization inefficiency has a stronger impact on company performance. Hence, analysts are interested in knowing more accurate approaches for forecasting ROS for its own sake. We add to the knowledge of practitioners on forecasting financial ratios by examining ROS alongside with other popular profitability measures.

Table 1 summarizes the definitions of the four profitability measures and the variables used to compute these measures. To better understand any differences between the various profitability measures, we also analyze asset turnover and financial leverage. Finally, given the prominent role of growth in sales (GSL) in Fairfield, Ramnath, and Yohn (2009), we also consider this growth measure.

The first part of the paper uses the two-digit primary Standard Industry Classification (SIC) code to define the industry to which a firm belongs.[8] Observations with missing SIC codes are excluded from the sample. To avoid distortions caused by regulated industries, we exclude all firms and segments in the financial service and utilities sectors (i.e., with SIC between 6000 and 7000, or between 4900 and 4950). In addition, the U.S. postal service (SIC 4311) and non-classifiable establishments (SIC above 9900) are excluded.

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.[9]

To mitigate the impact of small denominators on the profitability measures, we exclude firm observations with total assets, net operating assets, and sales below USD 10mn and book value of equity below USD 1mn. For segment data, we exclude observations with total identifiable assets and sales below USD 1mn. To avoid the influence by outliers, observations with the absolute value of firm/segment profitability exceeding one are excluded. To reduce the influence by mergers and acquisitions, we remove observations with growth in operating assets, net operating assets, book value

[8] In later sections, we use alternative industry classifications based on the Fama-French Classification System (FF), North American Industry Classification System (NAICS), and Global Industry Classification Standard (GICS). Some studies (e.g., Fairfield, Ramnath, and Yohn 2009) classify industries using the GICS codes, which are often unavailable for segment-level data.

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

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 before the out-of-sample tests to avoid any look-ahead bias in the analysis.[10]

This study distinguishes between single- and multiple-segment firms. To do so, we match the firm data with the business segment data. Single-segment firms are those firms reporting one business segment, while multiple-segment firms report more than one segment. Yet, segment reporting standards have changed considerably in 1998, with the new Statement of Financial Accounting Standards No. 131 (SFAS 131) superseding SFAS 14. Following the introduction of SFAS 131, many single-segment firms increased the number of reported segments to more than one by 1999.[11] This suggests that they might not be genuinely single-segment firms prior to the introduction of SFAS 131. Owing to the doubt in correctly classifying these firms, they are excluded from the sub-samples of single- and multiple-segment firms but form a category on their own. We define this group of "change firms" as those that have changed the number of reported segments from one in 1997 to more than one in 1999.

Segment assets and segment sales of multiple-segment firms do not always add up to firm assets and firm sales. This is either because of firm assets or sales not fully allocated at the segment level, or because of missing data. To alleviate the data quality concern, we follow Berger and Ofek (1995) and Berger and Hann (2007) and exclude all firm and segment observations with the aggregated segment assets deviating from the firm assets by more than 25%. Similarly, we exclude those with a deviation of more than 5% for segment sales.[12] The remaining discrepancies can still lead to measurement errors in segment ROA and ROS. To mitigate the problem, we allocate the deviation proportionally to each segment based on the segment assets to firm assets ratio (and its counterpart for sales).

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

Panel A of table 2 summarizes the number of observations after applying each of the exclusion

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[10] All exclusion criteria are similar to those in Fairfield, Ramnath, and Yohn (2009).

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

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

criteria described above. For consistency, only observations with all measures available are used in the firm-level analysis, and only those with ROA, ROS and sales growth measures available are used in the segment-level analysis. About half of the firm-year observations belong to single-segment firms, while another 36% can be traced back to multiple-segment firms. Another 15% of the observations are categorized as change firms.

Panels B and C of table 2 give an overview of the firm and segment data used to compute the average forecast improvements reported in the main analysis. The firm-level analysis uses 66,504 firm-year observations of 8,586 unique firms; the segment-level analysis is based on 95,544 segment-year observations of 18,807 unique segments. For firms, the ROE on average is 8.0%, while the mean ROS and ROA are slightly higher at around 8.6% and 9.3%. With 15.0%, the mean RNOA is considerably higher. These statistics are similar to those in prior studies, such as Fama and French (2000) and Fairfield, Ramnath, and Yohn (2009). The average levels of segment profitability are somewhat lower than their firm profitability counterparts. The mean segment ROA and ROS are 7.7% and 6.7%, respectively.

Panel C reports for each industry the number of observations, as well as average profitability. With 5,635 firm-year and 8,288 segment-year observations, *electronic & other electric equipment* (SIC 36) constitutes the largest industry in the sample. Other important 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 average profitability across industries, ranging from 0.9% to 20.6%. For firms, *printing & publishing* (SIC 27) and *apparel & accessory stores* (SIC 56) are the industries with the highest levels of profitability. The lowest levels come from *agricultural production – crops* (SIC 01), *special trade contractors* (SIC 17) and *motion pictures* (SIC 78). The highest levels of segment profitability are from *railroad transportation* (SIC 40) and *pipelines, except natural gas* (SIC 46). *Motion pictures* (SIC 78) and *food stores* (SIC 54) exhibit the lowest levels of segment profitability.

## 4. FIRM-LEVEL ANALYSIS

### 4.1. FIRM PROFITABILITY FORECAST IMPROVEMENT

We begin by replicating Fairfield, Ramnath, and Yohn's (2009) main analysis on profitability forecasting to set a benchmark for our results. Their analysis examines the firm profitability forecast improvement of industry-specific analysis over economy-wide analysis. The results presented in table 3 confirm Fairfield, Ramnath, and Yohn's (2009) *no industry effect* result for ROE and RNOA in our out-of-sample test period (1977-2011).[13] For these two profitability measures, the mean forecast

[13] Unlike Fairfield, Ramnath, and Yohn's (2009) original analysis that uses all the firm data available, table 3 uses only observations for which we can reliably match firm and segment data. In untabulated analyses using all the firm data available in the out-of-sample tests, we can replicate the *no industry effect* result for ROE, RNOA, and ROA. The results are available on request.

improvements (of industry-specific over economy-wide analysis) are not significantly different from zero. Furthermore, the grand median forecast improvement for ROE is even negatively significant. Essentially, this results mirrors a standard result in the forecasting literature Baltagi and Griffin (1997), stating that homogenous estimators are generally better than heterogeneous estimators in time-series forecasting. The advantage comes from a considerably higher stability of the estimated model parameters.

Further evidence of the *no industry effect* result is obtained when using ROA as profitability measure. Including ROA in the firm-level analysis facilitates comparison with the results from the segment-level analysis (where ROE and RNOA cannot be computed owing to data limitations). The evidence based on ROA is similar to those for ROE and RNOA.

Table 3 also shows an interesting new finding: In terms of ROS, the mean firm profitability forecast improvements are highly significantly positive. This suggests that Fairfield, Ramnath, and Yohn's (2009) *no industry effect* result for profitability forecasting is sensitive to the profitability measure used.[14]

The prominent role of sales in the ROS ratio helps to understand the industry effect in forecasting this profitability measure. Fairfield, Ramnath, and Yohn (2009) show a strong and significant industry effect when forecasting sales growth, a result we confirm for our sample as well (see section 7.1). This strong industry effect in sales growth forecasting seems to induce a similar industry effect when predicting a firm's ROS.

Although ROS is a Du Pont decomposition component of ROA and ROE, the industry effect of ROS is not strong enough to produce an industry effect for these profitability measures. In section 7.1, we show that there is no industry effect when forecasting the firms' asset turnover that connects ROS to ROA. This explains why the industry effect disappears for ROA, RNOA and ROE.

**4.2. FIRM PROFITABILITY FORECAST IMPROVEMENT BY FIRM TYPE**

The benchmark results above confirm the earlier results by Fairfield, Ramnath, and Yohn (2009) that industry-specific forecasting models are not more accurate than simpler economy-wide models in predicting firm profitability–except for ROS. This result is counter-intuitive given that prior literature has documented the importance of industry effects in explaining firm profitability.

It is important to realize that many firms are actually diversified firms operating in various industries Berger and Ofek (1995). These different activities are usually organized in separate business segments. For such diversified multiple-segment firms, no single industry can accurately represent the entire firm. As a result, the primary industry classification of multiple-segment firms represents only a part of the firm, ignoring the activities from all other segments. The aggregated

[14] Although industry-specific forecasting models not are better in predicting firm profitability than economy-wide models (with the exception of ROS), there is considerable variation in the relative advantage of industry-specific models across industries. Appendix A3 analyzes the relation between the forecast accuracy of industry-specific models and selected industry characteristics.

reporting of the various business segments of multiple-segment firms therefore explains the lack of industry effects in firm profitability forecasting. Put differently, the aggregation of different activities in different industries breaks the relation between firm profitability and industry characteristics.

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. Hence, industry effects in profitability forecasting should reappear when confining the analysis to single-segment firms. For multiple-segments, however, the advantage of industry-specific forecasting models should remain indistinguishable from zero.

To test this hypothesis, we partition the forecast improvements into subsamples of single-segment firms, multiple-segment firms, and change firms. Change firms are firms that increased the number of reported segments from one in 1997 to more than one by 1999 following the introduction of SFAS 131 (see section 3.2. for details). Table 4 presents the forecast improvements for each of the sub-groups. In addition, the table also reports the difference in forecast improvements between the three sub-samples of firms.[15]

The table allows for several important conclusions. First, there is a strong evidence for industry effects when forecasting firm profitability of single-segment firms. With the exception of ROE, the forecast improvement of single-segment firms is significant at high confidence levels, regardless of the test statistics used. Next, as conjectured, there is no industry effect for multiple-segment firms. In none of the profitability measures considered, there is a positive forecast improvement of the industry-specific forecasting model. In many cases, the forecasting improvement is even negatively significant, i.e., the industry-specific model generates worse predictions than the economy-wide model. As a result, the difference in forecast improvement between single-segment and multiple-segment firms is highly significant. In other words, the industry-specific forecasting model is significantly better for single-segment firms relative to multiple-segment firms. Taken together, these results present strong support for one of the main conjectures of the paper: Industry effects in profitability forecasting exist, but are often hidden by aggregated reporting at the firm level.

The table also highlights another interesting finding regarding change firms, i.e., the firms that changed from single-segment firms to multiple-segment firms after the introduction of SFAS 131. The results of these firms are much more similar to those of multiple-segment firms than of single-segment firms. First, the forecast improvement is either indistinguishable from zero or negatively significant. Second, the difference in forecast improvement relative to single-segment firms is significantly positive – again with the exception of the ROE. Third, there is very little difference in forecast improvement between multiple-segment firms and change firms, except for ROA. All in all,

[15] Tests of the difference in the pooled means are based on a t-test on the estimated slope coefficient of a regression on the dummy for multiple-segment firms (or change firms), with the standard error corrected for the clustering by firm and year following Rogers (1993). For the grand mean, p-values are obtained by correcting standard errors following Newey and West (1987). Tests of the difference in the grand medians are based on a paired-sample Wilcoxon (1945) signed-rank test.

this suggests that change firms were indeed disguised multiple-segment firms before SFAS 131, i.e., change firms used the greater discretion allowed under SFAS 14 to avoid reporting their segments separately. This result is in line with Berger and Hann (2003) that show that the introduction of SFAS 131 induced firms to reveal previously hidden information on their diversified activities.

The exceptional results for ROE require further explanation. For ROE, there is no incremental advantage of using industry-specific over economy-wide forecasting models, not even for single-segment firms. To understand the difference between ROE and the other profitability measures, it is again helpful to resort to the Du Pont analysis that decomposes ROE into ROA and financial leverage. Although there is a strong industry effect for ROA of single-segment firms, additional analysis in section 7.1 shows that there is no industry effect when forecasting financial leverage – not even for single segment firms. This explains why the industry effect on forecasting ROE disappears when financial leverage is combined with ROA to form ROE.

### 4.3. BALANCING ESTIMATION RELIABILITY AND CAPTURING INDUSTRY EFFECTS

Although the results in the previous section provide strong support for industry effects in profitability forecasting for single-segment firms, two concerns remain. First, there is no industry effect for single-segment firms in terms of ROE, which is probably the most important profitability measure for investors. This casts doubt on whether the findings are economically relevant. Second, the mean forecast improvement of multiple-segment and change firms is often negative. This seems peculiar, given that the economy-wide forecasting model is a restricted version of the industry-specific model (i.e., the industry-specific coefficient estimates are not restricted to be identical across industries). In other words, the industry-specific model is more general and flexible, subsuming the economy-wide model as a special case.

The observation that restricted homogeneous estimators can perform better than more flexible heterogeneous estimators has been recognized in the forecasting literature. Baltagi, Griffin, and Xiong (2000) and Baltagi et al. (2003) show that there is a trade-off between capturing the heterogeneity in data (the advantage of heterogeneous estimators) and estimation reliability (the advantage of homogenous estimators). Homogenous estimators are often better in forecasting time-series models since pooling all observations together leads to substantially higher stability of the estimated model parameters. However, if there is considerable heterogeneity in the data, it is optimal to allow for some heterogeneity of the estimators as well.

In light of this, the main reason why economy-wide models generate better forecasts than industry-specific models is that the former estimate the model parameters using more observations. This leads to more reliable coefficient estimates relative to the industry-specific estimations. Although in theory industry-specific models are better to capture the heterogeneity in the data, the estimated model parameters are too noisy to reliably predict future profitability.

Following these considerations, this section presents an analysis that aims at correcting the problem of unequal estimation samples used in industry-specific and economy-wide analyses. Then we examine whether the accuracy of the industry-specific forecasting models can be increased by improving the trade-off between estimation reliability and capturing industry effects. The analyses allow for a better understanding of the causes driving the two models' relative forecast accuracy.

### 4.3.1. EQUAL SIZE OF ESTIMATION SAMPLE

To run an equal-footing horserace between economy-wide and industry-specific models, we keep the estimation sample of the two models constant. This ensures that any difference in the profitability forecasts is not due to a different number of observations when estimating the model parameters. Hence, instead of estimating the economy-wide model in one single regression using all observations, we estimate the economy-wide model for each industry separately. More precisely, for each industry, we randomly sample (with replacement) for the economy-wide model exactly the same number of observations that are available for the industry-specific model. For example, if the in-sample regression in a given industry uses 200 observations, we estimate the economy-wide model using 200 observations randomly sampled across all industries. This approach ensures that the industry-specific and economy-wide forecast parameters are estimated using exactly the same number of observations. Because the economy-wide model uses a randomly selected subsample, the coefficient estimates based on it should capture the economy-wide model parameters, just like using the full economy-wide sample. However, the full-sample estimates would have much smaller standard errors than the estimates based on the randomly-selected subsample.

The results, presented in panel A of table 5, show a strong industry effect in profitability forecasting for single-segment firms for all four profitability measured, including ROE. Relative to the previous analysis (see table 4), the forecast improvements of single-segment firms are considerable larger in magnitude and statistical significance. Furthermore, the forecast improvement of multiple-segment firms is much smaller in absolute terms, and with one exception no longer statistically significant. The picture is similar for change firms, with the exception of ROA.

All in all, the table shows that once the estimation of both forecasting models is based on an equal number of observations, the industry-specific model is clearly better than the economy-wide model in forecasting profitability for single-segment firms. In terms of the forecasting literature this shows that once the homogenous estimator is deprived of its advantage – the larger estimation sample – heterogeneous models are better. However, while this analysis clearly proves the superiority of industry-specific forecasting models for single-segment firms, this result is achieved not by improving the industry-specific models, but rather by removing the estimation advantage that favors the economy-wide approach.

### 4.3.2. TWO-STAGE IN-SAMPLE REGRESSIONS

Different from the analysis presented in the last section, we now aim at directly improving the industry-specific forecasts. Following the considerations on the trade-off between homogenous and heterogeneous estimators in the forecasting literature, it should be possible to improve the predictions of the industry-specific model by sorting all firms in fewer, but still sufficiently homogenous industry groups. Hence, this section proposes to form new industry groups depending on the firms' mean-reverting pattern in profitability. This procedure allows finding a better trade-off by acknowledging the heterogeneity in mean-reversion across industries (the advantage of the IS approach) while obtaining stable and reliable model parameters (the advantage of the EW approach).

To find industry groups that pool together sufficiently similar industries in terms of their mean-reversion properties, we adopt a two-stage in-sample regression approach. We collect the estimated mean-reversion coefficients of the first-stage in-sample regression, which uses the two-digit SIC code to sort firms into industries. Then we re-group all firms into 10 broader groups according to the firms' estimated mean-reversion coefficients. Using this reduced set of groups, we carry out a second round of in-sample regressions. Then we use the parameter estimates to predict the firms' profitability. In the forecasting literature, this approach is known as endogenous grouping (Bonhomme and Manresa 2015).

Over time, the mean-reversion properties of the industries can change. Since we re-group the firms into 10 broader groups every year, the composition of each group can change over time. Hence, the ten groups may not be called "industry groups" in the usual sense. Since some observations are lost in each in-sample regression, the sample for the out-of-sample tests is reduced by 21% (52,389 observations).

The results, presented in panel B of table 5, show again a strong industry effect in profitability forecasting for single-segment firms for all four profitability measures. In comparison to the original analysis (table 4), the forecast improvements of single-segment firms are considerable larger in magnitude and statistical significance. The mean forecast improvements are always statistically significant at the 1% level. With two exceptions, the forecast improvement of multiple-segment and change firms is not statistically significant. Similar results hold true when looking at the three columns that display the difference in forecast improvement between all three sub-groups: The difference between single-segment and both multiple-segment and change firms is substantial and always highly significant. In contrast, multiple-segment and change firms are undistinguishable in terms of forecast improvement.

This analysis shows that when collecting similar firms into sufficiently broad groups, industry-specific (i.e., heterogeneous) forecasting models are significantly better than economy-wide (i.e., homogenous) forecasting models. While the results of this analysis are very solid from an econometric point of view, the broader groups of firms do not represent industries in the conventional sense. The complex two-stage procedure also reduces its practical value to investors and finance practitioners.

#### 4.3.3. FAMA-FRENCH 12-INDUSTRY CLASSIFICATION

Instead of endogenously categorizing firms, an alternative is to directly use a broader industry classification, without going through a two-stage procedure. Using the two-digit SIC codes to define industries leaves us with 53 industries in the out-of-sample tests, many of which are rather small with just a few hundred observations over the entire time horizon. When resorting to a broader industry classification, each industry has substantially more observations, allowing a more reliable estimation of the forecasting parameters.

We hence repeat the original analysis as presented in section 4.2 using the 12-industry classification by Fama and French, instead of the two-digit SIC codes.[16] Similar to before, we exclude firms in regulated industries based on their SIC codes. Since the industry group number 12 (*other*) does not represent a genuine industry but merely combines all remaining non-allocated industries together, we exclude it from the sample. The data sample is thus slightly smaller than those based on the two-digit SIC codes. Appendix A presents the descriptive statistics of this data sample.

The results are presented in panel C of table 5. Similar to panels A and B, there is a strong industry effect in profitability forecasting for single-segment firms for all four profitability measures. Likewise, all other results of the previous subsections remain unchanged: there is no industry effect for both multiple-segment firms and change firms, which are again undistinguishable in terms of forecast improvement. As before, the difference between single-segment and both multiple-segment and change firms is large in magnitude and statistical significance.

All in all, this section shows that there is considerable heterogeneity in the mean-reverting pattern of profitability across industries, which can be exploited to improve the profitability forecasts of firms. However, two caveats have to be taken into account. First, industry effects in firm profitability are only visible for single-segment firms. For multiple-segment firms, no industry accurately represents the whole firm, such that economy-wide models provide more accurate profitability forecasts. Second, in order to reliably extract the industry patterns from the data, the industry classification have to be sufficiently broad – otherwise the model estimates are unreliable, leading to inaccurate forecasts.

Given the strong results based on the Fama-French 12-industry classification, together with its convenience for practical applications, we rely on this industry classification in the remaining analyses of the paper.

## 5. SEGMENT-LEVEL ANALYSIS

### 5.1. SEGMENT PROFITABILITY FORECAST IMPROVEMENT

The firm level-analysis documents industry effects in profitability forecasting for single-segment firms, but not for multiple-segment firms. These findings suggest that industry effects in profitability forecasting exist at the more refined segment level. For multiple-segment firms, the effects are not visible owing to aggregation of segment level data for external reporting of firm-level financials. If this conjecture is true, we should observe significant forecast improvements of profitability forecasting directly at the segment level.

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[16] Additional tests in section 7.2 show that the results are robust to other industry classifications.

We repeat the analysis presented in section 3 for all business segments in our sample. Since it is not possible to compute ROE and RNOA for business segments, we confine the analysis to the segments' ROA and ROS. The results, presented in panel A of table 6, confirm the industry effects in segment profitability forecasting for ROS. Indeed, there is a strongly significant forecast improvement of industry-specific forecasting models over economy-wide models. In combination with the findings of section 4.3, this suggests that industry effects in ROS forecasting exist at the segment level, but are obscured by aggregated reporting of multiple-segment firms.

Yet, in terms of ROA, there is no significant industry effect in profitability forecasting, with the exception of the grand median forecast improvement. This result suggests that, similar to the firm-level analysis, there is no industry effect when forecasting the segments' asset turnover that connects ROS to ROA. To some extent, this difference to ROS might also be explained by the better data quality of sales data relative to asset data at the segment level.

Still, this observation casts doubt on the view that it is only the aggregation of business segment reporting that causes the no-industry effect of profitability forecasting of multiple-segment firms. Rather, it seems that there are some additional explanations for the lack of industry effects in profitability forecasting of multiple-segment firms, going beyond the aggregation of business segment reporting at the firm level.

### 5.2. SEGMENT PROFITABILITY FORECAST IMPROVEMENT BY FIRM TYPE

The analysis in section 5.1 does not distinguish between segments of single-segment firms and segments of multiple-segment firms. Put differently, all segments are implicitly considered independent business units. Yet, the literature on corporate diversification suggests that conglomerates do not manage their business segments on a stand-alone basis, but rather transfer resources from one business segment to another in an attempt to increase the profitability of the entire firm. For example, the internal capital market literature argues that large firms tend to allocate resources across divisions over the business cycle (Maksimovic and Phillips 2002). The co-insurance literature suggests that coinsurance among a firm's business units can reduce systematic risk, thereby decreasing the firms' overall cost of equity capital (Hann, Ogneva, and Ozbas 2013).

To the extent that multiple-segment firms shift resources from one segment to another, the growth and profitability of their segments are influenced by these strategic moves of the firm, and thus less exposed to industry-specific factors. Hence, the industry effect in segment profitability forecasting should be considerably smaller for multiple-segment firms. In contrast – similar to the firm-level analysis – firms with a single business segment cannot transfer resources between segments. Hence, industry effects in profitability forecasting at the segment level should be substantial when confining the analysis to single-segment firms.

To test this hypothesis, we partition the forecast improvements into subsamples of segments for single-segment firms, multiple-segment firms, and change firms, similar to the firm-level analysis. The results are presented in panel B of table 6.

In line with the conjecture, there is indeed a significant industry effect for the segments of single-segment firms for both ROA and ROS. In contrast, the effect is much less pronounced for multiple-segment firms. Yet, the difference in the segments' forecast improvements between single-segment and multiple-segment is not that large, and fails to be significant for ROA. Besides, the table shows another interesting result: the segments' mean forecast improvement of change firms is negative for both profitability measures. As a result, the segment forecast improvement for both single- and multiple-segment firms is significantly larger than the segment forecast improvement for change firms.[17]

These results can be interpreted as evidence that the business segments of multiple-segment and change firms are indeed not managed completely separately. As a result, their performance is no longer primarily driven by their industry membership, but considerably affected by the firm to which the segments belong. Yet, why is this effect stronger for the group of change firms?

Remember that change firms increased the number of reported segments from one to more than one following the introduction of SFAS 131. This subset of firms was probably most affected by the change in disclosure regulations, which forced firms to provide more disaggregated information. In fact, Botosan and Stanford (2005) suggest that one of the firms' main reasons to avoid detailed disclosure prior to SFAS 131 was to conceal information on highly profitable segments which cross-subsidize other business units. Against this backdrop, it seems that change firms were not only multiple-segment firms in disguise prior to SFAS 131, but also those with the largest internal transfers between their business segments. The considerable cross-subsidization of change firms eliminates the industry-specific characteristics of their segments more than those of multiple-segment firms, such that only economy-wide profitability effects remain.

Overall, the segment-level analysis shows that the lack of industry effects in firm profitability forecasting of multiple-segment firms is likely to be explained by two separate aspects, the aggregation of business segment data at the firm level and the re-allocation of resources among business segments.

### 5.3. CHANGE IN SEGMENT REPORTING STANDARDS

In 1998, disclosure of segment information was changed following the introduction of Statement of Financial Accounting Standards No. 131 (SFAS 131). The stated purpose of the new standard was to increase the transparency and accuracy of firm segment structure. Under the previous standard SFAS 14, firms were asked to disclose segment information according to the industry classification of their segments. 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

[17] The large grand median forecast improvements for multiple-segment and change firms are due to the asymmetric distribution of the segments' forecast improvements following the introduction of SFAS 131 (see section 5.3).

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

Taken together, the introduction of SFAS 131 has two important implications for segment profitability forecasting models. First, the data to calculate segment profitably is less comparable across firms. Second, business segment data is no longer primarily organized by their industry affiliation. In light of this, we conjecture that industry-specific segment profitability forecasting models are likely to lose some of their relative advantage under SFAS 131.

To analyse the impact of the introduction of SFAS 131 on industry-specific segment profitability forecasting models, Panel C of table 6 presents the forecast improvements for each of the two accounting regimes separately. While the mean forecast improvements are substantial and highly significant in the SFAS 14 period, they are not significantly different from zero after the introduction of SFAS 131 in 1998. As a result, the difference (or change) in forecast improvements from SFAS 14 to 131 is negatively significant.[19]

The large median positive forecast improvement of ROA after the introduction of SFAS 131 – despite an insignificant mean – results from a negatively skewed distribution in forecast improvements. Put differently, there are few segments with very high positive forecast improvements. Since prior to SFAS 131, segments with high forecast improvements tend to be highly profitable, this observation is consistent with the idea that the increased transparency under SFAS 131 led multiple-segment firms to engage in some earnings management to artificially reduce the earnings of their most profitable segments.

The results confirm the conjecture that worse segment data quality under SFAS 131 is partly to blame for the relatively poor segment forecast improvements for the entire sample (see panel A). Hence, it is not only the reallocation of resources between business segments of multiple-segment firms, but also the change in accounting regulations in 1998 that causes the lack of industry effect in segment profitability forecasting for ROA.

## 6. INDUSTRY EFFECTS AND STOCK RETURNS

Although the forecast improvement of industry-specific over economy-wide models for single-segment firms is highly significant in the statistical sense, the magnitude of the improvements seems small in absolute terms. This might cast doubt on the economic relevance of the results. In this section, we analyse whether the advantage of industry-specific models to forecast firm profitability can be valuable for market participants. If stock prices do not efficiently incorporate fundamental information related to the industry exposure of single-segment firms, then there should be profitable trading strategies based on the firms' industry-specific profitability forecasts.

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

[19] We report an analysis of the impact of the introduction of SFAS 131 on industry-specific profitability forecasting models at the firm level in appendix A.2.

We employ the standard time-series portfolio test to assess the relation between future stock returns and the information contained in the industry-specific forecasts. Against the backdrop of our results, we restrict our analysis to the subsample of single-segment firms with positive current forecast improvements. We expect that for this subsample of firms, the industry-specific profitability forecast for the next year is likely to be more accurate than the economy-wide forecast as well. We hence propose a trading strategy that exploits the difference in expected profitability between industry-specific and economy-wide forecasts.

Each year at the end of June[20], we sort the cross-section of this subsample of firms into five quintiles based on the difference in forecasted profitability (DIFF) between industry-specific and economy-wide models,

$$DIFF_t = E_{IS,t}[x_{i,t+1}] - E_{EW,t}[x_{i,t+1}],$$

and measure the quintiles' monthly portfolio returns. Stock return data are obtained from CRSP. Portfolios are rebalanced annually. We construct a dollar-neutral equal-weight hedge portfolio which is long (short) in the constituents of the top (bottom) quintile of the difference in the forecasted profitability. We then perform time-series regressions of the hedge portfolio return onto the three factor-mimicking portfolios of Fama and French (1993b)[21]:

$$HEDGE_t = \alpha + \beta_1 MKT_t + \beta_2 SMB_t + \beta_3 HML_t + \varepsilon_t.$$

If investors react inefficiently to industry-specific information of expected firm profitability, the hedge portfolio should yield positive risk-adjusted returns.

Table 7 presents the returns of three trading strategies based on the firms' difference in forecasted profitability). Panel A reports the returns when using the subsample of single-segment firms whose current forecast improvement is positive, as described above. Since firm profitability forecasts of a single financial year are likely to be noisy, we also consider two alternatives that take into account the firms' average forecast improvement over the most recent 10 years. Panel B reports the portfolio returns when including the subset of firms whose 10-year (moving) average forecast improvement is positive. Panel C includes only firms whose weighted 10-year (moving) average forecast improvement is positive, where the weight decreases linearly over the last 10 years.

The table shows that the monthly returns of the hedge portfolio are positive for the trading strategies based on the firms' expected ROE, RNOA and ROA. More important, the monthly risk-adjusted portfolio returns (portfolio alphas) are quite substantial and significant at high levels of statistical significance. For example, the trading strategy based on the firms' expected RNOA yields risk-adjusted annual returns of up to 5.6%. The risk-adjusted returns of ROE and ROA investments are similarly high. In unreported tests, we examine why risk-adjusted hedge portfolio returns are higher than the unadjusted long/short portfolio returns. The hedge portfolio loads negatively on all

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[20] To ensure that the strategy is implementable we require that the relevant information on firm fundamentals of the previous fiscal year is available. We hence only consider single-segment firms with a fiscal year end in December.

[21] Data on the three factor-mimicking portfolio returns are obtained from Kenneth French's website.

three Fama and French (1993b) risk factors, but especially on the size factor. Put differently, the hedge return is particularly high when the large firms perform well. All in all, these results show that investors do not seem to efficiently use information related to the industry exposure of single-segment firms, as exploited by industry-specific profitability forecasting models.

In contrast, the trading strategies based on the firms' expected ROS do not yield significant positive risk-adjusted returns. Although the forecast improvement of industry-specific over economy-wide models is the largest for ROS, the information from the forecasts seems reflected in stock prices, and thus of no additional value to equity investors. There might be several reasons for this finding.

Financial analysts usually start their analysis of a firm with the sales forecasts. In particular, the construction of the free cash flow forecasts for discounted cash flow analysis usually begins with the sales forecasts (Pinto et al. 2010). If financial analysts understand the sale forecasts much better than the forecasts of other accounting items, a large part of the information contained in the ROS forecasts (namely, the sales forecasts) might have been communicated to the market.

Another explanation for the insignificant risk-adjusted returns of the ROS-based trading strategies is that large industry effects in ROS do not necessarily imply large industry effects in ROE, since they are related to each other only via asset turnover and financial leverage. Yet, equity investors are ultimately interested in the returns of their investments. To the extent that industry effects of ROS do not translate into industry effects of ROE, a trading strategy based on the firms' expected ROS should not be profitable.

The risk-adjusted returns of the hedge portfolio reported in table 7 are gross of transaction costs, such as brokerage commissions and bid-ask spreads. Yet, actual investors implementing these strategies face transaction costs each time they rebalance their portfolios. Since this strategy requires only one rebalancing per year, their annual turnover is relatively low. Given that recent research suggests that average round-trip transaction costs are about 25 basis points (Frazzini, Israel, and Moskowitz 2012), the investment strategies based on ROE, RNOA and ROA are likely to be profitably even after taking into account the impact of transaction costs.

## 7. ADDITIONAL TESTS

### 7.1. SALES GROWTH, ASSET TURNOVER, AND FINANCIAL LEVERAGE

The results of the firm-level analysis show that the industry effects in profitability forecasting are much stronger for ROS relative to the other three profitability measures. Furthermore, the forecast improvements for ROE are only statistically significant when confining to the subset of single-segment firms, using a broad industry classification.

This section aims at shedding further light on these differences. Using Du Pont analysis, a firm's ROE can be broken down into financial leverage and ROA, which can be further split into asset turnover ratio and ROS. As argued in section 4, diverging degrees of industry effects in profitability forecasting across the four measures might be explained by the lack of industry effects in asset turnover and financial leverage. Accordingly, the strong industry effect of ROS is diluted once combined with asset turnover to form the ROA. Similarly, the remaining industry effects of ROA are further diluted when combined with financial leverage to form the firms' ROE.

We hence examine industry effects in forecasting asset turnover and financial leverage, using the same framework as before. In addition, we also examine industry effect in the growth of sales. Fairfield, Ramnath, and Yohn (2009) present evidence for industry effects in sales growth forecasting, and it is an interesting question whether this effect is also present in our sample. Furthermore, a strong industry effect in sales growth forecasting can also help to explain the strong industry effect in ROS.

Table 8 presents the results. Similar to Fairfield, Ramnath, and Yohn (2009), we find a significant industry effect in sales growth forecasting. The fact that the mean and median forecast improvement is lower relative to their study can be explained by the diverging time horizon analysed.[22] Yet, the table shows that there is no advantage of industry-specific forecasting models for asset turnover and financial leverage. In fact, the forecast improvement of financial leverage is even negatively significant. This is consistent with the view that – although firms differ in the product markets defining their industries – they all raise capital in the same financial market.

When dividing the firm sample into single-segment, multiple-segment and change firms, the standard pattern re-emerges. The forecast improvements for all three measures are the highest for single-segment firms, while they are significantly lower for multiple-segment and change firms (see panel B). However, in line with panel A, only the sales growth forecast improvement for single-segment firms is significantly positive.

Since it is not possible to compute asset turnover and financial leverage for business segments, we confine the segment-level analysis to the segments' sales growth (see panel C). With the exception of the grand median, the table shows a strong industry effect in sales growth forecasting of segments. Yet, and in accordance with the analysis for segment profitability, panel D shows that this industry effect is only driven by the segments of single-segment firms. The forecast improvement of multiple-segment and change firms is statistically not different from zero.

Overall, the results confirm our conjectures. We replicate the industry effect in sales growth forecasting of Fairfield, Ramnath, and Yohn (2009). Given the prominent role of sales in the ROS ratio, this can explain the strong industry effect in ROS forecasting. Yet, we show that this effect is – again – only driven by single-segment firms. Finally, the lack of industry effect in asset turnover and financial leverage forecasting can explain the smaller industry effect in ROE, RNOA and ROA, relative to ROS.

### 7.2. ALTERNATIVE INDUSTRY CLASSIFICATIONS

The main results of the paper are obtained when sorting firms according to the Fama-French 12-industry classification. Yet, there exist many alternative industry classifications. More important, the findings of Bhojraj, Lee, and Oler (2003) suggest that differences across industry classifications can

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[22] In the period from 1977 to 1986, the industry effect in sales growth forecasting is not significant.

drive the results of industry-specific analyses, depending on the application. Furthermore, firms can actively select their industry classification by manipulating sales data to increase the relative importance of largest industry segment, which is important to determine the primary industry (Chen, Cohen, and Lou 2016).

This section explores to which extent our results are affected by the choice of the industry classification. We replicate the main analysis of the paper (as in section 4.2) using three alternative industry definitions that allow for broad industry classifications. These classifications include the one-digit SIC codes, the (two-digit) GICS industry sectors, and the one-digit NAICS classification.

Similar to the main analysis, we exclude firms in regulated industries based on their SIC codes. Yet, the number of observations is different for each industry classification, since not all classifications are available for all firms in the sample. Furthermore, the minimum requirement of 100 observations in each of the in-sample estimations for every year and industry leads to different samples for the out-of-sample tests.

Table 9 compares the out-of-sample results for all profitability measures considered in this study when defining industries according to the one-digit SIC codes, the GICS industry sectors, and the one-digit NAICS.[23] The results are generally robust across the various industry classifications and very similar to those based on the Fama-French 12-industry classification (see table 5, panel C). Industry-specific forecasting models generate more precise predictions for future profitability for single-segment firms, but not for multiple-segment firms and change firms, with a few exceptions.[24] The fact that change firms and multiple-segment firms are very similar in terms of forecast improvement again suggests that change firms were using greater discretion under SFAS 14 to hide some of their segments. As before, the industry effect is the strongest for ROS, and least significant for the ROE. In direct comparison, the GICS industry sector classification yields the most distinct results, even better than those based on the Fama-French 12-industry classification. This is in line with the findings by Bhojraj, Lee, and Oler (2003) that show that the firms' industry profitability and industry growth measures have a higher correlation under GICS relative to other industry classifications.

## 8. CONCLUSION

This paper examines industry effects in profitability forecasting for firms and business segments. We measure industry effects in profitability forecasting by comparing the accuracy of industry-specific forecasting models relative to economy-wide models. Using a large variety of out-of-sample tests, this paper reveals considerable industry effects in profitability forecasting.

We reach our conclusions by incorporating two important aspects into the analysis that are crucial to understand industry effects in profitability forecasting. First, we distinguish between single-

[23] For brevity, only the pooled and grand mean forecast improvements are presented. All other results are available on request.

[24] In some few cases, the forecast improvement of multiple-segment firms is significantly different from change firms. Yet, there is no consistent picture, as the forecast improvement of multiple-segment firms tends to be higher for the GICS industry sectors, but lower for the one-digit SIC and one-digit NAICS codes.

segment and multiple-segment firms. Although industry effects in profitability forecasting exist, they are only visible for single-segment firms. For multiple-segment firms, industry effects are concealed by aggregated reporting of their business segments at the firm level. Second, we follow the insights of the forecasting literature to determine a better trade-off between the advantage of economy-wide models (high estimation reliability) and industry-specific models (less estimation bias). To reliably extract industry patterns from the data, the industry classification have to be sufficiently broad – otherwise industry-specific profitability forecasts are too noisy to accurately predict future profitability.

Our results have a number of implications for academics and practitioners. First of all, industry effects in profitability forecasting can by profitably exploited by market participants. A long/short trading strategy based on the firms' industry-specific profitability forecasts yields significant risk-adjusted returns of up to 5.6% annually. This trading strategy shows that the fundamental information related to the industry exposure of single-segment firms is not fully impounded in the stock market.

Second, our results are relevant to the accounting disclosure literature. The finding that information contained in segment-level data can help to improve a firm's profitability forecasts underlines the usefulness of less aggregated accounting disclosure. Yet, following the introduction of SFAS 131, the segment data is less comparable across firms, thereby limiting its use for investors. This result highlights the importance of ensuring a certain level of comparability of the reported business segment data across firms.

Finally, the existence of industry effects in profitability forecasting reconfirms to some extent the residual income valuation models by Gebhardt, Lee, and Swaminathan (2001) and Gode and Mohanram (2003). These models, which enjoy great popularity in the finance literature, rely on industry benchmarks as targets to which firm profitability converges.[25] However, as this paper shows, it is important to properly define and estimate these industry benchmarks, considering the balance between the accurate measurement of industry effects and estimation reliability.

[25] The models by Gebhardt, Lee, and Swaminathan (2001) and Gode and Mohanram (2003) have been used extensively in the finance literature to estimate 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).

## APPENDICES

### APPENDIX 1: DESCRITPIVE STATISTICS OF THE DATA SAMPLE USING 12 INDUSTRIES (FAMA AND FRENCH)

This appendix describes the data sample when classifying firms into 12 industries following Fama and French. Panel A of table A1 summarizes the number of observations after applying each exclusion criteria. Since firms sorted into industry group number 12 (*other*) do not present an actual industry, these firms are excluded from the sample.[26] Hence, the data sample is somewhat smaller relative to the sample based on the two-digit SIC (see table 2). Again, only observations with all measures available are used in the firm-level analysis, and only those with ROA, ROS and sales growth measures available are used in the segment-level analysis.

Panel B of table A1 gives an overview of the firm and segment data used to compute the average forecast improvements reported in the main analysis. The firm-level analysis uses 57,322 firm-year observations of 7,227 unique firms; the segment-level analysis is based on 80,188 segment-year observations of 15,560 unique segments.

For firms, the ROE on average is 8.3%, while the mean ROS and ROA are slightly higher at around 8.6% and 9.5%. With 15.3%, the mean RNOA is considerably higher. These statistics are only slightly higher than those using the two-digit SIC industry classification. In contrast, the average levels of segment profitability are almost identical to those based on the two-digit SIC industry classification. The mean segment ROA and ROS are 7.8% and 6.5%, respectively.

### APPENDIX 2: CHANGE IN SEGMENT REPORTING STANDARDS - FIRM-LEVEL ANALYIS

This appendix examines the effect of the introduction of the segment reporting standard SFAS 131 on firm profitability forecasting models. Since the accounting standard SFAS 131 only affects the disclosure of business segment information, we do not expect any significant changes to profitability forecasting models at the firm level. Table A.2 presents the forecast improvements by firm type (as in table 5, panel C) for the two accounting regimes separately, i.e., SFAS 14 and SFAS 131. For brevity, we only present the pooled and the grand mean forecast improvement in the table.

As expected, there is no significant change in industry effects in profitability forecasting at the firm level. In most cases, the change in forecast improvement from SFAS 14 to SFAS 131 is small, and not statistically different from zero. The only notable exception is the forecast improvement for the single-segment firms' ROE, which has considerably decreased after the introduction of SFAS 131. Further analysis suggests that this is likely to be a consequence on the financial crisis 2008/09. The financial debt crisis had considerable effects on the firms' financial leverage, regardless of their industry membership.

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[26] The Fama and French industry number 12 (*other*) includes firms operating in industries as mining, construction, building materials, transportation, hotels, business services, and entertainment.

**APPENDIX 3: INDUSTRY CHARACTERISTICS**

With the exception of the ROS, industry-specific forecasting models are better in predicting firm profitability than economy-wide models for single-segment firms only (see table 3). Yet, there is considerable variation in the relative advantage of industry-specific models across industries. For some industries, industry-specific models provide more accurate forecasts for all three groups of firms, including multiple-segment and change firms. Using the insights from the detailed firm- and segment-level analysis in sections 4 and 5, this appendix examines the relation between the forecast accuracy of industry-specific models and selected industry characteristics. In an attempt to better isolate cross-industry differences, all analyses presented in this appendix aggregate firm data at the industry level. In order to have sufficient cross-industry variation, the analyses are based on in-sample regressions using the two-digit SIC industry classification with 53 industries.[27]

The first conjecture is that industries with a higher proportion of single-segment firms benefit most from industry-specific forecasting models since the industry effect of such industries is more visible in the data. If there are only a few single-segment firms in a given industry, it is much more difficult to extract the industry pattern from the data using industry-specific analysis. Put differently, we expect a positive relation between the industries' average forecast improvement and the fraction of single-segment firms. We calculate for each industry and year the fraction of single-segment firms. Then we regress the mean industry forecast improvements on this fraction, using both panel regressions and the Fama and MacBeth (1973) approach. The results are presented in panel A. With the exception of the ROE, we find strong support for this hypothesis. As expected, there is a significant relation between forecast improvement and the fraction of single-segment firms in a given industry. The fact that this relation does not hold for the firms' ROE can be explained by the industry classification chosen in this analysis. As shown in section 4.1, the two-digit SIC is too narrow to reliably extract industry effects of the firms' ROE.

Second, industry-specific forecasting models are more valuable for industries whose firms are more homogenous, i.e., their various activities are more related to each other. In turn, if the firms of a given industry tend to be conglomerates operating in many different industries, it is rather difficult to extract industry effects. Similar to the previous analysis, the relative advantage of industry-specific analysis is likely to be minor only. We therefore expect a positive relation between an industry's average forecast improvement and the degree of relatedness of the firms in that industry. To test this hypothesis, we first estimate for each firm in our sample its degree of relatedness. We define this degree of relatedness as the largest SIC level that comprises all the firm's business segments. For example, if a firm has two segments with SIC codes 2413 and 2503, the degree of relatedness is 1 (i.e., a rather low degree of relatedness). In contrast, if a firm has two segments with SIC codes 2413 and 2414, the degree of relatedness is 3 (i.e., a rather high degree of relatedness). Single-segment

[27] We would like to thank an anonymous reviewer for suggesting this analysis.

firms are defined to have a degree of relatedness of 4. Then we calculate for each industry and year the firms' average degree of relatedness. Similar to the previous analyses, we then regress the mean industry forecast improvement for a year and industry on this measure of industry relatedness. Panel B presents the results. Again we find strong support for this hypothesis, with the exception of the ROE. As expected, there is a significant relation between forecast improvement and the industry's average degree of relatedness.

Third, we conjecture that the difference in forecast improvement between single-segment and multiple-segment firms is particularly large in industries where the multiple-segment firms have very little related business segments. If a multiple-segment firm is very diverse, the firm's main industry cannot reliably explain its profitability pattern – in stark contrast to single-segment firms. To test this hypothesis, we first compute for a given industry and year, the average degree of relatedness of multiple-segment firms. Then we discard all industry-year observations where the average degree of relatedness of multiple-segment firms is lower than 2. This means that most of the multiple-segment firms have at least two segments operating in different 1-digit SIC codes. We use same definition of a firm's degree of relatedness as in the previous analysis. For the remaining industry-year observations, we then calculate the average forecast improvement for single-segment and multiple-segment firms.[28] Panel C of table A3 reports the difference in industry forecast improvement between single-segment and multiple-segment firms for these industries. In line with the hypothesis, the difference in forecast improvement is positive, and with the exception of ROE, significant. Yet, the differences are smaller relative to the difference in forecast improvement between single-segment and multiple-segment firms presented in table 4. This suggests that aggregating firm-level to the industry considerably reduces the power of the analysis.

Finally, industry-specific forecasting models are most beneficial if the industry's profitability pattern substantially deviates from the economy. In contrast, for industries whose mean-reverting pattern is similar to those of the economy, there should not be any advantage of using industry-specific models. Hence, we expect a positive relation between an industry's average forecast improvement and the absolute deviation of the industry's mean-reversion coefficient from the economy's mean-reversion coefficient. To test this hypothesis, we calculate for each industry and year the absolute difference between the industry-specific and the economy-wide mean-reversion coefficients obtained in the in-sample regressions. Then we regress the mean industry forecast improvement on this difference. The results are presented in panel D of table A3. As conjectured, there is a positive relation between forecast improvements and the difference between industry and economy-wide mean-reversion coefficients. Yet, the relation is only significant for RNOA and ROA, thereby providing only moderate support for the hypothesis.

[28] In this analysis, change firms are excluded.

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**TABLE 1**
Variable definitions

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

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

**TABLE 2**

Sample selection and descriptive statistics

**Panel A:** Sample selection

| Adjustments to data sample | Firm-level data (firm-year observations) | | | | | | | Segment-level data (segment-year observations) | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | *ROE* | *RNOA* | *ROA* | *ROS* | *GSL* | *ATO* | *FLEV* | *ROA* | *ROS* | *GSL* |
| Observations for in-sample regressions | | | | | | | | | | |
| Total observations, excluding utilities and financial firms/segmer | 255,680 | 255,581 | 256,816 | 248,712 | 246,967 | 255,627 | 256,140 | 236,156 | 255,508 | 275,035 |
| Less observations with small denominators | 159,885 | 159,831 | 160,912 | 160,451 | 160,679 | 160,307 | 160,050 | 219,160 | 238,891 | 257,111 |
| Less observations with an absolute value larger than 1 | 156,311 | 156,946 | 160,874 | 159,208 | 160,679 | 160,307 | 160,050 | 215,819 | 230,101 | 275,111 |
| Less observations with more than 100% growth | 139,739 | 140,544 | 142,268 | 141,539 | 142,294 | 142,294 | 142,293 | 184,659 | 181,691 | 196,123 |
| Less upper and lower centiles observations | 136,945 | 137,734 | 139,424 | 138,709 | 139,451 | 139,450 | 139,449 | 180,967 | 178,059 | 192,201 |
| Observations for out-of-sample tests, out of which | | | | 66,504 | | | | | 95,544 | |
| Single-segment firms | | | | 32,363 | | | | | 47,076 | |
| Multiple-segment firms | | | | 23,856 | | | | | 35,323 | |
| Change firms | | | | 10,285 | | | | | 13,145 | |

This panel summarizes the sample selection procedure and the number of observations available after each filter. Besides utilities and financials, we also exclude the U.S. postal service (SIC 43), non-classifiable establishments (SIC 99) and observations without SIC code. 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. Change firms are firms that have changed the number of reported segments from one in 1997 to more than one in 1999, suggesting that they might not be genuinely single-segment firms prior to the introduction of SFAS 131 in 1998 (see section 3 for details). Firms with missing segment data or where the aggregate segment data deviate substantially from firm data are excluded in the out-of-sample tests. For more details, see section 3.

**TABLE 2** (continued)
Sample selection and descriptive statistics

**Panel B:** Descriptive statistics

| Variable | Mean | Std. deviation | First quartile | Median | Third Quartile |
|---|---|---|---|---|---|
| Firm-level: 8,586 firms (66,504 firm-year observations) | | | | | |
| *NI* | 116.000 | 697.120 | 1.124 | 8.386 | 46.617 |
| *OPINC* | 227.132 | 1,043.076 | 4.206 | 20.138 | 99.073 |
| *TA* | 2,551.746 | 11,038.380 | 76.579 | 258.156 | 1,107.754 |
| *NOA* | 1,518.097 | 6,663.887 | 48.580 | 161.336 | 704.150 |
| *BV* | 994.201 | 4,397.882 | 36.933 | 120.954 | 485.450 |
| *SALES* | 2,390.899 | 9,670.432 | 98.154 | 307.094 | 1,203.244 |
| *ROE* | 8.00% | 14.70% | 3.08% | 10.48% | 16.40% |
| *RNOA* | 15.01% | 14.12% | 7.09% | 14.15% | 22.36% |
| *ROA* | 9.25% | 7.97% | 4.70% | 9.26% | 14.03% |
| *ROS* | 8.64% | 9.10% | 3.50% | 7.56% | 12.72% |
| *GSL* | 8.67% | 16.70% | -0.43% | 7.94% | 17.01% |
| *ATO* | 1.340 | 0.747 | 0.824 | 1.219 | 1.681 |
| *FLEV* | 2.465 | 1.404 | 1.616 | 2.096 | 2.788 |
| Segment-level: 18,807 segments (95,544 segment-year observations) | | | | | |
| *OPINC* | 114.842 | 527.435 | 0.492 | 9.188 | 57.747 |
| *TA* | 1,235.240 | 4,975.927 | 31.668 | 144.469 | 639.757 |
| *SALES* | 1,340.604 | 6,170.427 | 39.957 | 172.142 | 708.045 |
| *ROA* | 7.70% | 13.79% | 1.98% | 8.43% | 14.94% |
| *ROS* | 6.71% | 13.49% | 1.44% | 6.79% | 13.20% |
| *GSL* | 7.21% | 19.87% | -3.42% | 6.27% | 17.14% |

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

**TABLE 2** (continued)
Sample selection and descriptive statistics

**Panel C:** Descriptive statistics by industry

| Two-digit SIC | Description | Firm-level data Obs. | *ROE* | *RNOA* | *ROA* | *ROS* | *GSL* | *ATO* | *FLEV* | Segment-level data Obs. | *ROA* | *ROS* | *GSL* |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | Agricultural production-crops | 97 | 1.99% | 8.27% | 4.74% | 7.14% | 5.26% | 0.695 | 3.107 | 274 | 6.39% | 8.66% | 4.62% |
| 10 | Metal mining | 404 | 3.77% | 7.88% | 5.21% | 9.38% | 7.03% | 0.534 | 1.888 | 444 | 4.85% | 8.00% | 5.29% |
| 12 | Coal mining | 6 | 9.00% | 14.55% | 9.88% | 16.54% | 10.76% | 0.742 | 2.036 | 227 | 7.08% | 9.20% | 2.41% |
| 13 | Oil & gas extraction | 1,799 | 5.83% | 10.11% | 6.84% | 14.23% | 9.94% | 0.585 | 2.444 | 2,819 | 6.14% | 12.17% | 9.69% |
| 14 | Nonmetallic minerals | 168 | 9.44% | 13.95% | 9.82% | 11.04% | 8.26% | 0.978 | 1.911 | 276 | 11.76% | 13.89% | 8.32% |
| 15 | General building | 662 | 9.85% | 11.55% | 7.96% | 7.58% | 12.53% | 1.151 | 3.589 | 773 | 5.52% | 4.30% | 7.21% |
| 16 | Heavy construction | 251 | 5.51% | 13.79% | 6.35% | 4.23% | 9.61% | 1.672 | 2.695 | 384 | 6.74% | 3.59% | 8.73% |
| 17 | Special trade contractors | 106 | 1.97% | 9.51% | 4.77% | 2.59% | 8.11% | 1.673 | 3.389 | 440 | 6.21% | 3.39% | 4.49% |
| 20 | Food & kindred products | 2,588 | 11.41% | 17.56% | 11.06% | 7.76% | 7.94% | 1.687 | 2.479 | 2,966 | 10.69% | 7.67% | 7.37% |
| 22 | Textile mill products | 991 | 5.74% | 13.17% | 9.35% | 6.24% | 5.70% | 1.556 | 2.399 | 916 | 7.90% | 5.47% | 2.41% |
| 23 | Apparel & other textile | 1,063 | 8.00% | 16.04% | 10.72% | 7.35% | 6.78% | 1.658 | 2.232 | 1,063 | 8.95% | 6.07% | 4.55% |
| 24 | Lumber & wood | 620 | 6.17% | 12.14% | 7.56% | 6.16% | 5.54% | 1.664 | 2.298 | 852 | 8.04% | 6.18% | 3.40% |
| 25 | Furniture & fixtures | 839 | 9.60% | 16.86% | 11.16% | 7.18% | 7.22% | 1.624 | 2.124 | 809 | 8.76% | 5.41% | 4.76% |
| 26 | Paper & allied products | 1,402 | 9.62% | 14.57% | 10.01% | 8.93% | 7.32% | 1.215 | 2.581 | 1,731 | 10.52% | 9.46% | 5.83% |
| 27 | Printing & publishing | 1,350 | 11.38% | 19.19% | 12.43% | 10.79% | 8.51% | 1.255 | 2.284 | 1,785 | 11.11% | 9.79% | 4.63% |
| 28 | Chemicals & allied products | 4,103 | 11.01% | 18.75% | 11.35% | 11.20% | 8.51% | 1.122 | 2.220 | 5,963 | 10.21% | 8.90% | 8.08% |
| 29 | Petroleum & coal | 778 | 10.49% | 15.99% | 9.58% | 8.42% | 9.93% | 1.431 | 2.738 | 703 | 8.25% | 4.84% | 8.93% |
| 30 | Rubber & plastic products | 1,224 | 7.89% | 16.09% | 10.48% | 7.57% | 6.70% | 1.416 | 2.622 | 1,878 | 11.01% | 7.61% | 6.12% |
| 31 | Leather | 369 | 7.35% | 16.79% | 10.76% | 6.49% | 5.14% | 1.660 | 2.172 | 468 | 7.29% | 4.42% | 4.70% |
| 32 | Stone, clay & glass | 863 | 9.23% | 13.26% | 9.13% | 8.89% | 6.51% | 1.123 | 2.379 | 1,094 | 9.64% | 8.95% | 4.48% |
| 33 | Primary metal products | 1,878 | 5.91% | 12.16% | 8.14% | 6.75% | 7.08% | 1.260 | 2.538 | 2,212 | 8.44% | 6.19% | 6.46% |
| 34 | Fabricated metal products | 1,932 | 9.13% | 16.82% | 10.76% | 8.47% | 6.78% | 1.346 | 2.400 | 2,621 | 11.23% | 7.92% | 5.92% |
| 35 | Industrial machinery & equipment | 4,939 | 7.33% | 14.79% | 8.81% | 7.41% | 8.55% | 1.209 | 2.215 | 7,930 | 6.62% | 4.75% | 6.20% |
| 36 | Electronic & other electric equipment | 5,635 | 5.57% | 13.39% | 7.91% | 6.80% | 8.98% | 1.186 | 2.011 | 8,288 | 5.85% | 4.28% | 7.00% |
| 37 | Transportation equipment | 2,307 | 9.42% | 16.17% | 9.45% | 7.55% | 8.49% | 1.363 | 2.833 | 3,151 | 9.83% | 7.08% | 6.03% |
| 38 | Instruments & related products | 4,044 | 7.67% | 15.18% | 9.28% | 8.93% | 9.81% | 1.090 | 1.912 | 6,468 | 6.38% | 5.45% | 8.38% |
| 39 | Misc. manufacturing industries | 926 | 5.55% | 14.38% | 9.02% | 7.14% | 6.02% | 1.284 | 2.251 | 1,134 | 6.70% | 5.42% | 4.04% |
| 40 | Railroad transportation | 610 | 9.25% | 10.98% | 6.84% | 15.27% | 5.76% | 0.482 | 2.852 | 396 | 7.23% | 16.48% | 5.34% |
| 42 | Trucking & warehouse | 910 | 8.38% | 14.93% | 9.00% | 5.85% | 9.93% | 1.814 | 2.763 | 1,058 | 8.80% | 6.04% | 8.95% |
| 44 | Water transportation | 417 | 5.82% | 8.29% | 6.07% | 13.71% | 6.43% | 0.523 | 2.684 | 718 | 6.24% | 14.18% | 5.70% |
| 45 | Transportation by air | 767 | 5.87% | 10.89% | 5.96% | 6.53% | 12.84% | 1.068 | 3.798 | 996 | 4.74% | 4.80% | 9.66% |

| Panel C: Descriptive statistics by industry (continued) | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Two-digit SIC | Description | Firm-level data | | | | | | | | Segment-level data | | | |
| | | Obs. | *ROE* | *RNOA* | *ROA* | *ROS* | *GSL* | *ATO* | *FLEV* | Obs. | *ROA* | *ROS* | *GSL* |
| 46 | Pipelines, except natural gas | 0 | - | - | - | - | - | - | - | 95 | 9.04% | 26.63% | 13.54% |
| 47 | Transportation services | 169 | 10.13% | 19.04% | 9.89% | 11.35% | 9.49% | 1.594 | 2.961 | 516 | 9.71% | 8.61% | 8.41% |
| 48 | Communications | 3,344 | 11.80% | 16.05% | 10.85% | 21.82% | 8.69% | 0.542 | 2.795 | 4,024 | 8.63% | 16.95% | 8.46% |
| 49 | Electric, gas & sanitary services | 380 | 4.26% | 10.23% | 6.48% | 10.59% | 8.31% | 0.788 | 3.197 | 849 | 5.30% | 8.57% | 7.81% |
| 50 | Wholesale trade-durable products | 2,507 | 6.99% | 13.14% | 8.41% | 4.82% | 8.80% | 2.115 | 2.739 | 3,505 | 7.23% | 3.52% | 7.25% |
| 51 | Wholesale trade-nondurable goods | 1,171 | 8.64% | 14.27% | 8.47% | 4.90% | 9.09% | 2.352 | 3.303 | 2,015 | 8.30% | 4.38% | 8.90% |
| 52 | Building materials | 289 | 8.40% | 16.35% | 11.05% | 5.61% | 11.37% | 2.093 | 2.607 | 310 | 6.94% | 3.54% | 7.12% |
| 53 | General merchandise stores | 1,141 | 9.08% | 15.64% | 9.71% | 5.14% | 9.02% | 2.064 | 2.673 | 946 | 7.24% | 3.73% | 5.97% |
| 54 | Food stores | 862 | 10.10% | 17.29% | 9.98% | 3.42% | 7.37% | 3.121 | 3.151 | 878 | 8.75% | 2.90% | 4.97% |
| 55 | Automotive dealers & services | 303 | 7.31% | 11.22% | 8.23% | 4.15% | 9.52% | 2.182 | 2.984 | 412 | 7.28% | 3.97% | 9.46% |
| 56 | Apparel & accessory stores | 937 | 9.25% | 20.57% | 10.70% | 5.23% | 8.42% | 2.132 | 1.942 | 1,166 | 11.35% | 5.31% | 8.41% |
| 57 | Furniture stores | 541 | 6.53% | 16.37% | 9.06% | 5.04% | 11.17% | 2.083 | 2.480 | 665 | 5.69% | 3.09% | 8.74% |
| 58 | Eating & drinking places | 1,499 | 7.62% | 14.81% | 10.33% | 7.36% | 9.66% | 1.552 | 2.332 | 1,952 | 7.42% | 5.03% | 6.63% |
| 59 | Miscellaneous retail | 1,529 | 7.38% | 15.70% | 9.53% | 5.28% | 10.41% | 2.028 | 2.377 | 2,002 | 7.74% | 4.08% | 9.60% |
| 70 | Hotels & other lodging places | 407 | 4.61% | 8.58% | 6.23% | 10.70% | 6.89% | 0.654 | 3.838 | 594 | 5.94% | 10.46% | 4.64% |
| 72 | Personal services | 227 | 8.53% | 14.85% | 9.61% | 10.79% | 7.39% | 1.187 | 2.720 | 262 | 8.91% | 9.33% | 10.83% |
| 73 | Business services | 3,900 | 6.07% | 16.57% | 8.04% | 7.97% | 9.89% | 1.273 | 2.335 | 8,368 | 4.97% | 4.70% | 8.10% |
| 75 | Auto repair, services & parking | 177 | 6.96% | 10.62% | 7.43% | 11.26% | 4.24% | 0.810 | 4.575 | 268 | 5.05% | 6.86% | 5.95% |
| 76 | Miscellaneous Repair Services | 0 | - | - | - | - | - | - | - | 6 | 12.42% | 6.97% | 14.86% |
| 78 | Motion pictures | 360 | 0.85% | 10.06% | 6.12% | 6.20% | 8.74% | 0.968 | 2.854 | 686 | 2.79% | 3.14% | 4.89% |
| 79 | Amusement & recreation services | 685 | 5.68% | 13.34% | 9.37% | 12.99% | 8.43% | 0.748 | 3.165 | 1,210 | 7.05% | 9.11% | 6.21% |
| 80 | Health services | 1,059 | 8.05% | 14.93% | 10.47% | 10.60% | 13.20% | 1.171 | 2.773 | 1,758 | 8.67% | 7.59% | 10.69% |
| 82 | Educational services | 64 | 6.39% | 16.49% | 9.69% | 8.61% | 12.95% | 1.219 | 1.708 | 332 | 11.93% | 9.51% | 9.87% |
| 83 | Social services | 0 | - | - | - | - | - | - | - | 122 | 10.29% | 8.59% | 8.88% |
| 87 | Engineering & management services | 905 | 7.10% | 16.12% | 8.63% | 6.82% | 10.12% | 1.404 | 2.437 | 1,766 | 8.22% | 5.64% | 8.01% |
| Total | | 66,504 | 8.00% | 15.01% | 9.25% | 8.64% | 8.67% | 1.340 | 2.465 | 95,544 | 7.70% | 6.71% | 7.21% |

This panel reports the number of observations and the average firm and segment profitability, sales growth, asset turnover and financial leverage by industry. Industries are defined using the two-digit SIC.

**TABLE 3**

Firm profitability forecast improvements (firm-year observations: 66,504)

| | Value | | *p*-Value |
|---|---|---|---|
| *ROE* | | | |
| Pooled mean | -0.0001% | | 0.997 |
| Grand mean | -0.0003% | | 0.985 |
| Grand median | -0.0196% | * | 0.074 |
| No. industries | 9 / 14 | | |
| No. years | 8 / 5 | | |
| *RNOA* | | | |
| Pooled mean | 0.0056% | | 0.653 |
| Grand mean | 0.0049% | | 0.670 |
| Grand median | -0.0127% | | 0.273 |
| No. industries | 6 / 8 | | |
| No. years | 9 / 7 | | |
| *ROA* | | | |
| Pooled mean | 0.0090% | | 0.177 |
| Grand mean | 0.0092% | | 0.124 |
| Grand median | -0.0068% | | 0.719 |
| No. industries | 8 / 11 | | |
| No. years | 10 / 3 | | |
| *ROS* | | | |
| Pooled mean | 0.0406% | *** | <0.001 |
| Grand mean | 0.0410% | *** | <0.001 |
| Grand median | 0.0109% | | 0.310 |
| No. industries | 11 / 12 | | |
| No. years | 18 / 1 | | |

This table summarizes the firm profitability forecast improvement of industry-specific analysis over economy-wide analysis. Industries are defined using the two-digit SIC. The out-of-sample period is from 1977 to 2011. For more details on the out-of-sample tests, see section 3.1.

The pooled mean is the mean forecast improvement pooling all the firm-year forecast improvements together. The grand mean (median) is the mean (median) of the yearly mean (median) forecast improvements for the firms in a year. For the pooled mean, the p-values are based on standard errors corrected for two-way clustering by firm and year following Rogers (1993). For the grand mean, the standard errors are adjusted following Newey and West (1987). The p-values for the grand median forecast improvements are obtained from a one-sample Wilcoxon (1945) signed-rank test using the yearly medians. “No. industries” is the number of industries (out of 53) for which the pooled mean forecast improvement of the industry-specific model is significantly positive / negative (at the 10% significance level). “No. years” is the number of years (out of 35) that the yearly pooled mean forecast improvement is significantly positive / negative (at the 10% significance level). ***,**, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

**TABLE 4**
Firm profitability forecast improvements by firm type

| Firm type | Single-segment (SS) firms | | Multiple-segment (MS) firms | | Change firms | | Difference SS-MS firms | | Difference SS-Change firms | | Difference MS-Change firms | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Observations | 32,363 | | 23,856 | | 10,285 | | | | | | | |
| | Value | *p* -Value | Value | *p* -Value | Value | *p* -Value | Value | *p* -Value | Value | *p* -Value | Value | *p* -Value |
| *ROE* | | | | | | | | | | | | |
| Pooled mean | 0.0240% | 0.213 | -0.0275% | 0.215 | -0.0122% | 0.690 | 0.0515% ** | 0.034 | 0.0362% | 0.299 | -0.0153% | 0.656 |
| Grand mean | 0.0210% | 0.162 | -0.0256% | 0.200 | -0.0164% | 0.413 | 0.0467% ** | 0.015 | 0.0375% | 0.121 | -0.0092% | 0.710 |
| Grand median | -0.0108% | 0.706 | -0.0611% *** | 0.003 | -0.0175% | 0.120 | 0.0503% *** | 0.004 | 0.0067% * | 0.092 | -0.0436% | 0.120 |
| No. industries | 8 / 11 | | 9 / 10 | | 9 / 8 | | | | | | | |
| No. years | 6 / 2 | | 4 / 10 | | 2 / 4 | | | | | | | |
| *RNOA* | | | | | | | | | | | | |
| Pooled mean | 0.0439% *** | 0.002 | -0.0388% ** | 0.024 | -0.0119% | 0.619 | 0.0827% ** | <0.001 | 0.0557% ** | 0.026 | -0.0270% | 0.286 |
| Grand mean | 0.0416% *** | 0.001 | -0.0349% ** | 0.032 | -0.0129% | 0.472 | 0.0765% *** | <0.001 | 0.0545% *** | 0.004 | -0.0220% | 0.236 |
| Grand median | 0.0151% ** | 0.032 | -0.0244% ** | 0.012 | -0.0153% * | 0.098 | 0.0395% *** | <0.001 | 0.0304% *** | 0.001 | -0.0090% | 0.265 |
| No. industries | 8 / 5 | | 3 / 7 | | 8 / 10 | | | | | | | |
| No. years | 14 / 0 | | 2 / 8 | | 2 / 5 | | | | | | | |
| *ROA* | | | | | | | | | | | | |
| Pooled mean | 0.0300% *** | <0.001 | -0.0186% ** | 0.048 | 0.0068% | 0.580 | 0.0486% *** | 0.001 | 0.0232% * | 0.083 | -0.0255% * | 0.062 |
| Grand mean | 0.0295% *** | <0.001 | -0.0173% ** | 0.042 | 0.0098% | 0.269 | 0.0468% *** | <0.001 | 0.0197% ** | 0.039 | -0.0271% *** | 0.007 |
| Grand median | 0.0095% ** | 0.017 | -0.0204% *** | 0.004 | -0.0037% | 0.831 | 0.0298% *** | <0.001 | 0.0132% ** | 0.035 | -0.0167% ** | 0.010 |
| No. industries | 9 / 5 | | 8 / 11 | | 10 / 9 | | | | | | | |
| No. years | 13 / 1 | | 3 / 9 | | 5 / 3 | | | | | | | |
| *ROS* | | | | | | | | | | | | |
| Pooled mean | 0.0923% *** | <0.001 | -0.0128% | 0.283 | 0.0019% | 0.909 | 0.1051% *** | <0.001 | 0.0904% *** | <0.001 | -0.0147% | 0.445 |
| Grand mean | 0.0957% *** | <0.001 | -0.0113% | 0.236 | 0.0011% | 0.935 | 0.1070% *** | <0.001 | 0.0946% *** | <0.001 | -0.0124% | 0.376 |
| Grand median | 0.0287% *** | <0.001 | -0.0114% | 0.089 | -0.0403% *** | 0.004 | 0.0401% *** | <0.001 | 0.0690% *** | <0.001 | 0.0289% | 0.219 |
| No. industries | 8 / 7 | | 9 / 10 | | 12 / 11 | | | | | | | |
| No. years | 25 / 1 | | 1 / 6 | | 4 / 3 | | | | | | | |

This table summarizes the firm profitability forecast improvement of industry-specific analysis over economy-wide analysis for three sub-samples of firms. Single-segment firms are firms that report only one business segment; multiple-segment firms are firms that report more than one business segment. Change firms are firms that have changed the number of reported segments from one in 1997 to more than one in 1999, suggesting that they might not be genuinely single-segment firms prior to the introduction of SFAS 131 in 1998 (see section 3 for details). Industries are defined using the two-digit SIC.

The three columns on the right present the differences between the three sub-samples. For the pooled mean, the p-values of the differences are based on standard errors corrected for two-way clustering by firm and year following Rogers (1993) using a regression on a constant and a firm-type dummy. For the grand mean, the p-values are based on a paired t-test on the yearly means. For the grand median, the p-values are based on a two-sample, paired Wilcoxon (1945) signed-rank test of the yearly medians. ***,**, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

**TABLE 5**

Firm profitability forecast improvements by firm type using equal footing analyis

**Panel A:** Equal sample size

| Firm type | Single-segment (SS) firms | | Multiple-segment (MS) firms | | Change firms | | Difference SS-MS firms | | Difference SS-Change firms | | Difference MS-Change firms | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Observations | 32,363 | | 23,856 | | 10,285 | | | | | | | |
| | Value | *p* -Value | Value | *p* -Value | Value | *p* -Value | Value | *p* -Value | Value | *p* -Value | Value | *p* -Value |
| *ROE* | | | | | | | | | | | | |
| Pooled mean | 0.0776% *** | <0.001 | 0.0173% | 0.453 | 0.0304% | 0.376 | 0.0603% ** | 0.015 | 0.0473% | 0.191 | -0.0130% | 0.733 |
| Grand mean | 0.0713% *** | <0.001 | 0.0192% | 0.368 | 0.0180% | 0.476 | 0.0522% *** | 0.009 | 0.0533% ** | 0.038 | 0.0012% | 0.969 |
| Grand median | 0.0352% ** | 0.044 | -0.0197% | 0.635 | 0.0119% | 0.844 | 0.0549% ** | 0.012 | 0.0233% | 0.219 | -0.0316% | 0.422 |
| No. industries | 9 / 7 | | 10 / 8 | | 12 / 7 | | | | | | | |
| No. years | 13 / 1 | | 8 / 4 | | 6 / 2 | | | | | | | |
| *RNOA* | | | | | | | | | | | | |
| Pooled mean | 0.0701% *** | <0.001 | -0.0128% | 0.455 | 0.0130% | 0.597 | 0.0829% *** | <0.001 | 0.0571% ** | 0.024 | -0.0258% | 0.330 |
| Grand mean | 0.0666% *** | <0.001 | -0.0084% | 0.579 | 0.0110% | 0.576 | 0.0750% *** | <0.001 | 0.0556% *** | 0.008 | -0.0194% | 0.344 |
| Grand median | 0.0279% *** | 0.003 | -0.0270% ** | 0.028 | 0.0119% | 0.534 | 0.0549% *** | <0.001 | 0.0160% * | 0.053 | -0.0389% ** | 0.026 |
| No. industries | 13 / 2 | | 9 / 5 | | 10 / 4 | | | | | | | |
| No. years | 13 / 0 | | 2 / 6 | | 2 / 4 | | | | | | | |
| *ROA* | | | | | | | | | | | | |
| Pooled mean | 0.0465% *** | <0.001 | -0.0012% | 0.902 | 0.0237% * | 0.071 | 0.0477% *** | <0.001 | 0.0228% * | 0.093 | -0.0249% * | 0.088 |
| Grand mean | 0.0467% *** | <0.001 | 0.0005% | 0.949 | 0.0291% *** | 0.009 | 0.0462% *** | <0.001 | 0.0177% * | 0.093 | -0.0285% ** | 0.017 |
| Grand median | 0.0359% *** | <0.001 | -0.0024% | 0.948 | 0.0120% ** | 0.041 | 0.0383% *** | <0.001 | 0.0239% * | 0.089 | -0.0144% ** | 0.044 |
| No. industries | 11 / 4 | | 9 / 5 | | 12 / 2 | | | | | | | |
| No. years | 15 / 0 | | 7 / 3 | | 6 / 2 | | | | | | | |
| *ROS* | | | | | | | | | | | | |
| Pooled mean | 0.1223% *** | <0.001 | 0.0084% | 0.517 | 0.0168% | 0.323 | 0.1139% *** | <0.001 | 0.1055% *** | <0.001 | -0.0084% | 0.673 |
| Grand mean | 0.1285% *** | <0.001 | 0.0084% | 0.424 | 0.0172% | 0.174 | 0.1201% *** | <0.001 | 0.1113% *** | <0.001 | -0.0088% | 0.516 |
| Grand median | 0.0381% *** | <0.001 | -0.0022% | 0.345 | -0.0131% | 0.201 | 0.0402% *** | <0.001 | 0.0512% *** | <0.001 | 0.0110% | 0.961 |
| No. industries | 14 / 3 | | 11 / 5 | | 10 / 8 | | | | | | | |
| No. years | 26 / 0 | | 7 / 3 | | 3 / 2 | | | | | | | |

This panel summarizes the firm profitability forecast improvement of industry-specific analysis over economy-wide analysis for three sub-samples of firms. Industries are defined using the two-digit SIC. In this analysis, the economy-wide in-sample regressions use the same number of observations as in each of the industry-specific in-sample regressions. ***,**, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively. For more details on the statistics presented in the table, see table 4.

**TABLE 5** (continued)
Firm profitability forecast improvements by firm type using equal footing analyis

**Panel B:** Two-stage in-sample regressions

| Firm type | Single-segment (SS) firms | | Multiple-segment (MS) firms | | Change firms | | Difference SS-MS firms | | Difference SS-Change firms | | Difference MS-Change firms | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Observations | 26,928 | | 16,389 | | 9,072 | | | | | | | |
| | Value | *p* -Value | Value | *p* -Value | Value | *p* -Value | Value | *p* -Value | Value | *p* -Value | Value | *p* -Value |
| *ROE* | | | | | | | | | | | | |
| Pooled mean | 0.0692% *** | <0.001 | -0.0198% | 0.344 | -0.0051% | 0.817 | 0.0890% *** | <0.001 | 0.0744% *** | 0.003 | -0.0146% | 0.591 |
| Grand mean | 0.0630% *** | <0.001 | -0.0191% | 0.252 | -0.0108% | 0.499 | 0.0821% *** | <0.001 | 0.0738% *** | <0.001 | -0.0083% | 0.653 |
| Grand median | 0.0667% *** | <0.001 | -0.0006% | 0.534 | 0.0116% | 0.929 | 0.0673% *** | <0.001 | 0.0551% *** | <0.001 | -0.0122% | 0.191 |
| No. industries | 4 / 4 | | 5 / 5 | | 4 / 3 | | | | | | | |
| No. years | 13 / 1 | | 2 / 4 | | 2 / 4 | | | | | | | |
| *RNOA* | | | | | | | | | | | | |
| Pooled mean | 0.0516% *** | <0.001 | -0.0073% | 0.719 | -0.0109% | 0.595 | 0.0590% ** | 0.014 | 0.0625% *** | 0.002 | 0.0035% | 0.895 |
| Grand mean | 0.0502% *** | <0.001 | -0.0065% | 0.712 | -0.0173% | 0.297 | 0.0567% *** | 0.009 | 0.0675% *** | <0.001 | 0.0108% | 0.615 |
| Grand median | 0.0265% *** | 0.002 | -0.0017% | 0.949 | -0.0078% | 0.439 | 0.0282% ** | 0.030 | 0.0343% *** | 0.001 | 0.0061% | 0.485 |
| No. industries | 4 / 2 | | 4 / 4 | | 4 / 3 | | | | | | | |
| No. years | 10 / 1 | | 4 / 6 | | 3 / 3 | | | | | | | |
| *ROA* | | | | | | | | | | | | |
| Pooled mean | 0.0324% *** | <0.001 | -0.0109% | 0.332 | -0.0010% | 0.923 | 0.0434% *** | 0.001 | 0.0335% *** | 0.003 | -0.0099% | 0.511 |
| Grand mean | 0.0312% *** | <0.001 | -0.0106% | 0.273 | -0.0025% | 0.732 | 0.0418% *** | <0.001 | 0.0337% *** | <0.001 | -0.0081% | 0.482 |
| Grand median | 0.0242% *** | <0.001 | -0.0133% | 0.304 | -0.0055% | 0.585 | 0.0375% *** | <0.001 | 0.0297% *** | <0.001 | -0.0078% | 0.603 |
| No. industries | 5 / 2 | | 4 / 4 | | 5 / 3 | | | | | | | |
| No. years | 13 / 1 | | 4 / 8 | | 2 / 2 | | | | | | | |
| *ROS* | | | | | | | | | | | | |
| Pooled mean | 0.0504% *** | <0.001 | -0.0033% | 0.797 | 0.0156% | 0.244 | 0.0537% *** | <0.001 | 0.0349% ** | 0.039 | -0.0188% | 0.317 |
| Grand mean | 0.0486% *** | <0.001 | -0.0028% | 0.787 | 0.0158% * | 0.080 | 0.0515% *** | <0.001 | 0.0328% *** | 0.008 | -0.0186% | 0.201 |
| Grand median | 0.0150% ** | 0.034 | -0.0259% ** | 0.023 | 0.0008% | 0.970 | 0.0408% *** | <0.001 | 0.0142% ** | 0.012 | -0.0267% * | 0.091 |
| No. industries | 3 / 4 | | 4 / 5 | | 4 / 4 | | | | | | | |
| No. years | 13 / 1 | | 2 / 5 | | 3 / 0 | | | | | | | |

This panel summarizes the firm profitability forecast improvement of industry-specific analysis over economy-wide analysis for three sub-samples of firms. This analysis uses two stages of in-sample regressions for the industry-specific analysis. After the standard, first-round in-sample regressions, firms are regrouped, each year, into 10 new groups based on their industry's mean-reversion coefficients. These 10 groups are then used as industry in the second-stage in-sample regression. ***,**, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively. For more details on the statistics presented in the table, see table 4.

**TABLE 5** (continued)

Firm profitability forecast improvements by firm type using equal footing analyis

**Panel C**: Fama-French industry classification (12 industries)

| Firm type | Single-segment (SS) firms | | Multiple-segment (MS) firms | | Change firms | | Difference SS-MS firms | | Difference SS-Change firms | | Difference MS-Change firms | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Observations | 27,356 | | 20,823 | | 9,143 | | | | | | | |
| | Value | *p*-Value | Value | *p*-Value | Value | *p*-Value | Value | *p*-Value | Value | *p*-Value | Value | *p*-Value |
| *ROE* | | | | | | | | | | | | |
| Pooled mean | 0.0511% *** | 0.008 | -0.0241% | 0.131 | -0.0098% | 0.702 | 0.0752% *** | 0.001 | 0.0609% ** | 0.042 | -0.0143% | 0.615 |
| Grand mean | 0.0450% *** | 0.005 | -0.0237% * | 0.075 | -0.0105% | 0.404 | 0.0687% *** | <0.001 | 0.0555% *** | 0.001 | -0.0132% | 0.384 |
| Grand median | 0.0150% * | 0.092 | -0.0522% *** | 0.006 | -0.0288% * | 0.072 | 0.0672% *** | <0.001 | 0.0438% *** | 0.003 | -0.0234% * | 0.089 |
| No. industries | 4 / 3 | | 5 / 3 | | 4 / 2 | | | | | | | |
| No. years | 10 / 3 | | 2 / 8 | | 3 / 1 | | | | | | | |
| *RNOA* | | | | | | | | | | | | |
| Pooled mean | 0.0506% *** | <0.001 | -0.0079% | 0.534 | -0.0171% | 0.524 | 0.0585% *** | <0.001 | 0.0676% ** | 0.016 | 0.0092% | 0.736 |
| Grand mean | 0.0471% *** | <0.001 | -0.0044% | 0.665 | -0.0131% | 0.442 | 0.0515% *** | <0.001 | 0.0601% *** | 0.001 | 0.0086% | 0.594 |
| Grand median | 0.0411% *** | 0.003 | -0.0080% | 0.145 | -0.0131% | 0.492 | 0.0491% *** | <0.001 | 0.0542% *** | 0.004 | 0.0051% | 0.232 |
| No. industries | 5 / 2 | | 3 / 3 | | 5 / 2 | | | | | | | |
| No. years | 10 / 0 | | 5 / 7 | | 3 / 6 | | | | | | | |
| *ROA* | | | | | | | | | | | | |
| Pooled mean | 0.0361% *** | <0.001 | -0.0030% | 0.678 | 0.0001% | 0.991 | 0.0391% *** | <0.001 | 0.0359% ** | 0.016 | -0.0032% | 0.822 |
| Grand mean | 0.0342% *** | <0.001 | -0.0019% | 0.734 | 0.0030% | 0.718 | 0.0361% *** | <0.001 | 0.0312% *** | 0.001 | -0.0049% | 0.531 |
| Grand median | 0.0265% *** | 0.001 | -0.0088% | 0.116 | 0.0081% | 0.870 | 0.0353% *** | <0.001 | 0.0184% *** | 0.001 | -0.0169% * | 0.064 |
| No. industries | 5 / 2 | | 4 / 2 | | 4 / 2 | | | | | | | |
| No. years | 11 / 0 | | 3 / 5 | | 3 / 3 | | | | | | | |
| *ROS* | | | | | | | | | | | | |
| Pooled mean | 0.1007% *** | <0.001 | 0.0046% | 0.698 | -0.0025% | 0.901 | 0.0961% *** | <0.001 | 0.1032% *** | <0.001 | 0.0071% | 0.737 |
| Grand mean | 0.1022% *** | <0.001 | 0.0078% | 0.417 | -0.0046% | 0.744 | 0.0944% *** | <0.001 | 0.1068% *** | <0.001 | 0.0124% | 0.359 |
| Grand median | 0.0642% *** | 0.002 | -0.0065% * | 0.086 | -0.0101% * | 0.053 | 0.0707% *** | <0.001 | 0.0744% *** | <0.001 | 0.0037% | 0.682 |
| No. industries | 4 / 2 | | 4 / 3 | | 3 / 3 | | | | | | | |
| No. years | 25 / 0 | | 7 / 5 | | 5 / 4 | | | | | | | |

This panel summarizes the firm profitability forecast improvement of industry-specific analysis over economy-wide analysis for three sub-samples of firms. In this analysis, industries are defined using the Fama and French industry classification with 12 industries. ***,**, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively. For more details on the statistics presented in the table, see table 4.

**TABLE 6**
Segment-level analysis

**Panel A:** Segment profitability forecast improvements (segment-year observations: 80,188)

| | Value | | *p* -Value |
|---|---|---|---|
| *ROA* | | | |
| Pooled mean | 0.0091% | | 0.351 |
| Grand mean | 0.0065% | | 0.461 |
| Grand median | 0.1067% | *** | <0.001 |
| No. industries | 7 / 0 | | |
| No. years | 4 / 5 | | |
| *ROS* | | | |
| Pooled mean | 0.0517% | *** | <0.001 |
| Grand mean | 0.0480% | *** | <0.001 |
| Grand median | 0.0294% | *** | 0.004 |
| No. industries | 5 / 2 | | |
| No. years | 14 / 2 | | |

This panel summarizes the segment profitability forecast improvement of industry-specific over economy wide analysis. Industries are defined using the Fama and French industry classification with 12 industries. The out-of-sample period is from 1987 to 2011. For more details on the out-of-sample tests, see section 3.1.

The pooled mean is the mean forecast improvement pooling all the segment-year forecast improvements together. The grand mean (median) is the mean (median) of the yearly mean (median) forecast improvements for the segments in a year. For the pooled mean, the p-values are based on standard errors corrected for two-way clustering by segment and year following Rogers (1993). For the grand mean, the standard errors are adjusted following Newey and West (1987). The p-values for the grand median forecast improvements are obtained from a one-sample Wilcoxon (1945) signed-rank test using the yearly medians. “No. industries” is the number of industries (out of 9) for which the pooled mean forecast improvement from using the industry-specific model is significantly positive / negative (at the 10% significance level). “No. years” is the number of years (out of 25) that the yearly mean improvement is significantly positive / negative (at the 10% significance level). ***,**, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

**TABLE 6** (continued)
Segment-level analysis

**Panel B:** Segment profitability forecast improvements by firm type (segment-year observations: 80,188)

| Firm type | Single-segment (SS) firms | | Multiple-segment (MS) firms | | Change firms | | Difference SS-MS firms | | Difference SS-Change firms | | Difference MS-Change firms | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Observations | 39,458 | | 29,336 | | 11,394 | | | | | | | |
| | Value | *p* -Value | Value | *p* -Value | Value | *p* -Value | Value | *p* -Value | Value | *p* -Value | Value | *p* -Value |
| *ROA* | | | | | | | | | | | | |
| Pooled mean | 0.0195% * | 0.053 | 0.0163% | 0.341 | -0.0455% ** | 0.023 | 0.0031% | 0.861 | 0.0650% *** | 0.002 | 0.0618% ** | 0.015 |
| Grand mean | 0.0172% ** | 0.038 | 0.0140% | 0.357 | -0.0414% ** | 0.029 | 0.0032% | 0.829 | 0.0586% *** | 0.003 | 0.0554% ** | 0.018 |
| Grand median | 0.0671% *** | <0.001 | 0.1475% *** | 0.001 | 0.0991% ** | 0.020 | -0.0804% ** | 0.011 | -0.0320% | 0.946 | 0.0484% *** | 0.009 |
| No. industries | 5 / 1 | | 7 / 0 | | 6 / 2 | | | | | | | |
| No. years | 4 / 1 | | 7 / 5 | | 1 / 6 | | | | | | | |
| *ROS* | | | | | | | | | | | | |
| Pooled mean | 0.0902% *** | <0.001 | 0.0365% * | 0.088 | -0.0426% * | 0.057 | 0.0537% ** | 0.031 | 0.1328% *** | <0.001 | 0.0791% *** | 0.008 |
| Grand mean | 0.0888% *** | <0.001 | 0.0324% * | 0.086 | -0.0396% ** | 0.015 | 0.0564% ** | 0.010 | 0.1284% *** | <0.001 | 0.0720% *** | 0.004 |
| Grand median | 0.0560% *** | <0.001 | 0.0283% ** | 0.035 | 0.0091% | 0.946 | 0.0278% | 0.174 | 0.0470% *** | 0.001 | 0.0192% *** | 0.006 |
| No. industries | 5 / 1 | | 5 / 2 | | 4 / 1 | | | | | | | |
| No. years | 17 / 1 | | 8 / 4 | | 0 / 5 | | | | | | | |

This panel summarizes the segment profitability forecast improvement of industry-specific analysis over economy-wide analysis for three sub-samples of firms. Industries are defined using the Fama and French industry classification with 12 industries. Single-segment firms are firms that report only one business segment; multiple-segment firms are firms that report more than one business segment. Change firms are firms that have changed the number of reported segments from one in 1997 to more than one in 1999, suggesting that they might not be genuinely single-segment firms prior to the introduction of SFAS 131 in 1998 (see section 3 for details).

The three columns on the right present the differences between the three sub-samples. For the pooled mean, the p-values of the differences are based on standard errors corrected for two-way clustering by segment and year following Rogers (1993) using a regression on a constant and a firm-type dummy. For the grand mean, the p-values are based on a paired t-test on the yearly means. For the grand median, the p-values are based on a two-sample, paired Wilcoxon (1945) signed-rank test of the yearly medians. ***,**, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

**TABLE 6** (continued)
Segment-level analysis

**Panel C:** Segment profitability forecast improvements of industry-specific analysis over economy-wide analysis by reporting regime

| Period | Pre-SFAS 131 (1987-1997) | | Post-SFAS 131 (1999-2011) | | Change from SFAS 14 to SFAS 131 | |
|---|---|---|---|---|---|---|
| Observations | 40,378 | | 36,799 | | | |
| | Value | *p* -Value | Value | *p* -Value | Value | *p* -Value |
| *ROA* | | | | | | |
| Pooled mean | 0.0287% ** | 0.032 | -0.0113% | 0.360 | -0.0400% ** | 0.022 |
| Grand mean | 0.0282% ** | 0.040 | -0.0111% | 0.336 | -0.0394% ** | 0.025 |
| Grand median | 0.0932% *** | 0.003 | 0.1164% *** | 0.009 | 0.0232% | 0.977 |
| No. industries | 6 / 2 | | 3 / 1 | | | |
| No. years | 4 / 1 | | 0 / 4 | | | |
| *ROS* | | | | | | |
| Pooled mean | 0.0834% *** | <0.001 | 0.0147% | 0.364 | -0.0687% *** | 0.001 |
| Grand mean | 0.0828% *** | <0.001 | 0.0162% | 0.274 | -0.0666% *** | 0.001 |
| Grand median | 0.0191% *** | 0.010 | 0.0556% | 0.116 | 0.0365% | 0.664 |
| No. industries | 7 / 0 | | 4 / 1 | | | |
| No. years | 9 / 0 | | 4 / 2 | | | |

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

The p-values for the change in forecast improvements for the two periods are calculated as follows. For the pooled mean, the p-values are based on the standard errors corrected for two-way clustering by segment and year following Rogers (1993) using a regression on a constant and a post-SFAS 131 period dummy. For the grand mean, the p-values are based on a paired t-test on yearly means. For the grand median, the p-values are calculated using the paired-sample Wilcoxon (1945) signed-rank test. ***,**, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

**TABLE 7**
Industry effects and stock returns

**Panel A:** Monthly abnormal returns of portfolios of firms with positive forecast improvement

| Profitabilty measure | *ROE* | | *RNOA* | | *ROA* | | *ROS* | |
|---|---|---|---|---|---|---|---|---|
| | Return | *p* -Value | Return | *p* -Value | Return | *p* -Value | Return | *p* -Value |
| Long portfolio | 1.50% *** | <0.001 | 1.45% *** | <0.001 | 1.42% *** | <0.001 | 1.31% *** | <0.001 |
| Short portfolio | 1.24% *** | <0.001 | 1.22% *** | <0.001 | 1.35% *** | <0.001 | 1.42% *** | <0.001 |
| Hedge portfolio | 0.26% | 0.230 | 0.22% | 0.227 | 0.07% | 0.724 | -0.11% | 0.593 |
| Risk-adjusted hedge portfolio | 0.42% ** | 0.036 | 0.37% ** | 0.032 | 0.24% | 0.168 | 0.31% * | 0.092 |

**Panel B:** Monthly abnormal returns of portfolios of firms with positive moving average forecast improvement

| Profitabilty measure | *ROE* | | *RNOA* | | *ROA* | | *ROS* | |
|---|---|---|---|---|---|---|---|---|
| | Return | *p* -Value | Return | *p* -Value | Return | *p* -Value | Return | *p* -Value |
| Long portfolio | 1.53% *** | <0.001 | 1.48% *** | <0.001 | 1.56% *** | <0.001 | 1.38% *** | <0.001 |
| Short portfolio | 1.21% *** | <0.001 | 1.25% *** | <0.001 | 1.30% *** | <0.001 | 1.42% *** | <0.001 |
| Hedge portfolio | 0.32% | 0.121 | 0.23% | 0.208 | 0.26% | 0.140 | -0.04% | 0.838 |
| Risk-adjusted hedge portfolio | 0.42% ** | 0.029 | 0.34% ** | 0.048 | 0.38% ** | 0.023 | 0.13% | 0.454 |

**Panel C**: Monthly abnormal returns of portfolios of firms with positive weighted moving average forecast improvement

| Profitabilty measure | *ROE* | | *RNOA* | | *ROA* | | *ROS* | |
|---|---|---|---|---|---|---|---|---|
| | Return | *p* -Value | Return | *p* -Value | Return | *p* -Value | Return | *p* -Value |
| Long portfolio | 1.50% *** | <0.001 | 1.57% *** | <0.001 | 1.55% *** | <0.001 | 1.36% *** | <0.001 |
| Short portfolio | 1.20% *** | <0.001 | 1.22% *** | <0.001 | 1.26% *** | <0.001 | 1.39% *** | <0.001 |
| Hedge portfolio | 0.30% | 0.130 | 0.36% ** | 0.046 | 0.29% | 0.105 | -0.04% | 0.830 |
| Risk-adjusted hedge portfolio | 0.41% ** | 0.030 | 0.47% *** | 0.006 | 0.42% ** | 0.012 | 0.14% | 0.391 |

This table reports the monthly returns of three trading strategies based on the firms' difference in forecasted profitability (DIFF) between industry-specific and economy-wide models. The long portfolio contains the shares within the top quintile of DIFF, while the short portfolio contains the shares within the bottom quintile of DIFF. The hedge portfolio contains a dollar-neutral portfolio that combines both long and short positions. Panel A reports the returns when only including firms whose current forecast improvement is positive. Panel B reports the portfolio returns when including only firms whose 10-year (moving) average forecast improvement is positive. Panel C includes only firms whose weighted 10-year (moving) average forecast improvement is positive, where the weight decreases linearly over the last 10 years. The risk-adjusted returns are calculated using the Fama and French (1993) three-factor model. Only single-segment firms are considered. Industries are defined using the Fama and French industry classification with 12 industries. ***,**, and * indicate statistical significance at the 1%, 5%, and 10% level

**TABLE 8**
Sales growth, asset turnover, financial leverage

**Panel A:** Firm-level analysis (firm-year observations: 57,322)

| | Sales growth | | Asset turnover | | Financial leverage | |
|---|---|---|---|---|---|---|
| | Value | *p* -Value | Value | *p* -Value | Value | *p* -Value |
| Pooled mean | 0.0486% * | 0.059 | -0.0114% | 0.415 | -0.1616% *** | <0.001 |
| Grand mean | 0.0473% * | 0.081 | -0.0135% | 0.312 | -0.1727% *** | <0.001 |
| Grand median | 0.0622% *** | 0.006 | -0.0037% | 0.481 | -0.1007% ** | 0.016 |
| No. industries | 2 / 0 | | 1 / 1 | | 1 / 5 | |
| No. years | 12 / 3 | | 7 / 9 | | 0 / 15 | |

This panel summarizes the forecast improvement of industry-specific analysis over economy-wide analysis for sales growth (GSL), asset turnover (ATO) and financial leverage (FLEV). Industries are defined using the Fama and French industry classification with 12 industries. The out-of-sample period is from 1977 to 2011. For more details on the out-of-sample tests, see section 3.1. ***,**, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively. For more details on the statistics presented in the table, see table 3.

**TABLE 8** (continued)
Sales growth, asset turnover, financial leverage

**Panel B:** Firm-level analysis by firm type

| Firm type | Single-segment (SS) firms | | | Multiple-segment (MS) firms | | | Change firms | | | Difference SS-MS firms | | | Difference SS-Change firms | | | Difference MS-Change firms | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Observations | 27,356 | | | 20,823 | | | 9,143 | | | | | | | | | | | |
| | Value | | *p*-Value | Value | | *p*-Value | Value | | *p*-Value | Value | | *p*-Value | Value | | *p*-Value | Value | | *p*-Value |
| *Sales growth* | | | | | | | | | | | | | | | | | | |
| Pooled mean | 0.0945% | *** | <0.001 | 0.0091% | | 0.826 | 0.0013% | | 0.969 | 0.0854% | ** | 0.012 | 0.0932% | *** | 0.002 | 0.0078% | | 0.828 |
| Grand mean | 0.0946% | *** | <0.001 | 0.0177% | | 0.651 | -0.0246% | | 0.455 | 0.0769% | ** | 0.018 | 0.1192% | *** | <0.001 | 0.0423% | | 0.156 |
| Grand median | 0.1031% | *** | <0.001 | 0.0236% | | 0.432 | 0.0078% | | 0.555 | 0.0795% | ** | 0.035 | 0.0952% | ** | 0.012 | 0.0158% | | 0.534 |
| No. industries | 3 / 0 | | | 2 / 1 | | | 1 / 1 | | | | | | | | | | | |
| No. years | 17 / 2 | | | 9 / 7 | | | 7 / 6 | | | | | | | | | | | |
| *Asset turnover* | | | | | | | | | | | | | | | | | | |
| Pooled mean | 0.0195% | | 0.224 | -0.0531% | *** | 0.009 | -0.0090% | | 0.620 | 0.0726% | *** | 0.001 | 0.0285% | | 0.146 | -0.0441% | ** | 0.037 |
| Grand mean | 0.0155% | | 0.327 | -0.0530% | *** | 0.002 | -0.0114% | | 0.471 | 0.0685% | *** | <0.001 | 0.0269% | * | 0.092 | -0.0416% | *** | 0.009 |
| Grand median | 0.0232% | | 0.245 | -0.0516% | ** | 0.012 | -0.0040% | * | 0.057 | 0.0748% | *** | 0.004 | 0.0272% | *** | 0.006 | -0.0475% | | 0.555 |
| No. industries | 2 / 1 | | | 0 / 3 | | | 1 / 1 | | | | | | | | | | | |
| No. years | 7 / 3 | | | 4 / 10 | | | 1 / 1 | | | | | | | | | | | |
| *Financial leverage* | | | | | | | | | | | | | | | | | | |
| Pooled mean | -0.0813% | | 0.146 | -0.0028% | *** | <0.001 | -0.1256% | * | 0.081 | -0.0784% | ** | 0.012 | 0.0444% | | 0.606 | 0.1228% | * | 0.071 |
| Grand mean | -0.1018% | ** | 0.044 | -0.3078% | *** | <0.001 | -0.1702% | *** | 0.008 | 0.2060% | *** | 0.006 | 0.0684% | | 0.311 | -0.1376% | * | 0.062 |
| Grand median | -0.0008% | * | 0.077 | -0.1282% | *** | 0.002 | -0.0539% | | 0.116 | 0.1274% | | 0.481 | 0.0531% | | 0.471 | -0.0743% | | 0.252 |
| No. industries | 1 / 4 | | | 1 / 5 | | | 1 / 4 | | | | | | | | | | | |
| No. years | 4 / 7 | | | 1 / 12 | | | 0 / 5 | | | | | | | | | | | |

This panel summarizes the forecast improvement of industry-specific analysis over economy-wide analysis for sales growth (GSL), asset turnover (ATO) and financial leverage (FLEV) by firm type. Single-segment firms are firms that report only one business segment; multiple-segment firms are firms that report more than one business segment. Change firms are firms that have changed the number of reported segments from one in 1997 to more than one in 1999, suggesting that they might not be genuinely single-segment firms prior to the introduction of SFAS 131 in 1998 (see section 3 for details). Industries are defined using the Fama and French industry classification with 12 industries. The out-of-sample period is from 1977 to 2011. For more details on the out-of-sample tests, see section 3.1. ***,**, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively. For more details on the statistics presented in the table, see table 4.

**TABLE 8** (continued)

Sales growth, asset turnover, financial leverage

**Panel C:** Segment-level analysis (segment-year observations: 80,188)

| | Value | | $p$-Value |
|---|---|---|---|
| *Sales growth* | | | |
| Pooled mean | 0.0795% | *** | <0.001 |
| Grand mean | 0.0817% | *** | 0.002 |
| Grand median | 0.0151% | | 0.231 |
| No. industries | 3 / 0 | | |
| No. years | 13 / 1 | | |

This panel summarizes the forecast improvement of industry-specific analysis over economy-wide analysis for sales growth (GSL). Industries are defined using the Fama and French industry classification with 12 industries. The out-of-sample period is from 1987 to 2011. For more details on the out-of-sample tests, see section 3.1. ***,**, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively. For more details on the statistics presented in the table, see table 6 (panel A).

**TABLE 8** (continued)
Sales growth, asset turnover, financial leverage

**Panel D:** Segment-level analysis by firm type

| Firm type | Single-segment (SS) firms | | | Multiple-segment (MS) firms | | Change firms | | Difference SS-MS firms | | | Difference SS-Change firms | | | Difference MS-Change firms | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Observations | 39,458 | | | 29,336 | | 11,394 | | | | | | | | | |
| | Value | | *p*-Value | Value | *p*-Value | Value | *p*-Value | Value | | *p*-Value | Value | | *p*-Value | Value | *p*-Value |
| *Sales growth* | | | | | | | | | | | | | | | |
| Pooled mean | 0.1236% | *** | <0.001 | 0.0310% | 0.347 | 0.0518% | 0.114 | 0.0926% | *** | <0.001 | 0.0718% | ** | 0.040 | -0.0208% | 0.564 |
| Grand mean | 0.1303% | *** | <0.001 | 0.0368% | 0.269 | 0.0485% | 0.115 | 0.0934% | *** | 0.001 | 0.0818% | ** | 0.021 | -0.0117% | 0.727 |
| Grand median | 0.0848% | | 0.109 | 0.0000% | 0.757 | 0.0291% | 0.253 | 0.0848% | ** | 0.030 | 0.0557% | | 0.166 | -0.0291% | 0.581 |
| No. industries | 3 / 0 | | | 1 / 0 | | 1 / 0 | | | | | | | | | |
| No. years | 16 / 0 | | | 8 / 4 | | 4 / 1 | | | | | | | | | |

This panel summarizes the segment forecast improvement of industry-specific analysis over economy-wide analysis for sales growth (GSL) for the three sub-samples of firms. Industries are defined using the Fama and French industry classification with 12 industries. The out-of-sample period is from 1987 to 2011. For more details on the out-of-sample tests, see section 3.1. ***,**, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively. For more details on the statistics presented in the table, see table 6, panel B.

**TABLE 9**
Alternative industry classifications

**Panel A:** One-digit SIC

| Firm type | Single-segment (SS) firms | | Multiple-segment (MS) firms | | Change firms | | Difference SS-MS firms | | Difference SS-Change firms | | Difference MS-Change firms | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Observations | 32,949 | | 24,533 | | 10,458 | | | | | | | |
| | Value | *p* -Value | Value | *p* -Value | Value | *p* -Value | Value | *p* -Value | Value | *p* -Value | Value | *p* -Value |
| *ROE* | | | | | | | | | | | | |
| Pooled mean | 0.0216% * | 0.076 | -0.0172% | 0.262 | 0.0072% | 0.724 | 0.0387% ** | 0.024 | 0.0144% | 0.496 | -0.0243% | 0.303 |
| Grand mean | 0.0195% ** | 0.028 | -0.0184% | 0.158 | 0.0085% | 0.479 | 0.0378% *** | 0.005 | 0.0110% | 0.338 | -0.0268% * | 0.066 |
| *RNOA* | | | | | | | | | | | | |
| Pooled mean | 0.0363% *** | <0.001 | -0.0078% | 0.468 | 0.0097% | 0.447 | 0.0440% *** | 0.001 | 0.0265% * | 0.099 | -0.0175% | 0.214 |
| Grand mean | 0.0351% *** | <0.001 | -0.0069% | 0.424 | 0.0142% | 0.104 | 0.0420% *** | <0.001 | 0.0209% * | 0.063 | -0.0211% ** | 0.012 |
| *ROA* | | | | | | | | | | | | |
| Pooled mean | 0.0233% *** | <0.001 | -0.0064% | 0.339 | 0.0187% ** | 0.022 | 0.0297% *** | <0.001 | 0.0046% | 0.623 | -0.0251% *** | 0.005 |
| Grand mean | 0.0233% *** | <0.001 | -0.0066% | 0.232 | 0.0214% *** | <0.001 | 0.0300% *** | <0.001 | 0.0020% | 0.741 | -0.0280% *** | <0.001 |
| *ROS* | | | | | | | | | | | | |
| Pooled mean | 0.0707% *** | <0.001 | 0.0046% | 0.612 | 0.0181% | 0.228 | 0.0661% *** | <0.001 | 0.0526% *** | 0.005 | -0.0135% | 0.386 |
| Grand mean | 0.0743% *** | <0.001 | 0.0068% | 0.334 | 0.0150% | 0.181 | 0.0675% *** | <0.001 | 0.0593% *** | <0.001 | -0.0082% | 0.403 |

**Panel B:** GICS Industry sectors

| Firm type | Single-segment (SS) firms | | Multiple-segment (MS) firms | | Change firms | | Difference SS-MS firms | | Difference SS-Change firms | | Difference MS-Change firms | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Observations | 31,729 | | 22,982 | | 10,456 | | | | | | | |
| | Value | *p* -Value | Value | *p* -Value | Value | *p* -Value | Value | *p* -Value | Value | *p* -Value | Value | *p* -Value |
| *ROE* | | | | | | | | | | | | |
| Pooled mean | 0.0590% *** | 0.002 | 0.0069% | 0.700 | -0.0463% * | 0.078 | 0.0522% ** | 0.017 | 0.1053% *** | 0.001 | 0.0531% * | 0.058 |
| Grand mean | 0.0555% *** | 0.001 | 0.0066% | 0.633 | -0.0397% ** | 0.017 | 0.0489% *** | 0.002 | 0.0953% *** | <0.001 | 0.0464% *** | 0.005 |
| *RNOA* | | | | | | | | | | | | |
| Pooled mean | 0.0565% *** | <0.001 | 0.0027% | 0.850 | -0.0319% | 0.242 | 0.0538% *** | 0.001 | 0.0884% *** | 0.002 | 0.0346% | 0.210 |
| Grand mean | 0.0504% *** | <0.001 | 0.0056% | 0.625 | -0.0314% | 0.117 | 0.0448% *** | <0.001 | 0.0819% *** | <0.001 | 0.0370% ** | 0.046 |
| *ROA* | | | | | | | | | | | | |
| Pooled mean | 0.0358% *** | <0.001 | 0.0035% | 0.677 | -0.0124% | 0.360 | 0.0323% *** | <0.001 | 0.0483% *** | 0.001 | 0.0159% | 0.242 |
| Grand mean | 0.0335% *** | <0.001 | 0.0045% | 0.516 | -0.0096% | 0.303 | 0.0290% *** | <0.001 | 0.0431% *** | <0.001 | 0.0141% * | 0.073 |
| *ROS* | | | | | | | | | | | | |
| Pooled mean | 0.0880% *** | <0.001 | 0.0064% | 0.520 | -0.0217% | 0.272 | 0.0816% *** | <0.001 | 0.1097% *** | <0.001 | 0.0281% | 0.175 |
| Grand mean | 0.0938% *** | <0.001 | 0.0092% | 0.254 | -0.0203% * | 0.099 | 0.0846% *** | <0.001 | 0.1141% *** | <0.001 | 0.0296% ** | 0.020 |

**TABLE 9** (continued)
Alternative industry classifications

**Panel C:** One-digit NAICS

| Firm type | Single-segment (SS) firms | | Multiple-segment (MS) firms | | Change firms | | Difference SS-MS firms | | Difference SS-Change firms | | Difference MS-Change firms | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Observations | 31,907 | | 23,111 | | 10,461 | | | | | | | |
| | Value | *p*-Value | Value | *p*-Value | Value | *p*-Value | Value | *p*-Value | Value | *p*-Value | Value | *p*-Value |
| *ROE* | | | | | | | | | | | | |
| Pooled mean | 0.0186% * | 0.069 | -0.0094% | 0.314 | 0.0079% | 0.465 | 0.0280% ** | 0.018 | 0.0108% | 0.437 | -0.0173% | 0.203 |
| Grand mean | 0.0187% * | 0.021 | -0.0095% | 0.209 | 0.0035% | 0.649 | 0.0281% *** | 0.002 | 0.0151% | 0.141 | -0.0130% | 0.191 |
| *RNOA* | | | | | | | | | | | | |
| Pooled mean | 0.0334% *** | <0.001 | -0.0075% | 0.334 | 0.0036% | 0.668 | 0.0410% *** | <0.001 | 0.0298% *** | 0.003 | -0.0111% | 0.232 |
| Grand mean | 0.0326% *** | <0.001 | -0.0076% | 0.205 | 0.0042% | 0.575 | 0.0402% *** | <0.001 | 0.0284% *** | 0.001 | -0.0118% * | 0.095 |
| *ROA* | | | | | | | | | | | | |
| Pooled mean | 0.0249% *** | <0.001 | -0.0028% | 0.585 | 0.0093% * | 0.096 | 0.0277% *** | <0.001 | 0.0156% ** | 0.021 | -0.0121% * | 0.064 |
| Grand mean | 0.0248% *** | <0.001 | -0.0030% | 0.450 | 0.0101% ** | 0.028 | 0.0278% *** | <0.001 | 0.0147% *** | 0.008 | -0.0131% *** | 0.005 |
| *ROS* | | | | | | | | | | | | |
| Pooled mean | 0.0674% *** | <0.001 | 0.0102% | 0.222 | 0.0206% * | 0.083 | 0.0571% *** | <0.001 | 0.0468% *** | 0.001 | -0.0103% | 0.444 |
| Grand mean | 0.0734% *** | <0.001 | 0.0117% * | 0.082 | 0.0160% * | 0.056 | 0.0617% *** | <0.001 | 0.0574% *** | <0.001 | -0.0043% | 0.617 |

This table reports the pooled mean and grand mean forecast improvement of industry-specific analysis over economy-wide analysis for the three sub-samples of firms using alternative industry classifications. Panel A reports the results when using the one-digit SIC; panel B reports the results when using the GICS industry sector classification, and panel C reports the results when using the one-digit NAICS. ***,**, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively. For more details on the statistics reported in the table, see table 4.

**TABLE A1**

Sample selection and descriptive statistics for sample based on Fama-French industry classification (12 industries)

| **Panel A:** Sample selection | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Adjustments to data sample | Firm-level data (firm-year observations) | | | | | | | Segment-level data (segment-year observations) | | | |
| | *ROE* | *RNOA* | *ROA* | *ROS* | *GSL* | *ATO* | *FLEV* | *ROA* | *ROS* | *GSL* |
| Observations for in-sample regressions | | | | | | | | | | |
| Total observations, excluding utilities and financial firms/segments | 209,935 | 209,859 | 210,905 | 207,140 | 205,915 | 210,009 | 210,262 | 194,520 | 212,537 | 228,652 |
| Less observations with small denominators | 133,550 | 133,504 | 134,436 | 134,126 | 134,314 | 133,998 | 133,668 | 181,038 | 199,298 | 214,425 |
| Less observations with an absolute value larger than | 130,676 | 131,010 | 134,403 | 133,060 | 134,314 | 133,998 | 133,668 | 178,215 | 191,621 | 214,425 |
| Less observations with more than 100% growth | 117,396 | 117,936 | 119,416 | 118,801 | 119,433 | 119,433 | 119,432 | 154,058 | 151,401 | 163,327 |
| Less upper and lower centiles observations | 115,050 | 115,578 | 117,028 | 116,425 | 117,045 | 117,045 | 117,044 | 150,978 | 148,373 | 160,061 |
| Observations for out-of-sample tests, out of which | | | | 57,322 | | | | | 80,188 | |
| Single-segment firms | | | | 27,356 | | | | | 39,458 | |
| Multiple-segment firms | | | | 20,823 | | | | | 29,336 | |
| Change firms | | | | 9,143 | | | | | 11,394 | |

Panel A summarizes the sample selection procedure and the number of observations available after each filter when using the Fama and French industry classification with 12 industries.

**TABLE A1** (continued)

Sample selection and descriptive statistics for sample based on Fama-French industry classification (12 industries)

**Panel B:** Descriptive statistics

| Variable | Mean | Std. deviation | First quartile | Median | Third Quartile |
|---|---|---|---|---|---|
| Firm-level: 7,227 firms (57,322 firm-year observations) | | | | | |
| *NI* | 123.776 | 728.565 | 1.223 | 8.636 | 47.688 |
| *OPINC* | 241.142 | 1093.074 | 4.254 | 20.314 | 101.477 |
| *TA* | 2650.712 | 11633.520 | 74.354 | 249.717 | 1087.513 |
| *NOA* | 1572.267 | 7016.889 | 47.507 | 156.870 | 685.879 |
| *BV* | 1042.229 | 4622.927 | 36.867 | 120.304 | 486.231 |
| *SALES* | 2553.959 | 10255.490 | 98.449 | 309.853 | 1238.646 |
| *ROE* | 8.25% | 14.46% | 3.35% | 10.72% | 16.50% |
| *RNOA* | 15.33% | 14.15% | 7.47% | 14.60% | 22.84% |
| *ROA* | 9.51% | 8.05% | 4.93% | 9.60% | 14.35% |
| *ROS* | 8.55% | 8.89% | 3.51% | 7.54% | 12.54% |
| *GSL* | 8.64% | 16.44% | -0.35% | 7.90% | 16.85% |
| *ATO* | 1.376 | 0.744 | 0.877 | 1.257 | 1.703 |
| *FLEV* | 2.384 | 1.289 | 1.597 | 2.053 | 2.702 |
| Segment-level: 15,560 segments (80,188 segment-year observations) | | | | | |
| *OPINC* | 123.119 | 570.206 | 0.470 | 9.227 | 59.279 |
| *TA* | 1243.053 | 5136.481 | 30.885 | 142.334 | 639.441 |
| *SALES* | 1424.893 | 6644.535 | 39.655 | 175.42 | 734.4016 |
| *ROA* | 7.77% | 13.94% | 1.99% | 8.68% | 15.21% |
| *ROS* | 6.47% | 13.34% | 1.40% | 6.77% | 13.00% |
| *GSL* | 7.19% | 19.79% | -3.48% | 6.20% | 17.11% |

Panel B gives an overview on the firm and segment data used to compute the average forecast improvements in the out-of-sample tests for the period from 1977 to 2011 in the firm-level analysis, and from 1987 to 2011 in the segment-level analysis. Industries are defined using the Fama and French industry classification with 12 industries. *OPINC* (operating income), *NI* (income before extraordinary items), *TA* (total assets), *SALES* (total sales), *BV* (common shareholder's equity), and *NOA* (net operating assets) are reported in USD million.

**TABLE A2**

Firm profitability forecast improvements of industry-specific analysis over economy-wide analysis by firm type and accounting regime

**Panel A:** *ROE*

| Firm type | | Single-segment | | Multiple-segment | | Change firms | | Difference SS firms - MS firms | | Difference SS firms - Change firms | | Difference MS firms - Change firms | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Value | *p* -Value | Value | *p* -Value | Value | *p* -Value | Value | *p* -Value | Value | *p* -Value | Value | *p* -Value |
| In-sample estimation AR(1) | | | | | | | | | | | | | |
| SFAS 14 | Pooled mean | 0.0824% *** | <0.001 | -0.0176% | 0.318 | -0.0183% | 0.550 | 0.1000% *** | <0.001 | 0.1007% *** | 0.004 | 0.0007% | 0.983 |
| | Grand mean | 0.0773% *** | <0.001 | -0.0154% | 0.310 | -0.0131% | 0.374 | 0.0927% *** | <0.001 | 0.0903% *** | <0.001 | -0.0023% | 0.874 |
| SFAS 131 | Pooled mean | -0.0026% | 0.917 | -0.0498% ** | 0.048 | -0.0077% | 0.819 | 0.0472% | 0.179 | 0.0051% | 0.877 | -0.0420% | 0.320 |
| | Grand mean | -0.0051% | 0.804 | -0.0489% ** | 0.043 | -0.0134% | 0.583 | 0.0438% | 0.156 | 0.0082% | 0.738 | -0.0356% | 0.297 |
| Change | Pooled mean | -0.0850% *** | 0.007 | -0.0322% | 0.248 | 0.0105% | 0.781 | -0.0528% | 0.165 | -0.0955% ** | 0.016 | -0.0427% | 0.340 |
| | Grand mean | -0.0824% *** | 0.005 | -0.0335% | 0.209 | -0.0003% | 0.992 | -0.0489% | 0.139 | -0.0821% *** | 0.009 | -0.0332% | 0.356 |

**Panel B:** *RNOA*

| Firm type | | Single-segment | | Multiple-segment | | Change firms | | Difference SS firms - MS firms | | Difference SS firms - Change firms | | Difference MS firms - Change firms | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Value | *p* -Value | Value | *p* -Value | Value | *p* -Value | Value | *p* -Value | Value | *p* -Value | Value | *p* -Value |
| In-sample estimation AR(1) | | | | | | | | | | | | | |
| SFAS 14 | Pooled mean | 0.0452% ** | 0.011 | -0.0122% | 0.414 | -0.0449% | 0.205 | 0.0573% *** | <0.001 | 0.0901% ** | 0.012 | 0.0327% | 0.329 |
| | Grand mean | 0.0410% *** | 0.010 | -0.0074% | 0.602 | -0.0253% | 0.259 | 0.0484% *** | <0.001 | 0.0663% *** | 0.008 | 0.0179% | 0.343 |
| SFAS 131 | Pooled mean | 0.0575% ** | 0.015 | -0.0064% | 0.753 | 0.0276% | 0.399 | 0.0638% ** | 0.035 | 0.0298% | 0.404 | -0.0340% | 0.337 |
| | Grand mean | 0.0544% ** | 0.013 | -0.0064% | 0.663 | 0.0134% | 0.634 | 0.0608% ** | 0.019 | 0.0410% | 0.160 | -0.0197% | 0.495 |
| Change | Pooled mean | 0.0123% | 0.659 | 0.0058% | 0.800 | 0.0725% * | 0.099 | 0.0065% | 0.838 | -0.0602% | 0.190 | -0.0667% | 0.126 |
| | Grand mean | 0.0134% | 0.569 | 0.0011% | 0.957 | 0.0387% | 0.275 | 0.0124% | 0.617 | -0.0252% | 0.481 | -0.0376% | 0.269 |

**Panel C:** *ROA*

| Firm type | | Single-segment | | Multiple-segment | | Change firms | | Difference SS firms - MS firms | | Difference SS firms - Change firms | | Difference MS firms - Change firms | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Value | *p* -Value | Value | *p* -Value | Value | *p* -Value | Value | *p* -Value | Value | *p* -Value | Value | *p* -Value |
| In-sample estimation AR(1) | | | | | | | | | | | | | |
| SFAS 14 | Pooled mean | 0.0332% *** | 0.002 | -0.0010% | 0.906 | -0.0164% | 0.398 | 0.0342% *** | 0.001 | 0.0496% ** | 0.017 | 0.0154% | 0.405 |
| | Grand mean | 0.0302% *** | 0.003 | 0.0014% | 0.850 | -0.0075% | 0.528 | 0.0288% *** | <0.001 | 0.0377% *** | 0.007 | 0.0089% | 0.337 |
| SFAS 131 | Pooled mean | 0.0406% *** | <0.001 | -0.0087% | 0.481 | 0.0246% * | 0.077 | 0.0494% *** | 0.002 | 0.0160% | 0.337 | -0.0333% * | 0.052 |
| | Grand mean | 0.0401% *** | <0.001 | -0.0084% | 0.369 | 0.0225% * | 0.055 | 0.0485% *** | 0.001 | 0.0176% *** | 0.144 | -0.0309% ** | 0.024 |
| Change | Pooled mean | 0.0074% | 0.590 | -0.0077% | 0.577 | 0.0410% * | 0.060 | 0.0151% | 0.389 | -0.0336% | 0.166 | -0.0487% ** | 0.031 |
| | Grand mean | 0.0099% | 0.378 | -0.0098% | 0.400 | 0.0300% * | 0.066 | 0.0197% | 0.132 | -0.0201% | 0.261 | -0.0398% ** | 0.012 |

**TABLE A2** (continued)

Firm profitability forecast improvements of industry-specific analysis over economy-wide analysis by firm type and accounting regime

**Panel D:** *ROS*

| Firm type | | Single-segment | | | Multiple-segment | | Change firms | | Difference SS firms - MS firms | | | Difference SS firms - Change firms | | | Difference MS firms - Change firms | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Value | | *p*-Value | Value | *p*-Value | Value | *p*-Value | Value | | *p*-Value | Value | | *p*-Value | Value | *p*-Value |
| In-sample estimation AR(1) | | | | | | | | | | | | | | | | |
| SFAS 14 | Pooled mean | 0.0989% | *** | <0.001 | 0.0088% | 0.509 | -0.0119% | 0.672 | 0.0901% | *** | <0.001 | 0.1108% | *** | <0.001 | 0.0207% | 0.452 |
| | Grand mean | 0.1014% | *** | <0.001 | 0.0147% | 0.218 | -0.0111% | 0.609 | 0.0866% | *** | <0.001 | 0.1125% | *** | <0.001 | 0.0259% | 0.189 |
| SFAS 131 | Pooled mean | 0.1089% | *** | <0.001 | -0.0012% | 0.957 | 0.0143% | 0.506 | 0.1101% | *** | <0.001 | 0.0946% | *** | <0.001 | -0.0155% | 0.582 |
| | Grand mean | 0.1074% | *** | <0.001 | -0.0003% | 0.989 | 0.0092% | 0.547 | 0.1076% | *** | <0.001 | 0.0982% | *** | <0.001 | -0.0095% | 0.603 |
| Change | Pooled mean | 0.0100% | | 0.674 | -0.0101% | 0.680 | 0.0262% | 0.399 | 0.0200% | | 0.494 | -0.0162% | | 0.644 | -0.0362% | 0.295 |
| | Grand mean | 0.0060% | | 0.755 | -0.0150% | 0.476 | 0.0204% | 0.441 | 0.0210% | | 0.358 | -0.0143% | | 0.598 | -0.0353% | 0.183 |

This table compares the firm profitability forecast improvement of industry-specific analysis over economy-wide analysis for three sub-samples of firms before and after the introduction of SFAS 131 in 1998. The observations of 1998 are excluded from the out-of-sample tests to account for the transition year. In this analysis, industries are defined using the Fama and French industry classification with 12 industries.

Single-segment firms are firms that report only one business segment; multiple-segment firms are firms that report more than one business segment. Change firms are firms that have changed the number of reported segments from one in 1997 to more than one in 1999, suggesting that they might not be genuinely single-segment firms prior to the introduction of SFAS 131 in 1998 (see section 3 for details).

Panels A to D report the results for the four profitability measures considered: ROE, RNOA, ROA, and ROS. For brevity, only the results for the pooled and grand mean forecast improvements are reported. The p-values for the difference between the forecast improvements for the two periods are calculated as follows. For the pooled mean, the p-values are based on the standard errors corrected for two-way clustering by segment and year following Rogers (1993) using a regression on a constant and a post-SFAS 131 period dummy. For the grand mean, the p-values are based on a paired t-test on yearly means. ***,**, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

**TABLE A3**
Cross-industry tests

| **Panel A:** Forecast improvement and fraction of single-segment firms. Observations: 1,666 industry-year observations | | | |
|---|---|---|---|
| | Coefficient | | *p* -Value |
| *ROE* | | | |
| Pooled regressions | -0.0935% | | 0.467 |
| FMB regressions | -0.0460% | | 0.683 |
| *RNOA* | | | |
| Pooled regressions | 0.1985% | ** | 0.040 |
| FMB regressions | 0.2477% | *** | 0.008 |
| *ROA* | | | |
| Pooled regressions | 0.0794% | * | 0.079 |
| FMB regressions | 0.1282% | *** | 0.009 |
| *ROS* | | | |
| Pooled regressions | 0.1918% | ** | 0.044 |
| FMB regressions | 0.2361% | *** | 0.001 |

| **Panel B:** Forecast improvement and relatedness of business segments. Observations: 1,666 industry-year observations | | | |
|---|---|---|---|
| | Coefficient | | *p* -Value |
| *ROE* | | | |
| Pooled regressions | -0.0111% | | 0.745 |
| FMB regressions | 0.0058% | | 0.853 |
| *RNOA* | | | |
| Pooled regressions | 0.0538% | ** | 0.028 |
| FMB regressions | 0.0649% | *** | 0.008 |
| *ROA* | | | |
| Pooled regressions | 0.0203% | ** | 0.049 |
| FMB regressions | 0.0333% | *** | 0.008 |
| *ROS* | | | |
| Pooled regressions | 0.0416% | * | 0.076 |
| FMB regressions | 0.0491% | *** | 0.008 |

| **Panel C:** Difference in forecast improvement between single-segment and multiple-segment firms for indutries whose multiple-segment firms have little related business segments. | | | |
|---|---|---|---|
| | Difference SS firms/MS firms | | *p* -Value |
| *ROE* | | | |
| Pooled mean | 0.0033% | | 0.953 |
| Grand mean | 0.0261% | | 0.474 |
| *RNOA* | | | |
| Pooled mean | 0.0762% | * | 0.066 |
| Grand mean | 0.0636% | ** | 0.019 |
| *ROA* | | | |
| Pooled mean | 0.0434% | ** | 0.032 |
| Grand mean | 0.0416% | *** | 0.010 |
| *ROS* | | | |
| Pooled mean | 0.0541% | ** | 0.029 |
| Grand mean | 0.0529% | *** | 0.009 |

**TABLE A3** (continued)
Cross-industry tests

| **Panel D:** Forecast improvement and industry mean-reversion coefficients. Obervations: 1,660 industry-year observations | | | |
|---|---|---|---|
| | Coefficient | | *p* -Value |
| *ROE* | | | |
| Pooled regressions | 0.5033% | | 0.296 |
| FMB regressions | 0.5211% | | 0.231 |
| *RNOA* | | | |
| Pooled regressions | 0.0122% | *** | 0.008 |
| FMB regressions | 0.9824% | *** | 0.001 |
| *ROA* | | | |
| Pooled regressions | 0.0046% | | 0.173 |
| FMB regressions | 0.4119% | ** | 0.031 |
| *ROS* | | | |
| Pooled regressions | 0.1797% | | 0.403 |
| FMB regressions | 0.1952% | | 0.420 |

This table presents the results of cross-industry analysis of the industry's average forecast improvements of IS over EW analysis. Panel A presents the results when regressing the forecast improvement on the fraction of single-segment firms in a given industry. Panel B presents the results when regressing the forecast improvement on the industry's average degree of relatedness of its firms. Panel C presents the difference in forecast improvement between single-segment firms and multiple-segment firms for industries whose multiple-segment firms have little related business segments. In panel C, change firms are not considered. Panel D presents the results when regressing the forecast improvement on the absolute difference between the industry’s mean-reversion coefficient and the economy’s mean-reversion coefficient.

In this table industries are defined using the two-digit SIC code. For the pooled regressions, the p-values are based on standard errors corrected for two-way clustering by firm and year following Rogers (1993). For the Fama-MacBeth regressions, the p-values are based on standard errors corrected for serial correlation following Newey and West (1987). ***,**, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.