The Impact of Diversification on Industry Effects in Firm Profitability Forecasting*

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The Impact of Diversification on Industry Effects in Firm Profitability Forecasting

Abstract

In this paper, we revisit the relative forecasting improvement from the use of an industry-specific model compared to that of an economy-wide model. We extend the results of Schröder and Yim (2018) who demonstrate that the industry-specific model only improves forecasting for single-segment firms due to the complication of different industries confounding the industry benchmark for multiple-segment firms. To explore the issues, we argue that the level of diversification is a more nuanced manner than a simple single-/multiple-segment dichotomy. Our results suggest that industry-specific models can provide more accurate forecasts of future performance and growth, not only for single-segment firms, but also for multiple-segment firms where the level of diversification is relatively low. The results help contribute to the forecasting literature to further explain when the use of different benchmarks is useful in predicting future performance.

Keywords: diversification; forecasting; industry; market; profitability

JEL Classification: G17; M4

1 Introduction

This study examines whether the level of diversification in a firm's operations is able to influence accurate forecasting when using an industry compared to an economy benchmark of profitability. Future profitability forecasting is viewed as an important part of improving fundamental analysis (Yohn 2020; Jackson 2022). Prior studies demonstrate that mean reversion, a phenomenon where profitability reverts back to its mean, enables more accurate forecasting of future earning ability (Fama and French 2000; Nissim and Penman 2001). Although prior studies demonstrate a mean reversion in profitability and growth (Fama and French 2000; Nissim and Penman 2001) signaling the importance in the use of benchmarks in forecasting, it remains ambiguous whether future profitability reverts towards an industry or an economy-wide benchmark.

Fairfield *et al.* (2009) use a first-order auto-regressive model, assuming the future profitability is mainly driven by its lag value, to assess the forecasting accuracy of the competing industry-specific and economy-wide forecasting models. They document that the industry-specific model performs no better than the economy-wide model in general when predicting future profitability, while forecasting growth is found to be improved by industry-level analysis. This contrasts with the view that industry effects play a crucial role in explaining firms' earnings ability (for example, Berger and Ofek 1995; Bhojraj *et al.* 2003; Hui and Yeung 2013; Hui *et al.* 2016). Schröder and Yim (2018) revisit Fairfield *et al.* (2009) by understanding the distinction between single-segment and multiple-segment firms. Schröder and Yim (2018) divide firm observations into single-segment and multiple-segment groups and confirm that the forecasting accuracy of future profitability is significantly improved from using an industry-specific model for single-segment but not multiple-segment firms.

However, the Schröder and Yim (2018) findings are based on a simplistic dichotomy that potentially limits the advantages of an industry-specific forecasting model to single-segment firms, whereas a more complete degree of diversification is able to provide a more nuanced approach to understanding the issue. We measure the level of firm diversification based on the relative size of the largest segment within a firm. Given that Schröder and Yim (2018) find that industry-specific models improve the forecasting accuracy of single-segment firms, we limit our analysis to multiple-segment firms.

Our paper contributes to the literature by confirming the effectiveness of an industry-specific forecasting model in a broader set of firms than simply single-segment firms. Specifically, the results from this paper are able to develop a further understanding of when and why some benchmarks are useful. Although an industry effect does not always add to a forecasting improvement for firms with high diversification levels, it should be able to drive the future profitability of less diversified firms. From a practical perspective, an appropriate choice of model helps to prepare more accurate forecasts and thus benefits the capital market as a whole.

Understanding the earnings-generating process of multiple-segment firms is important, with Berger and Ofek (1995) suggesting that an increasing number of firms are more diversified and operating in various industries. The ability to generate more accurate forecasts of future profitability assists in deriving more accurate valuations. Other studies have considered the question of single- versus multiple-segment firms in a valuation context.

Overall, our results support the notion that the forecasting improvement of using an industry-specific model is influenced by the level of firm diversification. First, we find that with more revenues being generated by the largest segment (i.e., being less diversified), the forecasting improvement increases in predicting profitability and growth. We also find that the likelihood of observing forecast improvements from an industry-specific model compared to an economy-wide model is increasing in less diversified firms. These results suggest firm diversification can be employed as a tool for predicting model selection.

The remainder of this paper is structured as follows. Section 2 reviews previous literature to develop our hypothesis. Section 3 outlines the research design and sample selection. Results are presented in Section 4 with sensitivity analysis in Section 5. Finally, Section 6 concludes and provides limitations of the study.

2 Literature Review

Demands on future profitability forecasting generally motivate the development of fundamental analysis research, which contributes to the broad literature on financial statement analysis (Yohn 2020; Jackson 2022). Early-stage studies use either firm-specific time-series models (Lev 1983) or cross-sectional regressions (Freeman *et al.* 1982) to examine profitability forecasting, and identify two main issues that influence firms' future profitability — industry impact and the mean reverting process. Mean reversion in profitability and growth is also demonstrated by Fama and French (2000) and is argued to be a foundation that assists the predictability of future earnings. Beyond confirming the existence of mean reversion, they also find that the reversion towards the mean is stronger when profitability deviates more from its mean value. Nissim and Penman (2001) distinguish between operating and financing activities and illustrate the nature of mean reversion across a number of ratios informed by DuPont analysis.

While mean reversion in profitability and growth is a well-documented phenomenon, relatively less is known about the mechanism that best explains it. Prior studies implicitly assume that the profitability and growth of firms revert to a common benchmark (Fairfield *et al.* 1996; Fama and French 2000), however, there are different benchmarks to which a firm's profitability may revert. For example, the Ohlson and Juettner-Nauroth (2005) theoretical model assumes an economy-wide benchmark while Gebhardt *et al.* (2001) apply an empirical study based on an industry-specific benchmark. In a similar vein,Vorst and Yohn (2018) consider firm life cycle stages and show that grouping firms within stages is able to improve the out-of-sample accuracy of profitability and growth forecasts relative to models where firms are pooled across the economy.

To further explore this question, Fairfield *et al.* (2009) adopt parsimonious first-order auto-regressive forecasting models to examine the incremental accuracy of predictions of an industry-specific model relative to an economy-wide model. In formulating their research question, they acknowledge that while some research suggests that industry membership influences future firm performance, others argue that industry effects are unimportant. Moreover, prior research suggests that industry effects may even differ across performance metrics.

Fairfield *et al.* (2009) find no improvement in forecasts at an industry level over the market level, based on out-of-sample tests of the prediction accuracy of five-year ahead return on equity or return on net operating assets. However, they do find that forecasts of growth are improved with an industry-level analysis compared to economy-wide models. Their results are consistent with findings in prior research on segment information that the use of segment-level data improves revenue predictions but not earnings predictions (Collins 1976), and approaches in fundamental analysis textbooks that suggest to forecast sales growth based on segment information but not for margins or other drivers of profitability (Palepu *et al.* 2021).

Schröder and Yim (2018) revisit Fairfield *et al.* (2009) and question whether the lack of findings is related to a failure to differentiate between single-segment and multiple-segment firms. They argue that the ability of an industry-level forecasting model to improve forecasting will be reduced when a firm operates across multiple industries so that the rate to which earnings revert is not clear. In order to resolve this, Schröder and Yim (2018) divide firm observations into single-segment and multiple-segment groups to further examine the forecasting accuracy of the industry-specific model. They find that forecasting accuracy is significantly improved by the industry-specific model for the single-segment group. However, the industry-specific model is not able to give more accurate forecasts than the economy-wide model when predicting multiple-segment firms, consistent with their expectations that "the aggregation of segment-level data for external reporting of firm-level financials obliterates the industry effects of their segments" (Schröder and Yim 2018, p. 2106).

2.1 Hypothesis

Fairfield *et al.* (2009) explain that the support for industry-specific mean reversion stems from a long body of research that industry membership is a fundamental determinant of firm performance (for example, King 1966; Schmalensee 1985). Reflecting this perspective, analysts routinely benchmark a firm's performance to its industry (Palepu *et al.* 2021). Industry-specific models of firm performance are appropriate if economic differences across industries, such as product demand, barriers to entry, or business risk, induce differences in the level or persistence of firm performance.

There are competing views about this, however. Industry effects have been reported to be negligible and firm-specific characteristics such as firm size and market share have a larger impact on firm profitability (Cubbin and Geroski 1987). Other studies have shown that firm profitability depends on the structure within industries, and profitability will differ by strategic groups within industries (Porter 1979). Additionally, different cost structures (Mills and Schumann 1985) and capital structures (MacKay and Phillips 2005) of firms within an industry will affect financial performance. Based on this, heterogeneity within industries will arguably reduce the incremental benefits of industry-level forecasting models.

Despite the competing views, academics and practitioners have long recognized the importance of a firm's industry membership in explaining its financial performance. This conventional wisdom, however, was not supported by Fairfield *et al.* (2009). Schröder and Yim (2018) demonstrate the effectiveness of the industry-specific model in predicting profitability and growth does hold in single-segment firms. As discussed earlier, Schröder and Yim (2018) put this result down multiple-segment firms not being clearly related to a single industry, so that the determination of an appropriate benchmark is not clear.

Schröder and Yim (2018) take a simplistic dichotomous classification to identify single- and multiple-segment firms. However, doing so restricts the industry-specific model's advantage only to firms that clearly operate within a single industry, and does not allow for a firm that operates in multiple segments, but with a single industry dominating, to benefit from adopting the industry-specific forecasting model. Take, for example, a firm that operates across three segments, but the main segment accounts for 90 per cent of total revenues. In this hypothetical case, it is clear that a single industry would dominate, and the industry-specific model would be expected to provide benefits in forecasting. In contrast, a firm operating with equal revenue generation from three industries would not be expected to benefit from an industry-specific model as the identification of the appropriate industry benchmark is not clear.

Therefore, we consider the level of diversification instead of a simple single- or multiple-segment dichotomy, which allows for greater nuance in the appropriate benchmark for multiple-segment firms. Accordingly, we would expect the benefits of an industry-specific model to be greater for less diversified firms. Formally stated:

H1: *For less diversified firms, industry-specific forecasting models are able to more accurately forecast future profitability and growth than an economy-wide model.*

3 Research Design and Data

3.1 Research Design

3.1.1 Forecasting Models

Following Fairfield *et al.* (2009) and Schröder and Yim (2018), we examine the incremental usefulness of an industry-specific forecasting model relative to an economy-wide model across three measures of profitability, and a growth measure. Profitability is measured using return on equity (ROE), return on assets (ROA), and return on sales (ROS), and growth is based on sales (GSL). We define earnings as the income before extraordinary items (Compustat $IBCOM$). Thus, ROE, ROA, and ROS are calculated using $IBCOM$ divided by book value of equity (average Compustat CEQ), total assets (average Compustat AT), and sales (Compustat $SALE$), respectively. The GSL is defined as the percentage change in sales from year *t-1* to year t (Compustat $SALE$).

Appropriate identification of industry is critical to the application of an industry-specific forecasting model. We follow Schröder and Yim (2018) in using a broad 12-industry classification by Fama and French (2000) to identify a firm's main industry, which provides the benchmark for the mean to which earnings are expected to revert. Different industry classification schemes have advantages and disadvantages in their use. The trade-off between estimation bias and reliability has been discussed which indicates that an industry-specific model could be too noisy to produce accurate forecasts in a narrow classification setting (for example, Pesaran and Zhou 2017; Wang *et al.* 2019). When classifying firms and segments into industries, we rely on the reported classifications for the firm from Compustat.

Our research design involves multiple steps, following prior studies that investigate the effectiveness of forecasting models (Fairfield *et al.* 2009; Schröder and Yim 2018). First, we conduct *in-sample* estimations using industry-specific and economy-wide models, respectively. We then obtain estimated parameters (coefficients) and use them to predict profitability for *out-of-sample* periods. Third, we compare the predicted profitability with its actual value to understand the forecasting accuracy. Finally, we focus on the *out-of-sample* periods to investigate the relative accuracy of these competing forecasting models.

First, the *in-sample* estimation models are:

Industry-specific forecasting model:

$$x_{i,t} = \alpha_{j,t} + \beta_{j,t} * x_{i,t-1} + \varepsilon_{i,t} \tag{1}$$

Economy-wide forecasting model:

$$x_{i,t} = \alpha_{t} + \beta_{t} * x_{i,t-1} + \varepsilon_{i,t} \tag{2}$$

where x represents profitability measures (i.e., ROE, ROA and ROS) and growth (GSL). The subscript i represents an individual firm, j denotes the main industry classification of a firm, and ε is the error term. The industry-specific (IS) model allows β to be estimated by separate industry groups, while the economy-wide (EW) model pools all observations together by year.

The parameters are also subscripted by year t, given that our estimation is conducted on a 10-year rolling basis. Specifically, the estimation on year t is based on the profitability or growth data of firms from year *t-9* to year t and their lag values from year *t-10* to year *t-1*. Moreover, the estimation of the economy-wide model is based only on the observations that are contained in the industry-specific model to allow equal-footing comparisons. A minimum of 100 observations for each rolling regression is required to generate reliable estimations.

In order to assess the forecasting accuracy of each model, we first predict the value of x in year *t+1* using estimated *in-sample* parameter α and β (labeled as $\hat{\alpha}$ and $\hat{\beta}$) based on the rolling regression in the current year t from equations (1) and (2):

Industry-specific forecasting model:

$$E_{IS,t}[x_{i,t+1}] = \hat{\alpha}_{j,t} + \hat{\beta}_{j,t} * x_{i,t} \tag{3}$$

Economy-wide forecasting model:

$$E_{EW,t}[x_{i,t+1}] = \hat{\alpha}_{t} + \hat{\beta}_{t} * x_{i,t} \tag{4}$$

This is followed by an *out-of-sample* test, which compares our *in-sample* predicted value of

x for year *t+1* and its actual value of each model. We define the absolute difference between the *in-sample* prediction and its actual value as forecasting error:

$$AFE_{IS,t+1} = |x_{i,t+1} - E_{IS,t}[x_{i,t+1}]| \quad (5)$$

$$AFE_{EW,t+1} = |x_{i,t+1} - E_{EW,t}[x_{i,t+1}]| \quad (6)$$

where AFE_{IS} and AFE_{EW} are the absolute forecasting errors for a firm in a year *t+1* of two competing models, respectively.

Then the advantage of adopting an industry-specific model over an economy-wide model is defined as forecasting improvement (FI):

$$FI = AFE_{EW} - AFE_{IS} \quad (7)$$

where a positive (negative) value on *FI* indicates the industry-specific outperforms (underperforms) the economy-wide model.

3.1.2 Empirical Models

To investigate the effect of firm diversification on the forecasting accuracy of two competing models, we conduct two types of analyses. First, we run an OLS regression model to examine whether firm diversification is associated with the amount of improvements in forecasting using an industry-specific compared to an economy-wide model. We then use a logit model where the dependent variable is replaced with an indicator variable to determine if the industry-specific forecasting model is more accurate than the economy-wide model:

$$FI = \alpha + \beta * Largest + \gamma * Controls + Fixed\_Effect + \varepsilon \quad (8)$$

where *FI* represents the forecasting improvement defined in equation (7) and being replaced by an indicator variable in a logit model, and *Largest* represents the degree of firm diversification as proxied by the size of the sales of the largest reported segment relative to total firm sales. Control variables are included to control for factors that have been shown to influence forecasting difficulty, cost structure and capital structure. Specifically, we include controls for market-to-book ratio (MTB), firm size ($Size$), leverage (Lev), asset turnover (ATO), profit margin (PM), total accruals ($Accruals$), earnings volatility ($\sigma Earn$), cash-flow volatility (σCF), and proportion of loss years ($PropLoss$). We also include a year-fixed effect and cluster standard errors by firm. All variables are defined in Table 1.

- - - INSERT TABLE 1 ABOUT HERE

3.2 Sample Selection

The firm-level data is sourced from the Compustat Fundamental Annual files, and segment-level data is obtained from the Compustat Historical Segment files. Given that segmental data is only available from 1977 onward, and there is a requirement for ten years of observations to generate the *in-sample* coefficients, our *out-of-sample* tests are based on a sample starting from 1988. The sample period ends in 2022, being the latest year with full availability of data. Given that Schröder and Yim (2018) document that industry-specific forecasting models are superior to economy-wide models for single-segment firms, we limit our sample to multiple-segment firms.

As described above, we use SIC codes to allocate firms into the Fama-French 12 industry groupings. We exclude firms that operate in the financial service (SIC 6000-7000) and utilities (SIC 4900-4950) sectors to avoid distortions resulting from regulated industries. We also exclude observations with a SIC code above 9900, as they are not a self-contained industry but a combination of non-classifiable industries. Where firms have two observations per fiscal year, we drop the duplicate entries, retaining the last records. We are also forced to rely on the industry classification of segments within the Compustat Historical Segment Files.

To mitigate the impact of small denominators on profitability measure and control variables, we exclude firm observations with total assets and total sales below USD $10 million, and book value of equity below USD $1 million. In addition, to reduce the influence of mergers and acquisitions, we remove observations with annual growth in book value of equity or sales above a hundred percent. We winsorize all variables at the 1^{st} and 99^{th} percentiles to partition out the influence of extreme values, with the exception of $Largest$ which is bound by (0, 1], and $PropLoss$. We retain 28,785 firm-year observations in our final sample.

4 Results

4.1 Descriptive Statistics

Table 2 reports the descriptive statistics of the sample. The mean and median forecasting improvements across the profitability and growth measures are negative (FI_ROE mean -0.0002, median 0.0000; FI_ROS mean -0.0003, median -0.0001; FI_GSL mean -0.0005, median -0.0002) with the exception of FI_ROA (mean 0.0000, median 0.0001). This result is consistent with Schröder and Yim (2018) that for multiple-segment firms, economy-wide forecasting models outperform industry-specific models. However, there is variation in the forecasting improvement across the sample, with standard deviations ranging from 0.0059 for FI_ROA to 0.0176 for FI_GSL. For the forecast improvements across all variables, the distributions are fairly symmetrical, in that the first and third quartiles and 1^{st} and 99^{th} percentiles mirror each other, and around half of the observations generating forecasting improvements with the use of industry-specific models ranging from 49.1% for ROS to 51.2% for ROA. These descriptive results align with the two prior studies we base the forecasting models on (Fairfield *et al.* 2009; Schröder and Yim 2018).

- - - INSERT TABLE 2 ABOUT HERE

The key explanatory variable, *Largest*, has a mean (median) value of 0.8347 (0.9051) indicating that, on average, the largest segment is responsible for around 83.47% of total firm sales. There is a significant variation with a standard deviation of 0.1843, a first quartile of 0.6937 and a 1^{st} percentile of 0.3761. At the upper quartile, the value of *Largest* is reported as 1.0000 which would suggest these are single-segment firms, but a closer examination explains that this is due to rounding with sales revenue from other segments being immaterial compared to its main segment. This only serves to illustrate the point that a single-/multi-segment approach is too simplistic to capture the nuances in the data.

Table 3 reports the Pearson correlations across all our variables. Our measure of firm diversification, *Largest*, has a statistically significant correlation with forecasting improvements in return on equity (FI_ROE $\rho = 0.021$), return on sales (FI_ROS $\rho = 0.038$) and the growth in sales (FI_GSL $\rho = 0.024$) at a 1% level, and return on assets (FI_ROA $\rho = 0.014$) at a 5% level.

- - - INSERT TABLE 3 ABOUT HERE

The correlations between the forecasting improvements in profitability measures, i.e., ROE, ROA and ROS, are all high being indicative of them being different formulations of the same construct (ranging from 0.293 to 0.507). The use of different profitability measures does, however, have different applications in forecasting activities. The correlation of the forecasting improvement of the growth in sales with the improvement in profitability measures is not as strong, but remains positive, reflecting the differences in construct. Correlations between the remaining variables are consistent with what has been shown in prior literature.

4.2 Firm-level Regression

Table 4 reports the results of estimating equation (8) for the full sample. We consider the forecasting improvements in return on equity (FI_ROE), return on assets (FI_ROA), return on sales (FI_ROS) and growth in sales (FI_GSL) in columns (1) through (4), respectively.

- - - INSERT TABLE 4 ABOUT HERE

The results indicate that the level of *Largest*, our variable of interest, has a significant association with the forecasting improvements of ROE (FI_ROE 0.0015, t-stat 2.33), ROS (FI_ROS 0.0019, t-stat 4.19), and the growth in sales (FI_GSL 0.0016, t-stat 2.52). We find that forecasting improvements in ROA are not significantly associated with the level of diversification. These results demonstrate that, consistent with the univariate correlations, there are significant forecasting improvements in the use of an industry-specific model in multiple-segment firms where the relative size of the largest segment, based on sales revenue, is such that the industry within which a firm operates is clear and the benchmark to which earnings should theoretically revert is cleaner.

Given that the mean and median of all the forecasting improvement variables are close to zero, we provide an economic interpretation of the results in reference to how a change in

Largest can be assessed relative to moving from the median value of the forecast improvement to the third quartile. For a one standard deviation change in *Largest* (0.1843 from Table 2), the forecasting improvements of using an industry-specific model in ROE, ROS and GSL correspond to 4.3%, 8.8% and 3.4%, respectively of the difference between the median and third quartile. While the magnitude of the forecasting improvement may seem small, any improvement in the ability to forecast is meaningful, and the raw amounts are consistent with prior literature examining forecasting improvements (for example, Fairfield *et al.* 1996, 2009).

Next, rather than examining the magnitude of the forecasting improvement, we consider whether the use of an industry-specific model is more accurate than an economy-wide model. As the dependent variable is now dichotomous, we adopt a logit model to estimate equation (8), with results presented in Table 5. Consistent with the linear regression results on the magnitude of the forecast improvement, we find that the probability of an improvement in forecasting is significantly associated with *Largest* across the same three forecasting variables: ROE (0.2337, z-stat 2.50), ROS (0.3869, z-stat 4.25), and GSL (0.1157, z-stat 1.70). The economic interpretation is that the probability of the industry-specific model providing a more accurate forecast than an economy-wide model is 12.4%[1], 21.3%[2] and 6.0%[3] higher, respectively, for a firm that is theoretically undiversified, i.e. when a multiple-segment firm generates all its revenues from a single segment, than a diversified firm generates half its revenue from its largest segment.

- - - INSERT TABLE 5 ABOUT HERE

5 Sensitivity Analysis

We perform a series of sensitivity analyses to assess the robustness of our results. We first consider the impact of the introduction of SFAS 131 in 1998 which changed segment disclosure requirements. The stated purpose of SFAS 131 was to increase the transparency of firm segment reporting, compared with the previous standard, SFAS 14, where firms were required to disclose

[1] $\exp(0.5 * 0.2337) - 1 = 0.1240$.
[2] $\exp(0.5 * 0.3869) - 1 = 0.2134$.
[3] $\exp(0.5 * 0.1157) - 1 = 0.0596$.

segment information according to the industry classification of their segments. Schröder and Yim (2018) find that the introduction of SFAS 131 resulted in no change in forecast improvements for multiple-segment firms. In line with this, we split our sample by reporting regime and repeat our main analysis. Results reported in Table 6, however, document that the positive relation between forecast improvement and the level of firm diversification is concentrated under SFAS 131 for ROE, ROS and GSL. We also find, however, in the SAS 131 period, firms that an industry-specific model provides more accurate forecasts, on average, for firms that are relatively less diversified for ROA. This result appears to be consistent with Berger and Hann (2003) that SFAS 131 led firms to reveal previously concealed information regarding their diversified activities.

- - - INSERT TABLE 6 ABOUT HERE

We then consider how industry-level diversification may impact on our results. To do this, we take the industry-year average measure of $Largest$, including single-segment firms. We then take the different between the firm-level $Largest$ and the industry-year average. The rationale behind this approach is that firms who are less-diversified than their industry peers should be more likely to experience forecasting improvements from an industry-specific model. In untabulated analysis, we find that the improvement in forecasting only holds for ROE and ROS where firm-level diversification is relatively larger than industry-year averages. Overall, while industry-level diversification does appear to have some impact on the relation between firm diversification and the improvements in an industry-specific forecasting model, it is still the level of firm-specific diversification that plays a significant role.

As previously noted, appropriate identification of industry is critical to the application of an industry-specific forecasting model. Defining industry too broadly limits the ability of an industry-specific model to isolate industry effects over an economy-wide model, while defining industry too narrowly may lead to insufficient observations to allow for stable estimates, leading to a trade-off between estimation bias and reliability. In the main analysis, we follow Schröder and Yim (2018) and use a Fama-French 12 industry classification. For purposes of sensitivity, we also re-estimate our industry-specific forecasting models using a Fama-French 48 industry classification, and 2-digit SIC codes. Due to the requirements of 100 observations per industry year, we do lose some observations with the narrower industry classifications, with a sample of 25,729 (25,579) using the Fama-French 48 (2-digit SIC) classifications.

Overall, our results with the alternate industry classifications are generally consistent with the main analysis. Based on the Fama-French 48 industry classifications, we still find that, as the level of diversification decreases, the industry-specific model provides more accurate forecasts for ROS and GSL, albeit with larger coefficient estimates. However, we find no significant result on $Largest$ for ROE, but there is an improvement for ROA (0.0008, t-stat 1.93). Turning to the 2-digit SIC codes to classify industry, we find that the industry-specific model provides statistically significant more accurate forecasts than an economy-wide model for all forecasting variables, and the magnitudes are much larger than the main results presented (ROE 0.0029, t-stat 2.70; ROA 0.0009, t-stat 2.29; ROS 0.0025, t-stat 4.04, GSL 0.0036, t-stat 4.18). Note, in this study we do not compare forecast errors across industry classification schemes thus are unable to comment on which classification scheme is able to provide more accurate forecasts.

In untabulated analysis, we also consider alternate measures of firm diversification. When using a simple count of the number of segments, or through the use of a Herfindahl-Hirschman Index (HHI) as proxies for firm diversification, we fail to find any forecasting improvement in multiple-segment firms for any of our measures being forecasted. We consider that a count of the number of segments will not capture the degree of diversification as it is not able to identify the relative degree of diversification. The use of an HHI can be viewed as potentially noisy, and taking the square of the proportion of segment revenues diminishes the importance of the main segment, which is of importance when considering the effect of industry in the mean reversion process.

We then also consider the role of the type of firm diversification in multiple segment firms. That is, whether the effect of $Largest$ is likely to be more pronounced for vertically or horizontally integrated firms. To do so, we classify vertically integrated firms as those with all segments classified in the same Fama-French 12 industry classification. When we split our sample in this manner, we did not find any significant differences in the level of diversification across vertically or horizontally integrated firms. We also repeat our analysis using the 2-digit

SIC classification, with vertically integrated firms those with all segments within the same 2-digit SIC code, and find the same results.

One somewhat surprising result in our main set of analyses is that the industry-specific forecasting model improves forecast accuracy where there is less diversification for ROE, but not ROA. However, from a DuPont analysis, including leverage with ROA will provide ROE. We include the three components of a simple DuPont analysis as controls in our model (leverage (Lev), asset turnover (ATO) and profit margin (PM)), finding that, on average, higher leverage is associated with a negative forecasting improvement of the industry-specific model. To further explore whether it is the influence of leverage that leads to the non-significant result of $Largest$ for ROA, we first split our sample at the median of leverage. Our results do not show that there are any differences for $Largest$ across the two subsamples. We then consider whether the amount of interest expense (Compustat $XINT/AT$) plays a role, splitting the sample at the median. Again, we find no difference in the coefficient on $Largest$ across the subsamples.

Finally, we consider other points in the distribution than the mean as presented in the OLS models. Specifically, we use quantile regressions from the 1^{st} to the 99^{th} percentiles, in increments of one percentile, with the coefficient estimates on $Largest$ presented in Figure 1. The effect of firm diversification follows a cubic functional form on ROE, ROA and ROS. At the lower (higher) percentiles, the use of an industry-specific forecasting model performs worse (better) for less diversified firms, with the coefficient on $Largest$ turning positive at around the 22^{nd}, 34^{th} and 10^{th} percentiles for ROE, ROA and ROS, respectively. This result is notable in that, while at the mean we do not find there to be any forecasting improvement on ROA for less diversified multiple-segment firms, there are improvements at different points in the distribution.

- - - INSERT FIGURE 1 ABOUT HERE

From Panel D of Figure 1, we find a different result for forecast improvements for growth. Specifically, we do not observe any noticeable difference across different points in the distribution for $Largest$. Rather, the results show that there is a consistent improvement in forecasting using an industry-specific model for less diversified firms when predicting future GSL.

6 Conclusion

In this paper, we investigate the impact of firm diversification on industry effects in forecasting firm profitability and growth. Although previous research demonstrates a mean reversion in firm profitability forecasting (Fama and French 2000; Nissim and Penman 2001), to what rate does profitability revert remains unclear. Fairfield *et al.* (2009) find no advantage of using an industry-specific benchmark for future profitability forecasting, while Schröder and Yim (2018) verifies the effectiveness of using an industry-specific model to predict the future profitability for single-segment firms. We focus on multiple-segment firms to further test whether the utility of the industry-specific model can be generalized to a broader group of firms in accordance with their diversification levels.

The results align with our prediction that the level of firm diversification has an impact on the effectiveness of using an industry benchmark for future profitability and growth forecasting. We observe significant associations between forecasting improvement using the industry-specific model and firm diversification scores when predicting ROE, ROS, and GSL, but not ROA. Also, the likelihood of obtaining forecasting improvements increases when firms are less diversified.

These results suggest that firm diversification, on average, can be referred to as a tool for the choice of economy-wide and industry-specific models. That is, the industry-specific model can be particularly beneficial when forecasting less diversified firms. In addition, the diversification score provides additional nuances compared to either a single-/multiple- segment dichotomy, or a simple count of the number of segments that a firm operates.

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Table 1: Variable Definition

Forecasting Improvements	
FI_ROE	Forecasting improvement of ROE, defined as the forecasting error of ROE using an economy-wide model less the forecasting error from an industry-specific model, where ROE is defined as income (Compustat *IBCOM*) scaled by average total equity (Compustat *CEQ*)
FI_ROA	Forecasting improvement of ROA, defined as the forecasting error of ROA using an economy-wide model less the forecasting error from an industry-specific model, where ROE is defined as income (Compustat *IBCOM*) scaled by average total equity (Compustat AT)
FI_ROS	Forecasting improvement of ROS, defined as the forecasting error of ROS using an economy-wide model less the forecasting error from an industry-specific model, where ROS is defined as income (Compustat *IBCOM*) scaled by sales (Compustat $SALE$)
FI_GSL	Forecasting improvement of the growth in sales (Compustat $SALE$), defined as the forecasting error of GSL using an economy-wide model less the forecasting error from an industry-specific model.
Firm Diversification	
Largest	The proportion of sales for the largest segment relative to total firm sales.
$LargeDiff$	The difference in the size of the largest segment based on sales for firm i in industry j and year t relative to the mean of the largest segment based on sales for all firms in industry j in year t.
Control Variables	
MTB	The market to book ratio, estimated as the market value (Compustat *CSHO* $*$ *PRCC_F*) of equity divided by book value of equity (Compustat *CEQ*).
Size	The logarithm of total assets (Compustat AT).
Lev	Leverage, defined as total assets divided by the book value of equity (Compustat AT/CEQ).
ATO	Asset Turnover, defined as sales divided by total assets (Compustat $SALE/AT$).
PM	Profit margin, defined as income divided by sales (Compustat *IB-COM*/*SALE*).
Accruals	Total accruals as a proportion of total assets, measured as (Compustat $(\Delta ACT - \Delta LCT - \Delta CHE + \Delta DLC - DP)/AT$)
$\sigma Earn$	The standard deviation of return on assets (Compustat *IBCOM* / average AT) over five years, *t-4* to *t*.
σCF	The standard deviation of cash flows scaled by average total assets, where cash flows is estimated using a balance sheet approach (Compustat (*IBCOM* - *Accruals*)/AT) over five years, *t-4* to *t*.
PropLoss	The proportion of the number of years with negative earnings (i.e., Compustat *IBCOM* less than 0) over five years, *t-4* to *t*.

Table 2: Descriptive Statistics

	Mean	Std. Dev	p1	Q1	Median	Q3	p99	% positive
FI_ROE	-0.0002	0.0128	-0.0371	-0.0067	0.0000	0.0064	0.0369	49.8%
FI_ROA	0.0000	0.0059	-0.0184	-0.0031	0.0001	0.0032	0.0176	51.2%
FI_ROS	-0.0003	0.0086	-0.0306	-0.0041	-0.0001	0.0039	0.0246	49.1%
FI_GSL	-0.0005	0.0176	-0.0610	-0.0088	-0.0002	0.0086	0.0534	49.4%
Largest	0.8347	0.1843	0.3761	0.6937	0.9051	1.0000	1.0000	
MTB	2.2155	1.6165	0.2527	1.1372	1.7774	2.7973	9.1831	
Size	7.0334	2.0487	3.0548	5.5160	6.9957	8.4540	11.8703	
Lev	2.4785	1.2353	1.1242	1.6597	2.1715	2.8626	8.1879	
ATO	1.1574	0.6776	0.2251	0.6959	1.0099	1.4405	3.9800	
PM	0.0399	0.0777	-0.2689	0.0101	0.0402	0.0770	0.2631	
Accruals	-0.0418	0.0565	-0.2162	-0.0718	-0.0409	-0.0113	0.1266	
$\sigma Earn$	0.0384	0.0345	0.0034	0.0154	0.0274	0.0491	0.1894	
σCF	0.0559	0.0402	0.0077	0.0279	0.0446	0.0726	0.2208	
PropLoss	0.1694	0.2449	0.0000	0.0000	0.0000	0.2000	1.0000	

Notes: This table presents the descriptive statistics for the full sample (N = 28,785). All variables are as defined as in Table 1.

Table 3: Correlation Matrix

	FI_ROE	*FI_ROA*	*FI_ROS*	*FI_GSL*	*Largest*	*MTB*	*Size*	*Lev*	*ATO*	*PM*	*Accruals*	$\sigma Earn$	σCF
FI_ROA	**0.507**												
FI_ROS	**0.293**	**0.412**											
FI_GSL	**0.043**	**0.065**	**0.073**										
Largest	**0.021**	***0.014***	**0.038**	**0.024**									
MTB	**0.046**	**0.081**	-0.002	**0.025**	**0.045**								
Size	0.001	0.002	**-0.012**	**-0.033**	**-0.030**	**0.241**							
Lev	**0.023**	-0.003	**0.039**	0.000	**-0.053**	**0.138**	**0.262**						
ATO	***0.014***	***0.013***	**0.017**	-0.004	***0.012***	**-0.042**	**-0.279**	***0.012***					
PM	-0.004	**0.020**	**-0.035**	0.005	0.003	**0.341**	**0.250**	**-0.156**	**-0.139**				
Accruals	-0.007	*0.010*	**-0.033**	0.006	***-0.014***	**0.037**	**-0.026**	**-0.062**	**0.093**	**0.177**			
$\sigma Earn$	*-0.010*	**-0.017**	**0.016**	-0.008	**0.093**	**-0.104**	**-0.278**	**-0.123**	**-0.026**	**-0.296**	**-0.099**		
σCF	-0.005	**-0.017**	*0.010*	0.003	**0.060**	**-0.138**	**-0.364**	**-0.064**	**0.139**	**-0.239**	**-0.029**	**0.643**	
PropLoss	0.002	*-0.010*	**0.035**	0.008	**0.063**	**-0.204**	**-0.244**	**0.167**	**-0.063**	**-0.519**	**-0.149**	**0.495**	**0.331**

Notes:This table presents the Pearson correlations for the sample. All variables are defined in Table 1. Significance indicated by boldface <0.01, bold italics p<.005, italics p<0.1.

Table 4: Forecast Improvement

	(1) FI_ROE	(2) FI_ROA	(3) FI_ROS	(4) FI_GSL
$Largest$	0.0015**	0.0003	0.0019***	0.0016**
	(2.33)	(1.21)	(4.19)	(2.52)
MTB	0.0004***	0.0003***	-0.0000	0.0004***
	(4.10)	(6.94)	(-0.43)	(4.51)
$Size$	-0.0001	-0.0000	-0.0001	-0.0004***
	(-0.89)	(-0.95)	(-1.23)	(-5.31)
Lev	0.0001	-0.0001**	0.0002***	0.0001
	(1.07)	(-2.20)	(3.71)	(0.82)
ATO	0.0002	0.0001*	0.0003*	-0.0004**
	(1.63)	(1.69)	(1.69)	(-2.27)
PM	-0.0026	-0.0006	-0.0010	0.0019
	(-1.17)	(-0.74)	(-0.67)	(0.98)
$Accruals$	-0.0015	0.0007	-0.0042***	0.0031
	(-0.91)	(0.94)	(-3.66)	(1.41)
$\sigma Earn$	-0.0065*	-0.0033**	0.0030	-0.0185***
	(-1.76)	(-1.99)	(1.12)	(-3.94)
σCF	0.0008	-0.0013	-0.0012	0.0030
	(0.30)	(-1.02)	(-0.59)	(0.81)
$PropLoss$	0.0004	0.0004**	0.0004	0.0014**
	(0.86)	(2.07)	(1.07)	(2.27)
Constant	-0.0022***	-0.0005	-0.0024***	0.0010
	(-2.81)	(-1.36)	(-4.04)	(1.21)
Fixed Effect	Year	Year	Year	Year
Cluster	Firm	Firm	Firm	Firm
N	28,785	28,785	28,785	28,785
Adj. R^2	0.007	0.009	0.015	0.018

Notes: This table reports the results from estimating equation (8). All variables are as defined in Table 1. Standard errors are clustered by firm, with t-statistics in parentheses and significance indicated by *** p<0.01, ** p<0.05, * p<0.1.

Table 5: Likelihood of Forecast Improvement

	(1) ROE	(2) ROA	(3) ROS	(4) GSL
Largest	0.2337**	0.1244	0.3869***	0.1157*
	(2.50)	(1.49)	(4.25)	(1.70)
MTB	0.0549***	0.0986***	-0.0034	0.0076
	(4.44)	(8.08)	(-0.28)	(0.83)
Size	0.0082	0.0066	0.0072	-0.0170**
	(0.82)	(0.73)	(0.69)	(-2.30)
Lev	0.0063	-0.0450***	0.0226*	0.0166
	(0.46)	(-3.53)	(1.67)	(1.43)
ATO	0.0363	0.0582**	0.0602*	-0.0032
	(1.43)	(2.30)	(1.71)	(-0.17)
PM	-0.0702	-0.3592	-0.4059	-0.0144
	(-0.23)	(-1.42)	(-1.60)	(-0.07)
Accruals	-0.1535	0.5024**	-1.2780***	-0.4894**
	(-0.63)	(2.04)	(-5.30)	(-2.04)
$\sigma Earn$	-1.0301*	-1.8169***	0.5092	-1.4333***
	(-1.86)	(-3.37)	(0.90)	(-2.78)
σCF	0.2644	0.2616	-0.1536	0.2914
	(0.59)	(0.61)	(-0.33)	(0.72)
PropLoss	0.1547**	0.2230***	0.1024	0.0788
	(2.09)	(3.15)	(1.37)	(1.15)
Constant	-0.3547***	-0.0506	-0.5316***	0.1840
	(-2.76)	(-0.40)	(-3.73)	(1.59)
Fixed Effect	Year	Year	Year	Year
Cluster	Firm	Firm	Firm	Firm
N	28,785	28,785	28,785	28,785
Pseudo R^2	0.005	0.008	0.008	0.008

Notes: This table reports the results from estimating equation (8). All variables are as defined in Table 1. Standard errors are clustered by firm, with z-statistics in parentheses and significance indicated by *** p<0.01, ** p<0.05, * p<0.1.

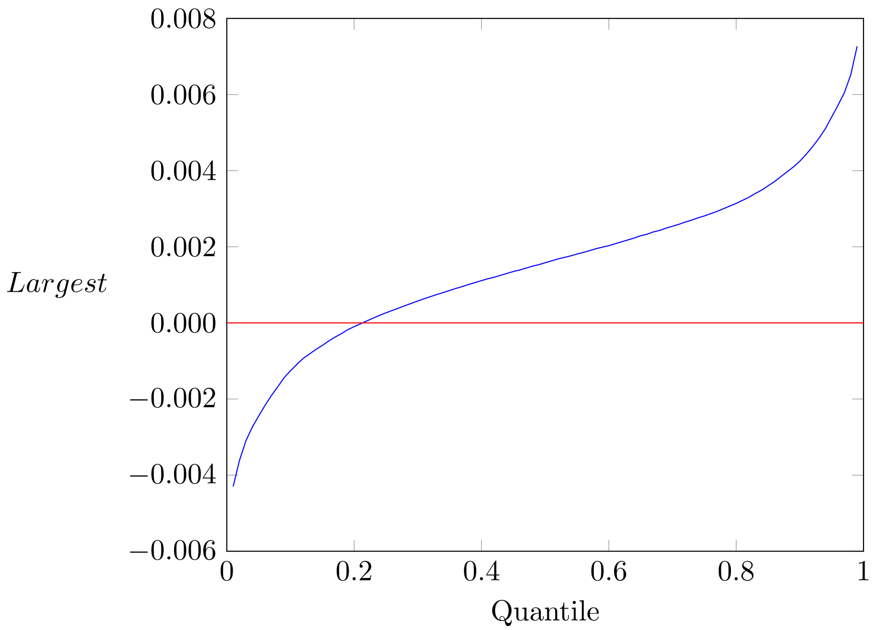
Table 6: Effect of SFAS 131

	FI_ROE		*FI_ROA*		*FI_ROS*		*FI_GSL*	
	Pre	Post	Pre	Post	Pre	Post	Pre	Post
Largest	0.0004	0.0018***	-0.0008	0.0008**	0.0006	0.0023***	0.0002	0.0020***
	(0.32)	(2.51)	(-1.46)	(2.34)	(0.93)	(4.13)	(0.18)	(2.74)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effect	Year	Year	Year	Year	Year	Year	Year	Year
Cluster	Firm	Firm	Firm	Firm	Firm	Firm	Firm	Firm
N	6,598	21,218	6,598	21,218	6,598	21,218	6,598	21,218
Adj. R^2	0.015	0.008	0.029	0.007	0.012	0.019	0.036	0.013

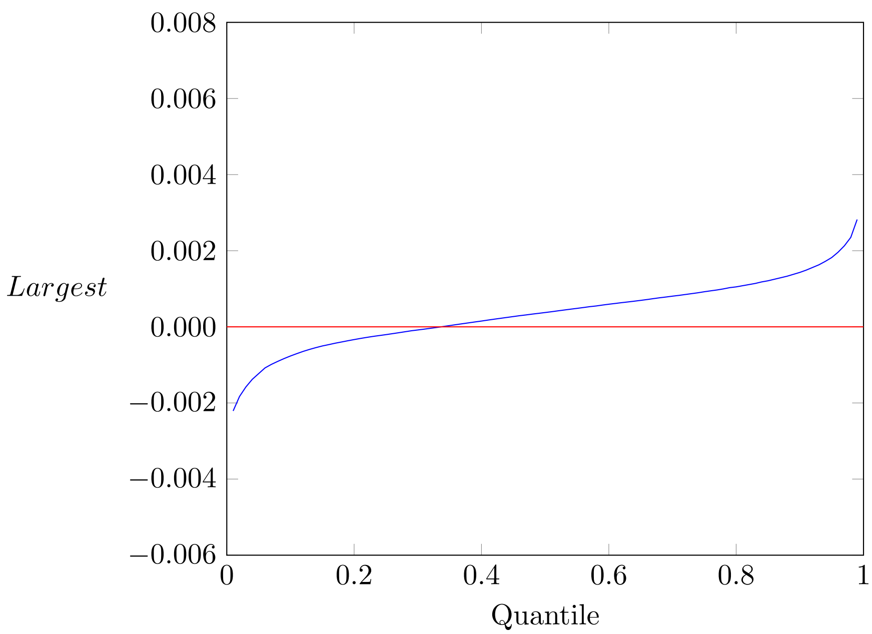
Notes: This table reports the results from estimating equation (8). All variables are as defined in Table 1. Standard errors are clustered by firm, with t-statistics in parentheses and significance indicated by *** p<0.01, ** p<0.05, * p<0.1.

Figure 1: Quantile Regression

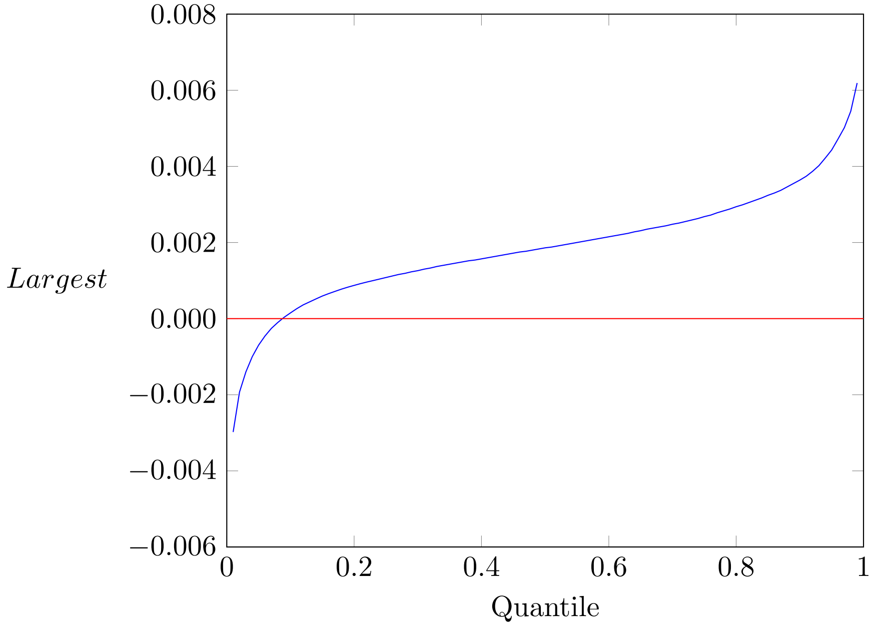
Panel A: ROE



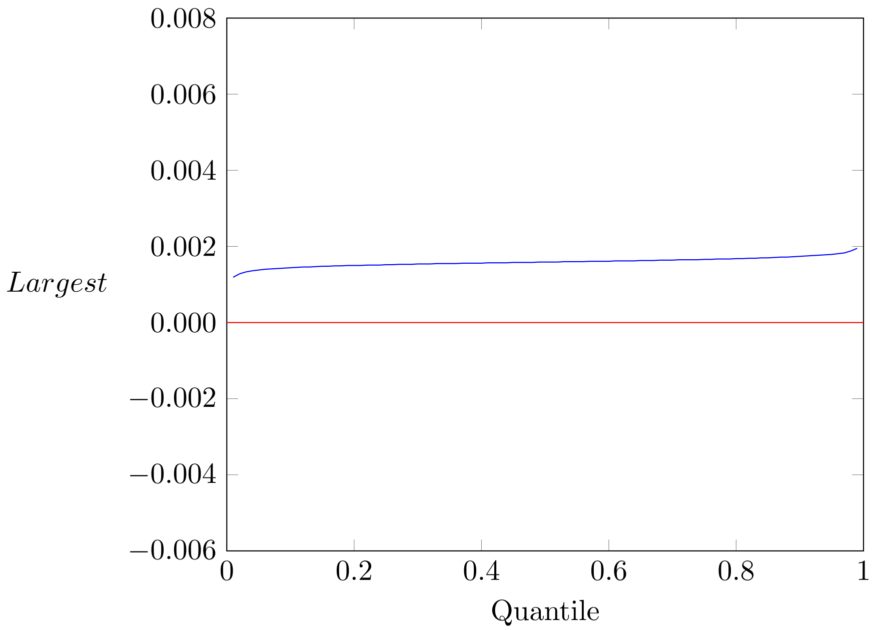
Panel B: ROA



Panel C: ROS



Panel D: GSL



Notes: This figure presents the coefficient estimates on *Largest* from estimating equation (8) using quantile regressions at every one percentile from the 1^{st} to the 99^{th} percentile.