DOI: 10.1111/j.1475-679X.2008.00313.x
Journal of Accounting Research
Vol. 47 No. 1 March 2009
Printed in U.S.A.

CHICAGO BOOTH

Do Industry-Level Analyses Improve Forecasts of Financial Performance?

PATRICIA M. FAIRFIELD,* SUNDARESH RAMNATH,† AND TERI LOMBARDI YOHN‡

Received 6 June 2005; accepted for publication 17 June 2008

ABSTRACT

Prior research documents mean reversion in firm profitability and growth under the implicit assumption that profitability and growth of all firms revert to a common benchmark at the same rate. However, a large body of academic research suggests that there are systematic interindustry differences (e.g., industry barriers to entry) that differentially affect firm performance based on industry membership. We evaluate the relative forecast accuracy of mean reverting models at the industry and economywide levels and find that industry-specific models are generally more accurate in predicting firm growth but not profitability.

1. *Introduction*

Prior research consistently documents mean reversion in firm performance (Freeman, Ohlson, and Penman [1982], Nissim and Penman [2001]). Fama and French [2000, p. 174] demonstrate that mean reversion in firm profitability is a robust statistical phenomenon and recommend that

*Georgetown University; †University of Miami; ‡Indiana University. We appreciate the comments of seminar participants at the McDonough School of Business, Carnegie-Mellon University, Emory University, Florida State University, Indiana University, Rutgers University, University of California–Berkeley, University of Massachusetts, University of Missouri, the University of Houston, and the Financial Accounting and Reporting Section midyear meeting. We would also like to thank two anonymous referees, B.W. Baer, Daniel Beneish, Phil Berger, Walt Blacconiere, Allan Eberhart, Zhaoyang Gu, Prem Jain, Ivo Jansen, Rick Johnston, Gerry Lobo, Derek Oler, Ray Pfeiffer, Jerry Salamon, Jake Thomas, Jim Wahlen, Joseph Weber, Scott Whisenant, and Michael Willenborg for their contributions.

"forecasts of earnings (e.g., by security analysts) should exploit the mean reversion in profitability." The implicit assumption in many of the prior studies of mean reversion is that profitability and growth of *all* firms revert to a common benchmark at the same rate (Fairfield, Sweeney, and Yohn [1996], Fama and French [2000]). However, a large body of academic research argues that there are systematic interindustry differences (e.g., industry barriers to entry) that differentially affect firm performance, suggesting that mean reversion in firm performance may be an industry-specific rather than an economywide phenomenon.

These conflicting perspectives are reflected in the academic literature. While some researchers assume that firm performance reverts to an economywide benchmark (Ohlson and Juettner-Nauroth [2005]), others assume that it reverts to an industry-specific benchmark (Gebhardt, Lee, and Swaminathan [2001]). Although important to academic research, accurately describing the mean reverting process is more than an academic exercise—accurate predictions of firm performance are important for price formation in efficient markets. If mean reversion contributes to predictability of firm performance and the mean reversion parameters differ systematically across industries, then it follows that industry-level prediction models will provide more accurate forecasts of firm performance than economywide models. We provide evidence on this issue by evaluating the relative performance of mean reverting models at the industry and economywide levels.

The support for industry-specific mean reversion stems from a large body of research suggesting that industry membership is a fundamental determinant of firm performance (e.g., King [1966], Schmalensee [1985]). Reflecting this perspective, financial institutions commonly organize research personnel by industry or sector, and analysts routinely benchmark a firm's performance to its industry. 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.

The descriptive validity of industry-specific performance models is, however, questioned in other research. Cubbin and Geroski [1987] report that industry effects are negligible and that firm profitability depends on firm-specific characteristics such as firm size and market share. Porter [1979] argues that firm profitability depends on the "structure *within* industries" and that profitability differs between "strategic groups" within an industry. Mills and Schumann [1985] argue that, even in equilibrium, firms within an industry could have heterogeneous cost structures, suggesting sustainable differences in profitability even among firms in the same industry. In addition, MacKay and Phillips [2005] present empirical evidence that firms within the same industry have persistently different capital structures and financial performance. Heterogeneity within industries and/or homogeneity across industries will reduce or eliminate the incremental benefits of industry-level forecasting models.

In light of the conflicting views on the relation between industry membership and firm performance, we examine the incremental information in industry-level analyses, compared to an economywide analysis, for predicting firm profitability and growth.[1] We use parsimonious first-order autoregressive forecasting models for profitability and growth where current profitability (growth) is modeled primarily as a linear function of lagged profitability (growth). We investigate the out-of-sample predictive accuracy of industry-specific versus economywide forecasting models of three measures of firm growth and two measures of firm profitability. To select these measures of firm performance, we refer to the residual income valuation model, which models firm value as a function of return on equity and growth in book value (Ohlson [1995], Feltham and Ohlson [1995], Nissim and Penman [2001]). We further examine the importance of industry-level analysis for forecasting the drivers of enterprise value—return on net operating assets and growth in net operating assets. We also examine the incremental predictive accuracy of industry-level models in forecasting sales growth, which is the fundamental driver of firm growth.

For each performance metric, we compare out-of-sample forecast errors from industry-specific and economywide models for both short-term forecasts (one year ahead) and long-term forecasts (five years ahead). Prior research suggests that short-term forecasts are important to analysts and investors (Brown [1993]). Moreover, the mean reversion evidence from prior research mostly relates to year-ahead firm performance (Freeman, Ohlson, and Penman [1982], Fama and French [2000]). We examine longer-term forecasts because the effect of industry membership on firm performance may not be immediate (Mueller and Raunig [1999]).

We find that industry-specific models are incrementally informative in predicting firm growth but not firm profitability. Specifically, we find that industry-specific models generate more accurate out-of-sample forecasts of short-term and long-term sales growth compared to economywide models. This evidence is not surprising because firms' sales growth depends on changes in product demand, which are generally determined at the industry level. We also find some evidence that long-term (but not short-term) forecasts of growth in book value and growth in net operating assets are significantly more accurate using industry-specific models. The evidence suggests that over longer forecast horizons firms' investment decisions are similarly influenced by changes in demand at the industry level.

In contrast to the results for growth metrics, we find no incremental information in industry-level analysis for forecasting profitability either in the short run or in the long run. The superiority of industry-specific models in predicting revenue growth, but not profitability, is consistent with the existence of sustainable differences in cost structures across firms within

[1] Industry comparisons may be useful on many levels, including evaluations of management performance. We provide no evidence on their usefulness in contexts other than predicting profitability and growth.

the same industry (Mills and Schumann [1985], Lippman, McCardle, and Rumelt [1991], Williams [1995]). Our results are also consistent with findings in prior research on segment information that the use of segment-level data improves revenue predictions but not earnings predictions (e.g., Collins [1976]).

To better understand the role of industry information in market expectations, we also examine whether the behavior of analysts and investors is consistent with our overall evidence that industry-level models provide more accurate forecasts of sales growth but not profitability. We find that Value Line analysts' year-ahead sales growth and return on equity forecasts are more closely associated with the more accurate prediction model—the industry-specific model for sales growth and the economywide model for return on equity. We also examine year-ahead returns to hedge portfolios constructed using sales growth and profitability predictions from the two competing models and find that investors appear to efficiently incorporate industry information into stock prices.

While our research provides evidence on the broader issue of mean reversion in firm performance, the results have particular implications for studies that rely on estimates of long-run firm performance. One such area is the fast growing literature on firms' cost of capital estimation, in which researchers assume firm profitability converges to a specific benchmark. Botosan and Plumlee [2005] point out that cost of capital estimates used in the academic literature differ primarily in the terminal value assumption, which is driven by the particular profitability benchmark selected. In computing terminal value estimates, some researchers assume that long-run firm profitability converges to industry benchmarks (e.g., Gebhardt, Lee, and Swaminathan [2001]), while others assume that firm profitability converges to an economywide benchmark (e.g., Ohlson and Juettner-Nauroth [2005]). We evaluate the appropriateness of these different assumptions by examining the path of firm return on equity (ROE) over long horizons, up to 12 years, and find that, on average, firms' long-run ROEs are closer to current economywide benchmarks than to industry-specific benchmarks. A direct implication of this finding, which is consistent with our prior results, is that cost of capital estimates are systematically biased if industry-specific profitability benchmarks are used in the terminal value assumptions.[2]

Our results also contribute to research that seeks to identify abnormal firm performance. We note that researchers often control for industry performance in assessing firms' future abnormal performance. Our results suggest that industry controls may be appropriate for growth metrics but not for profitability metrics. The evidence regarding profitability is consistent with the findings in Barber and Lyon [1996] that, in detecting abnormal

[2] Most studies estimate the cost of capital as the discount rate that equates estimated future cash flows to current value (stock price). If the estimates of future cash flows are biased upward (downward), the rate of return that equates future cash flows to current value will also be biased upward (downward).

firm profitability around corporate events, controlling for lagged firm profitability is more important than controlling for industry membership. The results are also consistent with the findings in Kothari, Leone, and Wasley [2005] that matching on firm profitability is more important in determining "abnormal" accruals than industry matching, suggesting that the accrual processes of firms are affected more by performance than by industry membership.

We note that our results do not suggest that there is no role for industry-level analysis in predicting future profitability. We only examine parsimonious models of mean reversion that have been used in previous research; industry-level analysis may be useful when other information is incorporated or when more sophisticated models are used. In addition, the results do not suggest that industry-level analysis is not useful for predicting profitability for all industries. In fact, we find evidence that industry-level analysis improves profitability predictions in industries that are less exposed to economywide forces, such as regulated industries, industries with high barriers to entry, and industries with larger firms. Our results, however, demonstrate that parsimonious forecasting models applied at the industry level do not, on average, provide incremental information over an economywide analysis for predicting firm profitability.

The rest of the paper is organized as follows. In the next section we discuss evidence on the influence of industry characteristics on firm performance. In section 3, we describe the data selection process and discuss overall data characteristics. In section 4, we present and discuss the empirical models used and the main results of the paper. Section 5 examines long-term profitability and growth forecasts. In section 6, we investigate whether analyst and investor behavior corresponds to our empirical findings. Section 7 presents additional analyses, and in the final section we discuss conclusions and implications of our study.

2. *Industry Analysis and Forecasts of Future Growth and Profitability*

Mean reversion in profitability and growth is well documented in the literature (Freeman, Ohlson, and Penman [1982], Fama and French [2000], Nissim and Penman [2001]).[3] However, prior research does not address the question of whether the mean reversion process is best modeled using industry-specific or economywide parameters. Pooling firms across industries (as in, e.g., Fama and French [2000]) forces the estimated impact of current firm performance on future firm performance to be uniform across

[3] To illustrate the concept of mean reversion, consider a simple univariate time-series model of the form:

$X_{i,t} = \alpha + \beta X_{i,t-1}$. If $\beta = 0$, X is fully mean reverting; $\beta = 1$, implies a fully persistent or random walk process. Prior studies report values of β between 0 and 1 for profitability and growth, consistent with partial mean reversion.

all firms, irrespective of industry.[4] An economywide estimation model is appropriate if, on average, all firms converge at the same rate to economywide benchmarks, for example, due to general competitive forces (Stigler [1963]).

However, research suggests that the benchmark to which firm profitability converges may differ systematically across industries. Schmalensee [1985] reports that industry effects explain much of the variation in firm profitability and that firm effects are negligible. Soliman [2005] shows an association between the components of firm operating profitability and industry membership. Studies in industrial organization consistently report a positive relation between industry concentration and industry profitability (Bain [1951], Mann [1966]). Average industry profitability may be higher in industries with higher risk (Fama and French [2000]), with higher barriers to entry (Cheng [2005]), with more conservative accounting (Cheng [2005]), and with a higher concentration of sales (Bain [1951], Demsetz [1973], Cheng [2005]). Other studies argue that the *rate* of mean reversion in firm profitability may depend on industry characteristics such as entry barriers (Kothari [2001], Cheng [2005]), economies of scale (Waring [1996]), capital intensity (Waring [1996]), and accounting practices that differ across industries (Cheng [2005]). If, as suggested by these studies, performance benchmarks and/or the rate of mean reversion differ across industries, we expect industry-specific forecasting models to predict firm performance more accurately than economywide models.

In contrast, other studies report that industry effects on individual firm performance are statistically and economically small (e.g., Brown and Ball [1967], Meyers [1973]). Evidence demonstrates that firm-specific characteristics dominate industry effects in explaining firm performance (Cubbin and Geroski [1987], Rumelt [1991], Mauri and Michaels [1998], Spanos, Zaralis, and Lioukas [2004]). Other studies document that profit rates of individual firms vary widely and do not converge to industry benchmarks even over long periods (e.g., Mueller and Raunig [1999]). Mackay and Phillips [2005, p. 1435] examine the effect of industry membership on capital structure and performance and conclude that "industry equilibrium forces may act to sustain intraindustry diversity rather than smooth it away." Barber and Lyon [1996] also report that industry effects are insignificant in explaining future abnormal firm performance.

Even if firm performance is affected by industry membership, the relation between firm and industry performance may be sensitive to the performance metric selected. Evidence from prior research suggests that revenues are more likely to be affected by industry membership than other growth or profitability measures. Givoly, Hayn, and D'Souza [1999] find a stronger correlation between firm sales and industry sales than between firm

[4] Fama and French [2000, p. 165] acknowledge the importance of industry effects and suggest that "More extensive tests for industry effects, would, of course, also be reasonable."

profits and industry profits, implying that cost structures exhibit greater variability than revenues within industries. Mills and Schumann [1985], Lippman, McCardle, and Rumelt [1991], and Williams [1995] argue that the core firms in an industry are likely to be high fixed cost producers whereas other firms (in the fringe) may have more flexible cost structures to meet varying demand in the industry. Ertimur, Livnat, and Martikainan [2003] argue that revenues are less subject to firm-specific aggregation and accounting measurement issues than expenses. Finally, most industry definitions group firms based on the product market in which they have primary operations.[5] Thus, by construction, industry groupings are more likely to pick up similarities in revenue growth than other measures of firm performance.

In summary, although extant research clearly documents that firm performance is mean reverting, the literature does not provide direct evidence on whether the well-documented mean reversion is an industry-specific or an economywide phenomenon. While some research suggests that industry membership influences future firm performance, others argue that industry effects are unimportant. Moreover, evidence from previous research suggests that industry effects may even differ across performance metrics. By comparing out-of-sample forecast errors from economywide forecasting models to the errors from industry-specific models for different measures of firm growth and firm profitability we provide empirical evidence on this issue.

3. Variable Definitions and Descriptive Statistics

We examine the usefulness of industry-level analyses in predicting three measures of growth, growth in book value (*GBV*), growth in net operating assets (*GNOA*), and growth in sales (*GSL*), and two measures of profitability, *ROE* and return on net operating assets (*RNOA*). All growth metrics are computed as the percentage change in the variable from the prior year to the current year. We define *ROE* using income before extraordinary items available for common stockholders in the numerator and average common shareholders' equity in the denominator. *RNOA* has net operating income (before any financing costs or investment income) in the numerator, and average net operating assets (operating assets net of operating liabilities) in the denominator.[6] We summarize the definitions in table 1.

[5] For example, Standard & Poor's (S&P) claims that Global Industry Classification Standard codes are designed to be more "market oriented" than "production oriented." See S&P's discussion at http://www.mscibarra.com/resources/pdfs/GICS_FAQ.pdf.

[6] We replicate the forecast models and out-of-sample tests using operating assets rather than net operating assets, for both growth (growth in operating assets) and profitability (return on operating assets). The basic results are unchanged for both performance measures when we use operating assets rather than net operating assets.

TABLE 1
Variable Definitions

Variable Name	Description	Computation
NI_t	Income before extraordinary items—available for common equity	Compustat data item 237
BV_t	Common shareholders' equity	Compustat data item 60
$OPINC_t$	Operating income after depreciation and amortization	Compustat data item 178
$SALES_t$	Net sales	Compustat data item 12
NOA_t	Net operating assets	Common stock (#60) + preferred stock (#130) + long-term debt (#9) + debt in current liabilities (#34) + minority interest (#38) − cash and ST investments (#1)
$AVGBV_t$	Average common equity	$\frac{BV_t+BV_{t-1}}{2}$
$AVGNOA_t$	Average net operating assets	$\frac{NOA_t+NOA_{t-1}}{2}$
ROE_t	Return on equity	$\frac{NI_t}{AVGBV_t}$
$RNOA_t$	Return on net operating assets	$\frac{OPINC_t}{AVGNOA_t}$
GBV_t	Growth in book value	$\frac{BV_t-BV_{t-1}}{BV_{t-1}}$
$GNOA_t$	Growth in net operating assets	$\frac{NOA_t-NOA_{t-1}}{NOA_{t-1}}$
GSL_t	Sales growth	$\frac{SALES_t-SALES_{t-1}}{SALES_{t-1}}$

In the main tables in the paper, we use the Global Industry Classification Standard (GICS) to define the industry to which a firm belongs.[7] Bhojraj, Lee, and Oler [2003] report that firms' profitability and growth measures generally have higher correlations with GICS-defined industry averages than with Standard Industrial Classification (SIC) codes, North American Industry Classification System (NAICS) codes, and the Fama–French classification system. In supplemental tests we find that the main results of this study are robust to alternative industry classification schemes.

We include all nonfinancial firms with data available on Compustat to compute the sales growth measure from 1969, and other ratios for the years 1979 to 2003.[8] We exclude financial firms with SIC codes from 6000 to 6999

[7] The GICS classification scheme became available only in 1990. We use the earliest available GICS code for observations in prior years. The GICS codes for individual firms appear to be fairly stable over time. Of the 5,232 unique firms in our sample, we find that 257 firms have a change in their GICS code over the period for which GICS data were available. Further, of the 257 firms that have at least one switch during this period, we find that many of these firms later switch back to the original GICS code. Deleting the switching firms from our sample does not alter the results.

[8] All our prediction models are based on rolling coefficient estimates derived from 10 years of prior data. In addition, we use predictions of sales growth as an input to our profitability prediction models (details in section 4.2). For example, our profitability predictions for the first hold-out year (1989) are based on coefficient estimates of the profitability model estimated using firm-year observations from 1979 to 1988. The 1979 data used in the profitability model

because separation of their financial and operating activities for computation of *RNOA* and *NOA* is artificial.[9] Our hold-out period is the 15 years from 1989 to 2003.[10] We exclude firms with lagged sales and net operating assets less than \$10 million and with book value less than \$1 million to avoid the effect of small denominators. In addition, we exclude firm-years with an absolute value of *ROE* or *RNOA* greater than one. We also exclude firm-years with growth in net operating assets, book value, or sales over 100% to reduce the effect of acquisitions on the relation between lagged and current year variables. In the estimation period, all values of the dependent and independent variables are truncated at 1% and 99%.[11] However, in the prediction years we do not truncate based on the value of the dependent (prediction) variable to avoid any look-ahead bias.[12]

Table 2 reports descriptive statistics for the full sample, after the exclusions described above. Panel A reports the descriptive statistics for the firm-level ratios. The means and medians of the variables, reported in panel A, are similar to those reported in prior research. Average growth rates in sales and net operating assets are comparable at approximately 9% over the sample period. The mean *ROE* is 7.69% over the 15-year period. The mean *RNOA* is almost twice as high (14.80%), mainly because we use operating income after depreciation (Compustat #178), which excludes income taxes and nonoperating items. In panel B we report the Spearman (Pearson) correlations below (above) the diagonal for the firm ratios. All variables are positively correlated, with the highest correlations within profitability measures and within growth measures. Profitability measures show higher persistence than growth measures.

In panel C of table 2, we report median industry values of profitability and growth over the 15-year period from 1989 to 2003 (the hold-out period). The number of observations over the 15-year period ranges from a low of 124 (multi-utilities) to 2,151 (commercial services and supplies). The median values of all profitability and growth measures are positive in every industry over the 15-year period. Median sales growth ranges from 2.60% (marine) to 15.26% (health care providers). *ROE* ranges from 4.81% (biotech) to

include our sales growth prediction for 1979, which in turn is derived from the sales growth model that is estimated using data from 1969 to 1978. Thus, our prediction models require 20 years of prior data. However, we do not require that *individual* firms have 20 years of continuous data.

[9] We also examine predictions of *ROE* and *GBV* for a sample that includes financial firms. The relative performance of the economywide and industry-specific models is similar to their relative performance when financial firms are excluded.

[10] This period also aligns closely with the Value Line analyst forecast tests described later in the study.

[11] We also perform the analyses after winsorizing all variables at their 1% (5%) and 99% (95%) values. The results are qualitatively similar to those reported in the tables for these alternative methods of dealing with outliers.

[12] To ensure that outliers in the prediction period do not drive the reported results, we also exclude observations in the 1% and 99% levels in the prediction years. Results (untabulated) are qualitatively similar to the reported results.

TABLE 2

Descriptive Statistics and Correlations

Panel A: Descriptive statistics

Variable	Mean (Std. Dev.)	Std. Dev.	First Quartile	Median	Third Quartile
Growth metrics:					
GSL	0.0919	0.2042	−0.0118	0.0735	0.1820
GBV	0.0792	0.2185	−0.0186	0.0693	0.1674
GNOA	0.0928	0.2451	−0.0391	0.0579	0.1964
Profitability metrics:					
ROE	0.0769	0.1725	0.0243	0.1029	0.1629
RNOA	0.1480	0.2196	0.0665	0.1305	0.2147

Panel B: Spearman and Pearson correlations

	GSL_{t+1}	GSL_t	GBV_{t+1}	GBV_t	$GNOA_{t+1}$	$GNOA_t$	ROE_{t+1}	ROE_t	$RNOA_{t+1}$	$RNOA_t$
GSL_{t+1}	**1.00**	0.22	0.43	0.20	0.47	0.25	0.32	0.14	0.29	0.12
GSL_t	0.28	**1.00**	0.22	0.41	0.24	0.47	0.15	0.27	0.18	0.27
GBV_{t+1}	0.49	0.27	**1.00**	0.27	0.49	0.16	0.61	0.28	0.37	0.26
GBV_t	0.25	0.47	0.36	**1.00**	0.30	0.47	0.25	0.58	0.23	0.39
$GNOA_{t+1}$	0.49	0.28	0.50	0.36	**1.00**	0.21	0.36	0.29	0.24	0.27
$GNOA_t$	0.28	0.48	0.19	0.49	0.26	**1.00**	0.10	0.32	0.10	0.26
ROE_{t+1}	0.38	0.22	0.64	0.34	0.37	0.14	**1.00**	0.53	0.58	0.47
ROE_t	0.17	0.34	0.37	0.64	0.36	0.34	0.64	**1.00**	0.43	0.63
$RNOA_{t+1}$	0.39	0.25	0.56	0.37	0.34	0.14	0.84	0.64	**1.00**	0.79
$RNOA_t$	0.17	0.36	0.37	0.56	0.36	0.33	0.63	0.84	0.76	**1.00**

See table 1 for variable definitions. Data are firm-year observations from 1989 to 2003. Number of observations is 35,727. In panel B, Spearman (Pearson) correlations are presented below (above) the diagonal. All correlations are significant at the 1% significance level.

(Continued)

17.96% (household products). Other profitability and growth measures also show substantial variation across industries.

4. *Incremental Information of Industry-Level Analyses over Pooled Analyses for Predicting One-Year-Ahead Growth and Profitability*

4.1 GROWTH

In table 3 we report in-sample estimates and out-of-sample tests comparing the industry-specific (henceforth, IS) and economywide (henceforth, EW) model performance for the three growth measures: growth in book value (*GBV*), growth in net operating assets (*GNOA*), and growth in sales (*GSL*). We model growth as a linear function of lagged growth. For each variable, the EW model pools all firms across all industries. The IS model allows the rate of regression to the mean as well as the intercept to differ across industries.[13] The competing models are:

[13] We note that the IS model allows both the intercept (level of performance) and the slope (rate of mean reversion) to vary across industries. Because the many free parameters can result in estimation error and therefore reduce out-of-sample accuracy, we also examine two additional models. The first model allows the intercept (level of firm performance) to differ across industries but constrains the slope (rate of mean reversion) to be the same. The

TABLE 2—*Continued*

Panel C: Descriptive statistics by GICS industry

GICS #	Description	*N*	*ROE*	*RNOA*	*GSL*	*GBV*	*GNOA*
101010	Energy equipment & services	664	0.0693	0.0985	0.0949	0.0763	0.0816
101020	Oil and gas	1,378	0.0804	0.0954	0.0669	0.0497	0.0507
151010	Chemicals	1,264	0.1216	0.1502	0.0499	0.0568	0.0481
151020	Construction materials	266	0.1060	0.1107	0.0565	0.0672	0.0341
151030	Containers & packaging	415	0.1062	0.1343	0.0589	0.0732	0.0563
151040	Metals & mining	1,281	0.0708	0.0917	0.0358	0.0445	0.0442
151050	Paper & forest products	435	0.0819	0.0962	0.0508	0.0393	0.0401
201010	Aerospace & defense	740	0.0940	0.1309	0.0436	0.0683	0.0418
201020	Building products	388	0.1220	0.1486	0.0811	0.0937	0.0494
201030	Construction & engineering	311	0.0811	0.1280	0.0803	0.0727	0.0410
201040	Electrical equipment	884	0.1186	0.1584	0.0719	0.0867	0.0541
201050	Industrial conglomerates	243	0.1458	0.1544	0.0407	0.0693	0.0523
201060	Machinery	1,777	0.1075	0.1416	0.0590	0.0682	0.0470
202010	Commercial services & supplies	2,151	0.1036	0.1449	0.0897	0.0711	0.0607
203010	Air freight & logistics	152	0.1433	0.1771	0.1039	0.1105	0.0719
203020	Airlines	192	0.1125	0.1197	0.1001	0.0892	0.0780
203030	Marine	167	0.0694	0.0760	0.0260	0.0245	0.0174
203040	Road & rail	715	0.1042	0.1261	0.0811	0.0846	0.0596
251010	Auto components	657	0.1275	0.1525	0.0883	0.0833	0.0698
251020	Automobiles	149	0.1076	0.1191	0.0931	0.0902	0.1070
252010	Household durables	1,510	0.1110	0.1471	0.0655	0.0776	0.0512
252020	Leisure equipment	514	0.0869	0.1476	0.0503	0.0568	0.0366
252030	Textiles, apparel, & luxury goods	1,122	0.0902	0.1318	0.0474	0.0588	0.0485
253010	Hotels, restaurants, & leisure	1,382	0.0918	0.1184	0.0863	0.0703	0.0738
254010	Media	1,120	0.0926	0.1297	0.0820	0.0679	0.0432
255010	Distributors	355	0.0746	0.0989	0.0673	0.0621	0.0546
255030	Multiline retail	437	0.1122	0.1487	0.0879	0.0866	0.0749
255040	Specialty retail	1,582	0.1070	0.1547	0.1091	0.1050	0.0988
301010	Food & drug retailing	629	0.1159	0.1503	0.0597	0.0789	0.0710
302010	Beverages	282	0.1153	0.1227	0.0683	0.0690	0.0478
302020	Food products	1,005	0.1240	0.1558	0.0517	0.0628	0.0536
303010	Household products	161	0.1796	0.2278	0.0577	0.0564	0.0438
303020	Personal products	249	0.1340	0.2007	0.0851	0.0876	0.0808
351010	Health care equipment & supplies	1,228	0.1042	0.1562	0.0941	0.0962	0.0761
351020	Health care provider & services	941	0.0996	0.1379	0.1526	0.1096	0.1031
352010	Biotechnology	240	0.0481	0.0693	0.1297	0.0896	0.0883
352020	Pharmaceuticals	470	0.1613	0.2368	0.1050	0.1158	0.0954
451020	IT consulting	417	0.0992	0.1561	0.1103	0.1104	0.0992
451030	Software	929	0.0709	0.1734	0.1247	0.0891	0.0854
452010	Communications equipment	979	0.0578	0.1076	0.0800	0.0638	0.0457
452020	Computer & peripherals	750	0.0612	0.1063	0.0762	0.0631	0.0377
452030	Electronic equipment & instruments	1,390	0.0783	0.1228	0.0738	0.0671	0.0542
452050	Semiconductor equipment & products	936	0.0632	0.1120	0.0774	0.0885	0.0865
501010	Diversified telecomm services	601	0.1404	0.1555	0.0777	0.0678	0.0637
551010	Electric utilities	1,196	0.1183	0.1163	0.0436	0.0386	0.0310
551020	Gas utilities	762	0.1129	0.1152	0.0500	0.0552	0.0675
551030	Multi utilities	124	0.1209	0.1195	0.0562	0.0448	0.0545
551040	Water utilities	187	0.1090	0.1185	0.0587	0.0460	0.0640

N is the number of firm-year observations available for the industry from 1989 to 2003. *ROE*, *RNOA*, *GSL*, *GBV*, and *GNOA* are the median values for the industry over the 15-year period (median of the *N* observations). See table 1 for variable definitions.

second model constrains the intercept (level of firm performance) to be the same but allows the slope (rate of mean reversion) to differ across industries. Neither of these constrained models outperforms the EW model in out-of-sample tests for any of the growth or profitability measures examined in the study.

TABLE 3

In-Sample Estimates and Improvement in Forecast Accuracy of Economywide and Industry-Specific Growth Models

Economywide (EW) model: $X_{i,t} = a_t + b_t X_{i,t-1} + e_{i,t}$

Industry-specific (IS) model: $X_{i,t} = a_{j,t} + b_{j,t}\ X_{i,t-1} + e_{i,t}$

(firm $i \epsilon$ Industry j; $X = GBV, GNOA, GSL$)

Panel A: In-sample estimation

	EW Model		IS Model	
	Mean	*t*-Statistic	Mean	*t*-Statistic
GBV				
Intercept	0.0374***	19.51	0.0459***	21.72
GBV	0.3265***	9.74	0.2736***	9.48
Adj. R^2	10.92%		11.43%	
GNOA				
Intercept	0.0525***	14.98	0.0563***	14.67
GNOA	0.3095***	26.73	0.2878***	51.80
Adj. R^2	8.44%		9.86%	
GSL				
Intercept	0.0470***	34.21	0.0516***	31.33
GSL	0.3647***	32.30	0.3272***	94.05
Adj. R^2	12.36%		14.66%	

(Continued)

EW model: $X_{i,t} = a_t + b_t X_{i,t-1} + e_{i,t}$; regression model estimated pooling all firms, across all industries.

IS model: $X_{i,t} = a_{j,t} + b_{j,t}\ X_{i,t-1} + e_{i,t}$; regression models estimated separately for each industry j of which firm i is a member.

For each of the three growth measures, $X_{i,t}$ is replaced by *GBV*, *GNOA*, and *GSL*, respectively, in the two models. For each year (t), we estimate "rolling" regression models using data from the preceding 10 years ($t - 10$ to $t - 1$). For example, for year 1989 (2003), the regression models use 10 years of data from 1979 (1993) to 1988 (2002). We require a minimum of 100 observations in the estimation period for both models. We note that the EW and IS models are estimated using the same sample of firms. For the EW model, panel A of table 3 reports mean coefficient estimates and the related *t*-statistics calculated using the Fama–MacBeth (Fama and MacBeth [1973]) approach. For the IS model, we compute the average ($\overline{a}_{j,t}$, $\overline{b}_{j,t}$) coefficient estimates across all industries ($j = 1, N$) in every year t, and report the mean of the 15 yearly average coefficients. *t*-statistics are computed using the Fama–MacBeth approach and adjusted for serial correlation in yearly coefficients (Bernard [1995]). Further, because we have multiple IS models in every year, we compute the yearly R^2 for the IS model as:

$$AdjR_t^2 = 1 - \left[\left(\frac{\sum_i (y - \hat{y})^2}{\sum_i (y - \bar{y})^2}\right) * \left(\frac{N-1}{N-2}\right)\right],$$

where N is the total number of firm-year observations i across all industries in year t, y is the dependent variable, $\hat{y}$ is the predicted value of y, and $\bar{y}$ is

TABLE 3—*Continued*

Panel B: Improvement in forecast accuracy

	EW Model vs. Naïve Model		IS vs. EW Model	
	Value	*p*-Value	Value	*p*-Value
Predicted variable: GBV_t				
Mean improvement	0.02984***	0.0001	−0.00030	0.3487
Median improvement	0.00790***	0.0001	−0.00003	0.6387
No. years	15/0		2/5	
No. industries			5/11	
Predicted variable: $GNOA_t$				
Mean improvement	0.03726***	0.0001	−0.00029*	0.0572
Median improvement	0.02148***	0.0001	−0.00028	0.1205
No. years	15/0		1/2	
No. industries			12/17	
Predicted variable: GSL_t				
Mean improvement	0.02713***	0.0001	0.00106***	0.0080
Median improvement	0.01525***	0.0001	0.00090**	0.0181
No. years	15/0		7/1	
No. industries			16/8	

See table 1 for variable definitions. Industries are defined using the Global Industry Classification Standard (GICS). Models are estimated on a rolling basis for 1989 to 2003 using data from the previous 10 years. In panel A, we report the mean of the yearly coefficient estimates for the EW model. For the IS model, we compute the average $(\bar{a}_{j,t}, \bar{b}_{j,t})$ coefficient estimates across all industries ($j = 1, N$) in every year t, and report the mean of the 15 yearly average coefficients. t-statistics are computed using the Fama-MacBeth [1973] procedure and adjusted for serial correlation in yearly coefficients (Bernard [1995]). For the industry-specific model the adjusted R^2 is computed every year t as:

$$AdjR_t^2 = 1 - \left[\left(\frac{\sum_i (y-\hat{y})^2}{\sum_i (y-\bar{y})^2}\right) * \left(\frac{N-1}{N-2}\right)\right]$$

where N is the total number of firm-year observations, i, across all industries in year t; y is the dependent variable; $\hat{y}$ is the predicted value of y; and $\bar{y}$ is the mean of y. The reported adjusted R^2 is the mean of the 15 yearly adjusted R^2 values.

In panel B, improvement in accuracy is measured through a matched-pair comparison of the absolute value of prediction errors from the two competing models. The naïve model assumes that the variable follows a random walk ($X_{i,t} = X_{i,t-1}$). The mean (median) improvement in accuracy is computed yearly and the reported grand mean (median) improvement is the mean (median) of the 15 yearly mean (median) improvements in predictive accuracy, using the first mentioned model. Positive (negative) values imply that the first mentioned model is more (less) accurate than the second model. "No. years" is the number of years (out of 15) that the yearly mean improvement is significantly positive/negative (at the 10% significance level). "No. industries" is the number of industries (out of 48) for which the mean improvement from using the industry-specific model is significantly positive/negative (at the 10% significance level). Tests of means are based on a t-test; tests of medians are based on a Wilcoxon signed rank test. The average number of predictions per year is 2,312 with a minimum (maximum) of 1,627 (2,715).

***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

the mean of y.[14] The reported R^2 is the mean of the 15 yearly adjusted R^2 values.

In panel A of table 3, we report the mean coefficients from the EW and IS models for each of the three growth variables. The average slope coefficient, capturing the persistence of the growth parameter, is roughly 0.30 for all

[14] $\sum_i (y-\hat{y})^2$ is the residual sum of squares (RSS) and $\sum_i (y-\bar{y})^2$ is the total sum of squares (TSS), both cumulated across all firm-year observations. This approach to computing the R^2 for the IS model provides a measure consistent with the R^2 for the EW model.

three variables and both models. The average adjusted R^2 value ranges from 8.44% to 14.66%. Because we rely on out-of-sample tests to evaluate the relative performance of the models, we do not directly compare the parameter estimates or the adjusted R^2 values from the EW and IS models.

In panel B, we compare out-of-sample predictions from the IS model to the EW model for the three growth metrics. We use regression estimates from 10 years of data up to year $t-1$ together with the realized values of the growth variables for year $t-1$ to predict growth in year t:

$$\text{EW Model}: E_{EW}\left(X_{i,t}\right) = \hat{a}_t + \hat{b}_t X_{i,t-1},$$

$$\text{IS Model}: E_{IS}\left(X_{i,t}\right) = \hat{a}_{j,t} + \hat{b}_{j,t} X_{i,t-1},$$

where $E_{EW}(X_{i,t})$ and $E_{IS}(X_{i,t})$ are predictions of $X_{i,t}$ ($X = GBV$, $GNOA$, or GSL) from the EW and IS models, respectively; $\hat{a}_t$ and $\hat{b}_t$ are estimated coefficients from the EW model and $\hat{a}_{j,t}$ and $\hat{b}_{j,t}$ are estimated coefficients from the IS model.

Panel B of table 3 reports univariate statistics for matched-pair prediction errors from the two models. For each year from 1989 to 2003, we calculate for each firm the absolute forecast error from each of the models:

$$AFE_{EW} = |X_{i,t} - E_{EW}(X_{i,t})|,$$

$$AFE_{IS} = |X_{i,t} - E_{IS}(X_{i,t})|.$$

For each firm-year observation, we calculate two paired forecast improvements: (1) the EW model compared to a random walk model ($|X_{i,t} - X_{i,t-1}| - AFE_{EW}$) and (2) the IS model compared to the EW model ($AFE_{EW} - AFE_{IS}$). A positive difference in (1) implies that the EW model is more accurate than the random walk model, and a positive difference in (2) implies that the IS model is more accurate than the EW model. For each comparison, we calculate the mean and median of the paired forecast improvements across all firms in each year. Panel B reports the grand means (medians) of these 15 annual mean (median) forecast improvements along with p-values based on t-tests (Wilcoxon signed-rank tests) of the 15 yearly means (medians). We also report the number of years and, for the IS model, the number of industries in which the grand mean for each of the two comparisons is significantly positive/negative.

The first set of results in panel B shows the forecast improvement comparing the EW model to the random walk model for each variable. The EW regression models are more accurate than the naïve model in every year for all three growth metrics, confirming that the linear estimation model has predictive validity for year-ahead growth in hold-out samples.[15]

[15] The IS model predictions are also more accurate than random walk predictions for all three growth metrics in every year. We do not report these results for brevity.

In the second set of results in panel B, we compare the IS model predictions to the EW model predictions. These out-of-sample results show that IS models of *GBV* and *GNOA* fail to improve predictions of firm growth relative to the EW model. Comparing the relative predictive accuracy across years and industries, we also note that the IS model more frequently reduces, rather than improves, forecast accuracy. The evidence suggests that even if interindustry differences in mean reversion exist, the differences are not strong enough to improve the accuracy of year-ahead predictions of growth in book value or net operating assets using the IS models.

In contrast, we find significant improvement in forecast accuracy of sales growth from the IS models. The mean (median) improvement in forecast accuracy from using the IS model relative to the EW model is positive and significant at less than the 1% (5%) significance level over the 15-year period. In addition, the IS model significantly increases forecast accuracy in 7 of the 15 years, and reduces forecast accuracy in only 1 year. Over the hold-out period, the IS model forecasts are also significantly more accurate in 16 industries and are less accurate in 8 industries.

In summary, our tests of the importance of industry membership for predictions of future growth yield mixed results. We find that industry-level analyses improve predictions of year-ahead sales growth, but not predictions of year-ahead investment. One reason for the conflicting results may be that firms' investment decisions lag changes in industry conditions. We investigate this issue in section 5.

4.2 PROFITABILITY

In table 4 we report on the incremental information in industry-level analyses for predicting one-year-ahead profitability metrics (*ROE* and *RNOA*). Our estimation and prediction models for profitability are similar to the growth models examined above, with the addition of two variables. First we add an indicator variable to allow the mean reversion of low and high profitability firms to differ. Fama and French [2000] document the importance of this asymmetry in explaining future profitability. Second, we include the predicted value of sales growth (*PREDGSL*) to allow for the possible effects of sales growth on the profitability measures. Lundholm and Sloan [2007] suggest a structured forecasting approach in which sales growth is the first step in the process. Penman [2007] suggests that if margins and turnovers remain constant, then profitability improves with sales growth. On the other hand, if profit margins fall or if turnover decreases due to increased investment to support the higher sales growth, then sales growth could have a negative effect on profitability. Consequently we do not predict the sign of the coefficient of *PREDGSL* in our profitability regressions. The predicted sales growth is from the more accurate IS model (see table 3).[16] The models

[16] Our objective here is to test the relative accuracy of the IS and EW profitability prediction models holding sales growth information constant. We acknowledge that the use

TABLE 4

In-Sample Estimates and Improvement in Forecast Accuracy of Economywide and Industry-Specific Profitability Models

Economywide (EW) model: $X_{i,t} = \alpha_t + \beta_t X_{i,t-1} + \gamma_t D_t * X_{i,t-1} + \lambda_t PREDGSL_{i,t} + \varepsilon_{i,t}$

Industry-specific (IS) model: $X_{i,t} = \alpha_{j,t} + \beta_{j,t} X_{i,t-1} + \gamma_{j,t} D_{j,t} X_{i,t-1} + \lambda_{j,t} PREDGSL_{i,t} + \varepsilon_{i,t}$ (firm $i \in$ industry j; $X = ROE, RNOA$)

Panel A: In-sample estimation

	EW Model		IS Model	
	Mean	Mean	Mean	Mean
ROE				
Intercept	0.0148***	0.0164***	0.0156***	0.0162***
ROE	0.7620***	0.7652***	0.7442***	0.7374***
D∗ROE	−0.1971***	−0.1987***	−0.2045***	−0.2053***
PREDGSL		−0.0228		0.0049
Adj. R^2	37.13%	37.15%	38.94%	39.23%
RNOA				
Intercept	0.0212***	0.0250***	0.0210***	0.0269***
RNOA	0.8432***	0.8512***	0.8280***	0.8349***
D∗RNOA	−0.0948***	−0.0943***	−0.0789***	−0.0756***
PREDGSL		−0.0569***		−0.0759***
Adj. R^2	66.07%	66.13%	65.08%	65.28%

Panel B: Improvement in forecast accuracy

	EW vs. Naïve Model		IS vs. EW Model	
	Value	*p*-Value	Value	*p*-Value
Predicted variable: ROE_t				
Mean improvement	0.00484***	0.0001	−0.00084***	0.0044
Median improvement	0.00088	0.4543	−0.00024	0.2128
No. years	15/0		0/8	
No. industries			9/19	
Predicted variable: $RNOA_t$				
Mean improvement	0.00205***	0.0001	−0.00024	0.2364
Median improvement	0.00098***	0.0034	−0.00017	0.1240
No. years	14/0		2/6	
No. industries			8/13	

In the EW model, D is a dummy variable that equals 1 if $X_{i,t-1}$ is less than the median value of X (X = *ROE* or *RNOA*) in year t−1, 0 otherwise. In the IS model, D_j is a dummy variable that equals 1 if $X_{i,t-1}$ is less than the median value of X (X = *ROE* or *RNOA*) for industry j ($i \in j$) in year t−1, 0 otherwise. $PREDGSL_{i,t}$ is the predicted sales growth for year t from the industry-specific sales growth prediction model. See table 1 for definition of other variables, and see table 3 for statistical computations. The average number of predictions per year is 2,255 with a minimum (maximum) of 1,602 (2,581).

*** indicates significance at the 1% level.

---

of the predicted sales growth estimate from the IS model suggests that the EW model incorporates industry-specific information. In untabulated tests, we re-estimate the EW profitability model using predicted sales growth from the EW model rather than the IS model. We find no significant difference in the predictive accuracy of the EW profitability model using predicted sales from the EW model compared to using predicted sales from the IS model. More importantly, the relative performance of the EW and IS profitability forecast models is unchanged when we force the EW profitability model to have no industry-specific information.

we use to estimate the different measures of profitability (*ROE* and *RNOA*) are:[17]

$$\text{EW model}: X_{i,t} = \alpha_t + \beta_t X_{i,t-1} + \gamma_t D_t * X_{i,t-1} + \lambda_t PREDGSL_{i,t} + \varepsilon_{i,t},$$

$$\text{IS model}: X_{i,t} = \alpha_{j,t} + \beta_{j,t} X_{i,t-1} + \gamma_{j,t} D_{j,t} * X_{i,t-1} + \lambda_{j,t} PREDGSL_{i,t} + \varepsilon_{i,t},$$

where firm $i \epsilon$ industry j; $X =$ *ROE* or *RNOA*; and D_t ($D_{j,t}$) is a dummy variable that equals one if profitability of firm i is below the median profitability of all firms (firms in the same industry) in year $t - 1$, and zero otherwise.

Because we rely on out-of-sample tests to investigate the relative performance of the models, we do not directly compare the average parameter estimates or the explanatory power of the regression models reported in panel A. The slope coefficients average about 0.75 for the *ROE* models and 0.84 for the *RNOA* models, consistent with the mean reversion in profitability commonly documented in the literature (e.g., Freeman, Ohlson, and Penman [1982], Fairfield, Sweeney, and Yohn [1996], Fairfield and Yohn [2001]). The negative coefficients on the low profitability dummy variables imply that low profitability is less persistent than high profitability. For both the EW and IS models, we include the predicted sales growth variable (*PREDGSL*) in the second regression. In the *ROE* forecast models, predicted sales growth is not significant. In the *RNOA* forecast models, it is negative and significant, implying that predicted sales growth negatively impacts year-ahead *RNOA*.

In panel B of table 4 we report the out-of-sample forecast improvements from the EW model relative to the random walk model, and from the IS model relative to the EW model.[18] Similar to panel B of table 3, we again report the grand mean (median) of the 15 yearly mean (median) improvements in forecasting accuracy from the EW model compared to the random walk model. Consistent with previous studies (Fairfield and Yohn [2001]), the profitability forecasts from the EW models are significantly more accurate than those from a random walk model, with the exception of the grand median improvement in the *ROE* prediction model, which is positive but not significant at conventional significance levels.[19]

Comparing the relative prediction accuracy of the IS and EW models, we find no evidence that the IS model yields more accurate predictions. In addition, comparing the relative prediction accuracy across years and

[17] Fama and French [2000] find evidence of nonlinearity in the mean reverting process for profitability. Banker and Chen [2006] report asymmetric changes in *ROE* for revenue increases versus revenue decreases, which they attribute to cost stickiness. We find no change in the relative performance of the IS and EW models using these alternative specifications.

[18] The forecasts are generated from the models incorporating the low profitability dummy variable and predicted sales growth. The relative performance of the IS and ES models is similar for predictions excluding either or both variables.

[19] The median improvement in *ROE* forecasts from the EW model relative to the random walk model is, however, significantly positive when we pool all firm-year observations. Further, the yearly median improvements are significantly positive (negative) in 9 (2) out of 15 years.

industries we note that the IS model more frequently reduces, rather than improves, forecast accuracy.[20] We conclude that industry-level analyses do not improve year-ahead forecasts of firm profitability. In contrast, we do find some improvement from industry-level analyses for one-year-ahead growth forecasts, although the evidence is limited to sales growth.[21]

5. Incremental Information of Industry-Level Analyses over Pooled Analyses for Predicting Five-Year-Ahead Growth and Profitability

IS models may perform poorly in the short term because the effect of industry forces on firm performance may occur over longer horizons (Mueller and Raunig [1999]). For example, industry conditions may affect growth in book value and net operating assets, but may occur with a lag as capital investments increase or decrease in response to changes in industry conditions. Similarly, profitability measures may converge to industry benchmarks gradually over time as firms leave less profitable industries and new firms enter more profitable industries. In this section we extend our analysis to investigate the incremental predictive accuracy of IS models over a five-year horizon.

We define five-year-ahead growth (*GBV*, *GNOA*, and *GSL*) as the compounded growth from year $t-1$ to $t+4$ and repeat the year-ahead analyses substituting five-year-ahead growth in place of year-ahead growth. We substitute five-year ahead *ROE* and *RNOA* as the dependent (target) variable in the estimation (prediction) model for profitability, but otherwise use similar estimation and prediction methods as detailed in the previous section of the paper.[22]

Table 5 compares out-of-sample forecasts of growth and profitability. As in table 3, predictions of sales growth from the IS models are significantly more accurate than predictions from the EW model ($p < 0.01$ for both the grand mean and median improvement in accuracy). We also find (weaker)

[20] We also compare out-of-sample forecast errors from EW models that incorporate lagged industry performance (growth or profitability) as an explanatory variable. The results from those models are similar to the results reported here. Specifically, sales growth forecasts are more accurate when we include industry data while *GBV*, *GNOA*, and profitability forecasts are not.

[21] Recall that we require a minimum of 100 observations for all our estimations. However, to ensure that the results are not driven by large errors from IS model predictions for industries with fewer observations in the estimation period, we examine the correlation between the natural log of the number of observations in the estimation period and the mean forecast improvement of the IS model relative to the EW model (industry-year observations). The correlation is -0.0204 ($p > 0.6$) for *ROE* and 0.0098 ($p > 0.8$) for sales growth. The relative forecast accuracy of the IS model does not appear to be related to the number of observations used in the estimation.

[22] We still require a minimum of 100 observations over the estimation period for the IS models. Because of the longer horizon examined, we lose six of the original 48 industries from the previous analyses for lack of sufficient data.

TABLE 5

Improvement in Forecast Accuracy of Five-Year-Ahead Economywide and Industry-Specific Growth and Profitability Models

Economywide (EW) model: $X_{i,t+5} = b_1 + b_2 X_{i,t} + e_{i,t+5}$

Industry-specific (IS) model: $X_{i,t+5} = b_{1,j} + b_{2,j} X_{i,t} + e_{i,t+5}$

(firm $i \in$ industry j; $X = GBV, GNOA, GSL, ROE, RNOA$)

	EW Model vs. Naïve Model		IS Model vs. EW Model	
	Value	p-Value	Value	p-Value
Predicted variable: GBV_{t+5}				
Mean improvement	0.04207***	0.0001	0.00062**	0.0174
Median improvement	0.02021***	0.0001	0.00011	0.3303
No. years	15/0		5/0	
No. industries			12/8	
Predicted variable: $GNOA_{t+5}$				
Mean improvement	0.06679***	0.0001	0.00026*	0.0635
Median improvement	0.03877***	0.0001	0.00052***	0.0043
No. years	15/0		1/0	
No. industries			10/11	
Predicted variable: GSL_{t+5}				
Mean improvement	0.04954***	0.0001	0.00120***	0.0004
Median improvement	0.02914***	0.0001	0.00098***	0.0012
No. years	15/0		8/0	
No. industries			14/7	
Predicted variable: ROE_{t+5}				
Mean improvement	0.01568***	0.0001	−0.00078**	0.0456
Median improvement	0.00978***	0.0001	−0.00006	0.1688
No. years	15/0		1/5	
No. industries			10/13	
Predicted variable: $RNOA_{t+5}$				
Mean improvement	0.01628***	0.0001	0.00007	0.8678
Median improvement	0.01073***	0.0001	0.00034	1.0000
No. years	15/0		2/2	
No. industries			9/12	

See table 1 for variable definitions. Industries are defined using the Global Industry Classification Standard (GICS). Growth in book value (GBV_{t+5}), growth in NOA ($GNOA_{t+5}$), and sales growth (GSL_{t+5}) are the compounded growth rates from year t to year $t + 5$. Models are estimated on a rolling basis for target years ($t + 5$) 1989 to 2003 using 10 years of data. Improvement in accuracy is measured through a matched-pair comparison of the absolute forecast errors from the two competing models. The naïve model assumes that the variable follows a random walk ($X_{i,t+5} = X_{i,t}$). The mean (median) improvement in accuracy is computed yearly and the reported grand mean (median) improvement is the mean (median) of the 15 yearly mean (median) improvements in predictive accuracy, using the first mentioned model. Positive (negative) values imply that the first mentioned model is more (less) accurate than the second model. "No. years" is the number of years (out of 15) that the yearly mean improvement is significantly positive/negative (at the 10% significance level). "No. industries" is the number of industries (out of 42) for which the mean improvement from using the industry-specific model is significantly positive/negative (at the 10% significance level).Tests of means are based on a t-test; tests of medians are based on a Wilcoxon signed rank test.

***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

evidence that predictions of *GBV* and *GNOA* from IS models are more accurate than those from the EW model. Taken together, these results suggest that industry membership affects growth metrics generally. However, the impact of industry conditions on investment is evident only over longer time horizons. In contrast, we continue to find that industry-level analyses do not improve forecasts of *ROE* and *RNOA*, even over this longer horizon. Our results are inconsistent with research that posits systematic interindustry differences in the mean reversion of firm profitability.

6. *Analysis of Analyst and Investor Expectations*

Our results show that the effect of industry membership on firm performance is dependent on the specific performance measure. In an efficient capital market, we expect these different impacts to be reflected in investor expectations of firm performance. In this section, we present evidence demonstrating that analysts' forecasts and market prices are consistent with the role of industry information as reflected in our findings.

6.2 VALUE LINE PREDICTIONS OF SALES GROWTH AND PROFITABILITY

The observed clustering of analyst coverage by industry group suggests that analysts find industry information to be useful for forecasting firm performance. In this section we examine the association of year-ahead sales growth and ROE forecasts of sell-side analysts with the sales growth and ROE predictions from EW and IS models. If analysts' use of firm and industry information is consistent with the more accurate prediction model, then analyst forecasts of year-ahead sales growth should be more closely associated with IS model forecasts than EW model forecasts. Similarly, because the IS model predictions are significantly less accurate for ROE forecasts, the association between analysts' *ROE* forecasts and IS model predictions should be lower than the association between analysts' ROE forecasts and EW model predictions.[23]

We compute one-year-ahead sales growth and *ROE* forecasts using data from the Value Line Investment Survey for the years 1989 to 2000. Value Line publishes explicit sales forecasts as well as earnings and book value forecasts, which we use to compute ROE forecasts. Both sales and ROE forecasts are the earliest forecast made by Value Line at least three months, but no later than seven months, after the fiscal year-end for year $t-1$. The final sample consists of over 1,200 unique firms and approximately 9,000 (10,000) firm-year observations for ROE (sales growth) over the 12-year period.

In Panel A of table 6, we present regression results for the following model:

$$VLGSL_{i,t} = b_1 + b_2 * PREDGSL_{i,t} + \varepsilon_{i,t},$$

where $VLGSL_{i,t}$ is firm i's sales growth forecast for year t computed as: $[\frac{VLSLFRC_{i,t}}{SALES_{i,t-1}} - 1]$; $VLSLFRC_{i,t}$ is firm i's sales forecast for year t obtained from the Value Line Investment Survey (VL) and $SALES_{i,t-1}$ is the actual sales for year $t-1$; $PREDGSL_{i,t}$ is the prediction of sales growth using either the

[23] The IS model ROE predictions are significantly less accurate than EW model predictions when we use the Value Line industry codes to form industries (see table 8).

TABLE 6

Relation between Analyst Forecasts and Economywide and Industry-Specific Sales Growth and ROE Predictions

Panel A: Analyst revenue forecasts

$VLGSL_{i,t} = a_1 + a_2 * PREDGSL_{i,t} + \varepsilon$

	EW Sales Forecast Model		IS Sales Forecast Model	
	Coefficient Estimate	t-Statistic	Coefficient Estimate	t-Statistic
Intercept	0.0333***	10.53	0.0334***	10.83
PREDGSL	0.7403***	25.76	0.7365***	28.48
Adj. R^2	14.11%		16.38%	
Diff. in Adj. R^2				
Vuong test (Z-statistic)		4.46***		

Panel B: Analyst ROE forecasts

$VLROE_{i,t} = a_1 + a_2 * PREDROE_{i,t} + \varepsilon$

	EW ROE Forecast Model		IS ROE Forecast Model	
	Coefficient Estimate	t-Statistic	Coefficient Estimate	t-Statistic
Intercept	0.0587***	23.13	0.0627***	23.60
PREDROE	0.6710***	58.87	0.6458***	54.80
Adj. R^2	58.24%		57.63%	
Diff. in Adj. R^2				
Vuong test (Z-statistic)		1.71*		

$VLGSL_{i,t}$ is firm i's sales growth forecast for year t computed as: $[\frac{VLSLFRC_{i,t}}{SALES_{i,t-1}} - 1]$ where $VLSLFRC_{i,t}$ is firm i's sales forecast for year t obtained from the Value Line Investment Survey (VL) and $SALES_{i,t-1}$ is the actual sales for year $t-1$. $VLROE_{i,t}$ is VL's forecast of firm i's net income before extraordinary items divided by VL's forecast of net worth. Both sales and ROE forecasts are the earliest forecast made by VL at least three months, but no later than seven months, after the fiscal year-end for year $t-1$. $PREDGSL_{i,t}$ is the predicted sales growth from the EW model (or IS model). $PREDROE_{i,t}$ is the predicted ROE from the EW model (or IS model). The regression models in panels A and B are estimated yearly from 1989 to 2000 and the average value of the coefficients is reported in the table. t-statistics are computed based on the standard deviation of the yearly coefficient estimates and are adjusted for serial correlation in coefficients (Bernard [1995]). The average number of observations per year is 838 (730) in panel A (panel B).

*** and * indicate significance at less than the 1% and 10% levels, respectively.

EW or IS model.[24] On the left (right) side of panel A, we report regression results on the association between VL sales growth forecasts and the EW (IS) sales growth prediction model. We estimate the regressions yearly and report the average value of the coefficients as well as the average adjusted R^2 over the 12-year period.

Consistent with analysts incorporating industry-specific sales growth information into sales growth forecasts for firms, we find that analysts' sales growth forecasts are more closely associated with IS sales growth predictions than EW sales growth predictions. Over the 12-year period, the IS (EW) sales growth forecasts, on average, explain 16.38% (14.11%) of the variation in VL analysts' sales growth forecasts. A Vuong [1989] test for the difference in

[24] To stay consistent with our forecast data source (i.e., Value Line), we use the Value Line industry groupings for the IS prediction models.

adjusted R^2 values between the two models confirms that the explanatory power of the IS model forecasts is significantly greater (at less than the 1% significance level) than that of the EW model forecasts.

In panel B of table 6 we present regression results for forecasts of *ROE*:

$$VLROE_{i,t} = a_1 + a_2 * PREDROE_{i,t} + \varepsilon_{i,t},$$

where $VLROE_{i,t}$ is VL's forecast of net income before extraordinary items divided by VL's forecast of net worth for firm i for year t; and $PREDROE_{i,t}$ is the predicted value of ROE from the EW or IS model.

We present regression results of the relation between VL's *ROE* forecasts and predicted *ROE* from the EW (IS) model in the left (right) side of panel B. If analyst forecasts are efficient with respect to ROE information, we expect analysts' *ROE* forecasts to be more closely associated with the EW model *ROE* predictions than the IS model *ROE* predictions. We find that the average adjusted R^2 value is slightly higher for the EW forecast model (58.24%) than for the IS model (57.63%). A Vuong [1989] test of the difference in adjusted R^2 values is marginally significant (at the 10% significance level). Overall, evidence from VL analyst forecasts of sales growth and ROE are consistent with the view that analysts use industry information to forecast firms' sales growth, but not profitability.

6.3 ANALYSIS OF INVESTOR EXPECTATIONS OF SALES GROWTH AND PROFITABILITY

Prior research suggests that investors may use financial information less efficiently than analysts (e.g., Abarbanell and Bernard [1992]). Inefficiency in the use of firm and industry information by investors leads to implementable trading strategies that exploit this inefficiency. If investor expectations of year-ahead sales growth (GSL) reflect predictions from the EW model (which is less accurate than the IS model), then buying (selling short) stocks of firms where the IS model predicts higher (lower) sales growth than the EW model should yield positive returns. Similar arguments apply to ROE, where the strategy is to buy (sell short) stocks of firms where the ROE predictions of the EW model are higher (lower) than the IS model. In this section we use an approach similar to Berger and Hann [2003] to examine whether hedge returns to portfolios that exploit the accuracy differences in the two competing GSL and ROE prediction models yield positive abnormal returns in the following 12-month period.

We report the buy-and-hold abnormal returns (*BHAR*) to three trading strategies based on GSL and ROE predictions from the EW and IS models. In the first (second) set of results, we report returns to the strategy based on sales growth (ROE) predictions. We then report the hedge portfolio returns to a strategy based on a combination of the first two strategies, that is, buy and hold (sell short) stocks where the IS model predicts higher (lower) sales growth *and* the EW model predicts higher (lower) ROE than the EW sales growth model and the industry-specific ROE model, respectively. If investors react inefficiently to both GSL and ROE information the third strategy should produce returns superior to either the first or the second strategy.

Our return cumulation period starts from the fourth month of year t and extends into the third month after fiscal year-end. We use information up to year $t-1$ in forming our predictions (as detailed in the preceding sections). The 12-month abnormal returns are calculated as:

$$\prod_{k=1}^{k=12} [1 + R_{i,k}] - \prod_{k=1}^{k=12} [1 + VWRET_k],$$

where $R_{i,k}$ is the monthly return for firm i and $VWRET_k$ is the value-weighted return for the corresponding month.

We determine hedge portfolio returns by summing up the returns for the long and short portfolios. We compute yearly returns for the long, short, and hedge portfolios and report the mean/median of the 15 yearly returns in table 7. The hedge portfolio returns are positive in general, but not significant at conventional significance levels.[25] We conclude that investors seem to efficiently use industry-level analyses in forming their sales growth and ROE expectations for the year ahead.

7. *Additional Analyses*

7.1 ALTERNATIVE INDUSTRY DEFINITIONS

Some researchers have questioned the impact of errors in industry classification on tests of industry influences on firm performance (Bhojraj, Lee, and Oler [2003], Krishnan and Press [2003]). Our findings may be partly attributable to an incorrect classification of firms into industries. In this section we explore the possibility that alternative industry definitions may improve the predictive power of industry-level analyses. Table 8 compares the out-of-sample prediction results for all growth and profitability measures examined previously for four different definitions of industry—NAICS codes, the Fama–French classification system, the industry groups used in VL, and two-digit SIC codes obtained from Compustat.[26]

As with the main tests using GICS codes, we require a minimum of 100 firm-year observations in each industry for every estimation period. This requirement creates some variation in the number of industries included in the tests every year, with fewer (more) industries included in earlier (later) years. In table 8, we first report results from the NAICS classification, where we use the first three digits of the coding scheme (Bhojraj, Lee, and Oler [2003]). We next report results using the Fama–French definition of industry. The Fama–French industry algorithm classifies firms into 48 industry

[25] Only the mean return for the ROE-based portfolio (in column 2) is significant (at the 10% level). The median return is not significant even for this portfolio.

[26] Although the limitations of SIC codes in identifying related firms are well documented in prior research (see, e.g., Clarke [1989]), we include them here for completeness. In unreported tests, we also use three-digit SIC codes and find no changes in our overall results.

TABLE 7

Analysis of Stock Returns Based on Economywide and Industry-Specific Sales Growth and ROE Predictions

Twelve-month abnormal return of trading rule portfolios

	Long: $GSL_{i,t}$ (IS) > $GSL_{i,t}$ (EW) Short: $GSL_{i,t}$ (IS) < $GSL_{i,t}$ (EW)		Long: $ROE_{i,t}$ (EW) > $ROE_{i,t}$ (IS) Short: $ROE_{i,t}$ (EW) < $ROE_{i,t}$ (IS)		Long: $GSL_{i,t}$ (IS) > $GSL_{i,t}$ (EW) and $ROE_{i,t}$ (EW) > $ROE_{i,t}$ (IS) Short: $GSL_{i,t}$ (IS) < $GSL_{i,t}$ (EW) and $ROE_{i,t}$ (EW) < $ROE_{i,t}$ (IS)	
	12-Month Return	*p*-Value	12-Month Return	*p*-Value	12-Month Return	*p*-Value
Hedge portfolio						
Mean return	2.71%	0.3660	3.42%*	0.0951	6.10%	0.1828
Median return	0.73%	0.5614	1.47%	0.2293	3.76%	0.1688
Years positive/negative and significant (5% level)	6/3		6/1		5/3	
Short portfolio						
Mean return	−3.63%	0.4548	−3.47%	0.3894	−3.17%	0.4754
Median return	4.30%	0.6788	−4.47%	0.4887	2.06%	0.6387
Long portfolio						
Mean return	6.34%	0.1594	6.89%	0.1721	9.27%*	0.0986
Median return	2.54%	0.3028	4.50%	0.3303	1.94%	0.1688

This table reports the 12-month hedge returns for three trading portfolios based on (1) sales growth ($GSL_{i,t}$) predictions, (2) return on equity ($ROE_{i,t}$) predictions, and (3) combined $GSL_{i,t}$ and $ROE_{i,t}$ predictions for firm i in year t. $GSL_{i,t}$ and $ROE_{i,t}$ predictions are based on regression estimates from economywide (EW) and industry-specific (IS) models using 10 years of prior data (years $t-10$ to $t-1$). The return cumulation period begins in the fourth month of fiscal year t and extends into the third month after the end of fiscal year t. The 12-month abnormal returns are calculated as.

$$\prod_{k=1}^{k=12}[1+R_{i,k}]-\prod_{k=1}^{k=12}[1+VWRET_k]$$

where $R_{i,k}$ is the monthly return for firm i in month k and $VWRET_k$ is the value-weighted return for the corresponding month. Returns to the hedge portfolio are the sum of the returns for the long and short portfolios. Returns are computed yearly and the mean/median of the 15 yearly returns is reported in the table. The average number of yearly observations for the *GSL*, *ROE*, and combined portfolios are 2,143, 2,143, and 1,042, respectively.

* indicates significance at the 10% level.

TABLE 8

Improvement in Forecast Accuracy of Industry-Specific vs. Economywide Forecast Models: Different Industry Definitions

	NAICS		Fama–French		Value Line		Two-Digit SIC	
	Mean/Median	*p*-Value	Mean/Median	*p*-Value	Mean/Median	*p*-Value	Mean/Median	*p*-Value
Panel A: Predicted variable: GBV_t								
Mean improvement	−0.00036	0.1286	−0.00018	0.4995	−0.00046	0.3462	−0.00052**	0.0326
Median improvement	−0.00065***	0.0026	−0.00014	0.5245	−0.00027	0.9780	−0.00066***	0.0026
Panel B: Predicted variable: $GNOA_t$								
Mean improvement	−0.00033*	0.0779	−0.00018	0.1717	−0.00044	0.1618	−0.00036**	0.0220
Median improvement	−0.00031**	0.0302	−0.00013	0.7197	−0.00039	0.2769	0.00006	0.8040
Panel C: Predicted variable: GSL_t								
Mean improvement	0.00050	0.2567	0.00091***	0.0049	0.00159**	0.0492	0.00072**	0.0302
Median improvement	0.00085	0.2769	0.00093**	0.0151	0.00148**	0.0302	0.00079*	0.0946
Panel D: Predicted variable: ROE_t								
Mean improvement	−0.00089***	0.0079	−0.00082***	0.0035	−0.00069**	0.0325	−0.00077**	0.0101
Median improvement	−0.00078**	0.0302	−0.00051**	0.0256	−0.00053**	0.0187	−0.00083**	0.0222
Panel E: Predicted variable: $RNOA_t$								
Mean improvement	−0.00043**	0.0408	−0.00010	0.5329	−0.00073***	0.0063	−0.00015	0.4292
Median improvement	−0.00041	0.1354	−0.00001	0.5614	−0.00055**	0.0151	−0.00004	0.2676

See table 1 for variable definitions. This table reports the mean and median improvement in predictive accuracy using an industry-specific (IS) forecast model versus an economywide (EW) forecast model for different industry definitions. Improvement in accuracy is measured through a matched-pair comparison of the absolute forecast errors from the IS versus EW model. The mean improvement in accuracy is computed yearly and the reported mean (median) improvement is the mean (median) of the 15 yearly mean improvements. NAICS industries are grouped on the first three digits of the North American Industry Classification System; Fama-French industry groups follow the classification scheme detailed in Fama and French [1997]; Value Line industries are formed using the first three digits of the industry codes assigned by The Value Line Investment Survey; and two-digit SIC (Compustat) codes are used to form two-digit SIC industries. The minimum (maximum) numbers of industries in a year are 55 (67) for NAICS, 39 (44) for Fama–French, 42 (54) for Value Line, and 47 (55) using the two-digit SIC codes. Tests of means are based on a *t*-test; tests of medians are based on a Wilcoxon signed rank test.

***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

groupings based on common risk characteristics. We omit four of the original Fama–French industries because firms in these industries are primarily drawn from SIC codes 6000–6999, representing financial firms. We then report results using the Value Line classification. Three-digit Value Line industry codes are available for roughly half the firm-year observations in our sample. Finally, we report forecast improvements from an industry-level analysis using two-digit SIC codes to define industries. The results are generally robust across the different industry classification schemes. Consistent with our primary results, we find that the IS models generally improve forecasts of sales growth one year ahead, but do not improve predictions of the other performance metrics.[27]

7.2 ROBUSTNESS TESTS

Prior research raises the possibility that significant economic differences exist between firms within industries and that even within an industry certain firms may be more alike than others (Caves and Porter [1977], Porter [1979]). Common effects may be more evident in these subgroups than in the industry as a whole. To investigate the robustness of our results to this issue, we group firms within industries based on various firm-level characteristics and repeat our tests for these subgroups. First, based on research showing that firm profitability varies by firm size (Gale [1972]), we divide firms in an industry into large (above median) and small (below median) groups based on sales levels. Second, we explore the possibility that firms may create niches or "subindustries" by electing to operate as low-margin, high-volume producers or high-margin, low-volume producers within an industry. We form two subsets from each industry in each year: (1) firms with asset turnover ratios (ATOs) higher than the industry median ATO combined with profit margins (PMs) lower than the industry median PM and (2) firms with ATOs lower than the industry median ATO combined with PMs higher than the industry median PM. [28] None of these additional tests change the overall conclusion of the paper (these results are available from the authors).

7.3 PREDICTION IMPROVEMENT AND INDUSTRY CHARACTERISTICS

Although, on average, the IS models improve predictive accuracy for sales growth but not for profitability, IS model profitability predictions are more accurate than EW profitability predictions in a few industries. In unreported

[27] The relative improvement of IS sales growth models for the NAICS grouping is positive but not significant at conventional levels. The Office of Management and Budget [1997, p.3] claims that the NAICS is unique in that "Economic units that have similar *production* processes are classified in the same industry." This focus on production processes rather than product markets may contribute to the poor performance of the NAICS IS models in predicting sales growth.

[28] Firms with ATO and PM values that are both above or both below the industry median are excluded from the analysis.

tests we examine whether the accuracy of out-of-sample predictions from IS models of ROE and sales growth are associated with industry characteristics. We find that the industry-specific ROE model, although no better than the EW model overall, does perform better in regulated industries, industries with high barriers to entry and industries with larger firms. In contrast, the relative performance of the IS sales growth model is unrelated to these industry characteristics, confirming the pervasive usefulness of the IS model for predicting sales growth. These results reinforce our conclusion that industry-specific analyses are generally useful for predicting sales growth, while they have limited usefulness for predicting profitability.

7.4 IMPLICATIONS FOR RESEARCH ON FORECASTING FUTURE PROFITABILITY

The preceding results suggest that industry benchmarks are no more informative about future firm profitability than are economywide benchmarks. Researchers rely on assumptions about the long-run behavior of firm profitability to forecast future firm performance and, in particular, to estimate the implied cost of capital. For example, Gebhardt, Lee, and Swaminathan [2001] (hereafter, GLS) assume that a firm's forecasted ROE in year $t + 3$ (year t is the measurement year) gravitates to the industry benchmark by year $t + 12$. Gode and Mohanram [2003] (hereafter, GM), compare the cost of capital estimates from the GLS model to a second model that also assumes firm profitability regresses to its industry benchmark over time. Both the GLS and GM models define the industry benchmark as the median ROE of all firms in the industry over the prior 10-year period ($t - 9$ to t). However, the GLS model only includes profitable firm-years over the 10-year period in computing the median, whereas the GM model includes all firm-years. In addition, the GM model sets the industry median equal to the risk-free rate when the industry median is less than the risk-free rate and also caps the industry median at 20%.

In table 9 we evaluate the appropriateness of these assumptions by comparing realized future ROE to current industry and economywide benchmarks at varying time intervals. Given the differences in the industry benchmarks between GM and GLS, we present two sets of comparisons—the percentage of firms whose future ROE is closer to the GLS industry median ROE (*INDGLS*) than to the economywide median ROE (*ECONOMY*) and the percentage of firms whose future ROE is closer to the GM industry median ROE (*INDGM*) than to the economywide median ROE. Specifically, for every year t from 1980 to 1992, we compute the two industry benchmarks discussed above and the median economywide ROE.[29] We then observe the divergence between firms' ROEs and these benchmarks 3, 6, 9, and 12 years ahead.

[29] We compute *INDGM* and *INDGLS* as described in the previous paragraph. *ECONOMY* is the median ROE of all firm-year observations available on Compustat over the prior 10-year period. To maintain consistency with the results reported in GLS and GM, these tests use the Fama–French definition of industry rather than the GICS classification as in previous tables.

TABLE 9

Movement of Firm's ROE Towards Industry/Economy Benchmarks

Panel A: Percentage of firms closer to industry (GLS) and economy benchmarks in year $t+k$

Year	$ECONOMY_t$	$INDGLS_{j,t}$
t	47.28%	52.72%*
$t+3$	52.93%*	47.07%
$t+6$	54.15%*	45.85%
$t+9$	53.04%*	46.96%
$t+12$	53.84%*	46.16%

Panel B: Percentage of firms closer to industry (GM) and economy benchmarks in year $t+k$

Year	$ECONOMY_t$	$INDGM_{j,t}$
t	44.52%	55.48%*
$t+3$	50.03%	49.97%
$t+6$	52.24%*	47.76%
$t+9$	50.53%	49.47%
$t+12$	51.90%*	48.10%

Observations are 11,758 firm-years from 1980 to 1992 with at least 12 years of subsequent financial data on Compustat. Year t is the year in which the economy and industry benchmarks are determined. $ECONOMY_t$ is the median ROE of all firm-year observations available on Compustat over the 10-year period from $t-9$ to t. $INDGLS_{j,t}$ is the median ROE using all *profitable* firm-year observations over $t-9$ to t for firms in the same Fama–French (Fama and French [1997]) industry j as the subject firm (see Gebhardt, Lee, and Swaminathan [2001]). $INDGM_{j,t}$ is the median ROE using *all* firm-year observations over $t-9$ to t for firms in the same Fama–French industry j as the subject firm. For $INDGM_{j,t}$, industries with ROE lower than the risk-free rate (10-year Treasury bond yield for that year) are set equal to the risk-free rate; industries with ROE greater than 20% are set equal to 20% (see Gode and Mohanram [2003]).

In year $t+k$ firm i's ROE is determined to be closer to benchmark X than benchmark Y, if $|ROE_{i,t+k} - X_t| < |ROE_{i,t+k} - Y_t|$. * indicates that the frequency of observations is greater than by chance ($p = 0.5$) at less than the 1% significance level.

In total, 11,758 firm-years from 1980 to 1992 have sufficient data over the subsequent 12 years for the tests. Panel A of table 9 reports the comparison between *INDGLS* and *ECONOMY*. At time *t,* the year in which we determine the benchmarks, firms are closer to the GLS industry benchmark than to the economywide benchmark. This is anticipated—there is a contemporaneous association between industry median ROE and the individual member firms' ROE. However, in all subsequent comparisons, from year $t+3$ to $t+12$, significantly more firms have realized ROEs that are closer to *ECONOMY* than to *INDGLS*. The assumption of firm ROE gravitating to industry benchmarks does not hold, on average, when we use the GLS industry definition.

Panel B reports the same comparisons using the GM definition of industry. Again, in year *t*, significantly more firms have ROEs that are closer to the industry benchmark than to the economywide benchmark. By year $t+3$, however, there is no significant difference between the percentage of firms whose ROEs are closer to *INDGM* versus *ECONOMY*. In subsequent years, more firms are closer to the economywide benchmark than to *INDGM*, although the difference is not significant in year $t+9$ at conventional significance levels.

The results in table 9 are consistent with the previous results reported in the paper, and suggest that industry-specific reversion in profitability such as that assumed in GLS and GM does not, on average, accurately describe the evolution of firm profitability over time. Consequently, forecast models assuming industry-specific mean reversion induce a systematic bias in terminal value estimates, resulting in biased cost of capital estimates. To illustrate, if we use the General Motors example from appendix A (p. 173) of the GLS paper, but assume that over the subsequent 12 years General Motors' ROE fades to the 1995 economywide median of 10.82%, rather than to the industry-specific target of 16% assumed by GLS, the implied cost of capital for General Motors changes to 11.31%. This is substantially lower than their 13.94% implied cost of capital in GLS. In general, assuming that firm profitability reverts to industry-specific benchmarks in the long run leads to systematically higher (lower) cost of capital estimates for firms in more (less) profitable industries.

8. *Summary and Conclusions*

In this paper we provide evidence on the relative performance of mean reverting models at the industry and economywide levels. We find that industry-level analyses are incrementally informative in forecasting growth metrics, but they do not improve forecasts of profitability metrics.

Our results contribute to the literature on the influence of industry membership on firm performance. Prior research suggests that industry membership is an important factor in explaining cross-sectional differences in firm performance. However, our results cast doubt on the usefulness of industry analyses in a generalized forecasting context for predicting firm profitability. Our results also raise questions about the common research practice of using industry benchmarks as targets to which firm profitability converges. The evidence also suggests that commonly used industry controls may be more appropriate for growth metrics than for profitability metrics. We also contribute to the literature on analyst forecasts by demonstrating an association between industry membership and analysts' sales forecasts, but not profitability forecasts. Finally, our findings provide guidance to researchers and analysts on using industry level models to improve forecasts of firm performance.

Because the objective of this paper is to investigate whether IS mean reversion models improve predictions of firm performance over EW models, we cannot rule out other possible contributions of industry membership to predictions of firm performance. It is possible that forecast errors can be reduced by fitting unique prediction models to each industry or by adding other information in the prediction model. We also note that different components of income, for example, gross margins or selling, general, and administrative (SG&A) expenses, may reveal significant industry effects, even when overall profitability does not. In addition, industry membership might play an important role in explaining segment performance rather than firm performance.[30] We leave these questions to future research.

REFERENCES

ABARBANELL, J., AND V. L. BERNARD. "Tests of Analysts' Overreaction/Underreaction to Earnings Information as an Explanation for Anomalous Stock Price Behavior." *Journal of Finance* 47 (1992): 1181–207.

BAIN, J. S. "Relation of Profit Rate to Industry Concentration: American Manufacturing 1936–1940." *The Quarterly Journal of Economics* 65 (1951): 293–324.

BANKER, R. D., AND L. CHEN. "Predicting Earnings Using a Model Based on Cost Variability and Cost Stickiness." *The Accounting Review* 81 (2006): 285–307.

BARBER, B., AND J. LYON. "Detecting Abnormal Operating Performance: The Empirical Power and Specification of Test Statistics." *Journal of Financial Economics* 41 (1996): 359–99.

BERGER, P. G., AND R. HANN. "The Impact of SFAS No. 131 on Information and Monitoring." *Journal of Accounting Research* 41 (2003): 163–223.

BERNARD, V. L. "The Feltham-Ohlson Framework: Implications for Empiricists." *Contemporary Accounting Research* 11 (1995): 733–47.

BHOJRAJ, S.; C. LEE; AND D. OLER. "What's My Line? A Comparison of Industry Classification Schemes for Capital Markets Research." *Journal of Accounting Research* 41 (2003): 745–74.

BOTOSAN, C., AND M. PLUMLEE. "Assessing Alternative Proxies for the Expected Risk Premium." *The Accounting Review* 80 (2005): 21–53.

BROWN, L. D. "Earnings Forecasting Research: Its Implications for Capital Markets Research." *International Journal of Forecasting* 9 (1993): 295–320.

BROWN, P., AND R. BALL. "Some Preliminary Findings on the Association Between the Earnings of a Firm, Its Industry, and the Economy." *Journal of Accounting Research* 5 (1967): 55–77.

CAVES, R. E., AND M. E. PORTER. "From Barriers to Entry to Mobility Barriers: Conjectural Decisions and Contrived Deterrence to New Competition." *The Quarterly Journal of Economics* 91 (1977): 241–62.

CHENG, Q. "What Determines Residual Income?" *The Accounting Review* 80 (2005): 85–112.

CLARKE, R. N. "SICs as Delineators of Economic Markets." *Journal of Business* 62 (1989): 17–31.

COLLINS, D. W. "Predicting Earnings with Sub-Entity Data: Some Further Evidence." *Journal of Accounting Research* 14 (1976): 163–77.

CUBBIN, J., AND P. GEROSKI. "The Convergence of Profits in the Long Run: Inter-Firm and Inter-Industry Comparisons." *The Journal of Industrial Economics* 35 (1987): 427–42.

DEMSETZ, H. "Industry Structure, Market Rivalry and Public Policy." *Journal of Law and Economics* 16 (1973): 1–10.

ERTIMUR, Y.; J. LIVNAT; AND M. MARTIKAINEN. "Differential Market Reactions to Revenue and Expense Surprises." *Review of Accounting Studies* 8 (2003): 185–211,

FAIRFIELD, P.; R. SWEENEY; AND T. YOHN. "Accounting Classification and the Predictive Content of Earnings." *The Accounting Review* (1996): 337–56.

FAIRFIELD, P., AND T. YOHN. "Using Asset Turnover and Profit Margin to Forecast Changes in Profitability." *Review of Accounting Studies* 6 (2001): 371–86.

FAMA, E. F., AND K. FRENCH. "Industry Costs of Equity." *Journal of Financial Economics* 43 (1997): 153–93.

FAMA, E. F., AND K. FRENCH. "Forecasting Profitability and Earnings." *The Journal of Business* 73 (2000): 161–75.

FAMA, E. F., AND J. D. MACBETH. "Risk, Return and Equilibrium: Empirical Tests." *Journal of Political Economy* 81 (1973): 607–36.

[30] However, prior research examining segment revenue and profit disclosures finds that the use of segment revenue data improves revenue forecast accuracy, but does not find improvements in earnings forecast accuracy using segment-level earnings data (Kinney [1971], Collins [1976]).

FELTHAM, G., AND J. OHLSON. "Valuation and Clean Surplus Accounting for Operating and Financial Activities." *Contemporary Accounting Research* 11 (1995): 689–731.

FREEMAN, R.; J. OHLSON; AND S. PENMAN. "Book Rate of Return and the Prediction of Earnings Changes." *Journal of Accounting Research* 20 (1982): 639–53.

GALE, B. "Market Share and Rate of Return." *The Review of Economics and Statistics* 54 (1972): 412–23.

GEBHARDT, W.; C. LEE; AND B. SWAMINATHAN. "Toward an Implied Cost of Capital." *Journal of Accounting Research* 39 (2001): 135–76.

GIVOLY, D.; C. HAYN; AND J. D'SOUZA. "Measurement Errors and the Information Content of Segment Reporting." *Review of Accounting Studies* 4 (1999): 15–43.

GODE, D., AND P. MOHANRAM. "Inferring the Cost of Capital Using the Ohlson-Juettner Model." *Review of Accounting Studies* 8 (2003): 399–431.

KING, B. F. "Market and Industry Factors in Stock Price Behavior." *The Journal of Business* 39 (1966): 139–90.

KINNEY, W. R., JR. "Predicting Earnings: Entity Versus Subentity Data." *Journal of Accounting Research* 9 (1971): 127–36.

KOTHARI, S. P. "Capital Markets Research in Accounting." *Journal of Accounting & Economics* 31 (2001): 105–231.

KOTHARI, S. P.; A. J. LEONE; AND C. E. WASLEY. "Performance Matched Discretionary Accruals." *Journal of Accounting & Economics* 39 (2005): 163–97.

KRISHNAN, J., AND E. PRESS. "The North American Industry Classification System and Its Implications for Accounting Research." *Contemporary Accounting Research* 20 (2003): 685–717.

LIPPMAN, S. A.; K. F. MCCARDLE; AND R. P. RUMELT. "Heterogeneity Under Competition." *Economic Inquiry* 29 (1991): 774–82.

LUNDHOLM, R., AND R. SLOAN, *Equity Valuation and Analysis*, Second edition. New York: McGraw-Hill Irwin, 2007.

MACKAY, P., AND G. M. PHILLIPS. "How Does Industry Affect Firm Financial Structure?" *Review of Financial Studies* 18 (2005): 1433–66.

MANN, H. M. "Seller Concentration, Barriers to Entry, and Rates of Return in Thirty Industries, 1950–1960." *The Review of Economics and Statistics* 48 (1966): 296–307.

MAURI, A. J., AND M. P. MICHAELS. "Firm and Industry Effects Within Strategic Management: An Empirical Examination." *Strategic Management Journal* 19 (1998): 211–9.

MEYERS, S. L. "A Re-examination of Market and Industry Factors in Stock Price Behavior." *The Journal of Finance* 28 (1973): 695–705.

MILLS, D. E., AND L. SCHUMANN. "Industry Structure with Fluctuating Demand." *The American Economic Review* 75 (1985): 758–67.

MUELLER, D. C., AND B. RAUNIG. "Heterogeneities Within Industries and Structure-Performance Models." *Review of Industrial Organization* 15 (1999): 303–20.

NISSIM, D., AND S. PENMAN. "Ratio Analysis and Equity Valuation: From Research to Practice." *Review of Accounting Studies* 6 (2001): 109–54.

OFFICE OF MANAGEMENT AND BUDGET. *North American Industry Classification System: United States*. Lanham, MD: Bernan Press, 1997.

OHLSON, J. "Earnings, Book Values, and Dividends in Security Valuation." *Contemporary Accounting Research* 11 (1995): 661–87.

OHLSON, J., AND B. JUETTNER-NAUROTH. "Expected EPS and EPS Growth as Determinants of Value." *Review of Accounting Studies* 10 (2005): 349–65.

PENMAN, S. *Financial Statement Analysis and Security Valuation*, Third edition. New York: McGraw-Hill Irwin, 2007.

PORTER, M. E. "The Structure Within Industries and Companies' Performance." *The Review of Economics and Statistics* 61 (1979): 214–27.

RUMELT, R. P. "How Much Does Industry Matter?" *Strategic Management Journal* 12 (1991): 167–85.

SCHMALENSEE, R. "Do Markets Differ Much?" *The American Economic Review* 75 (1985): 341–51.

SOLIMAN, M. "Using Industry-Adjusted DuPont Analysis to Predict Future Profitability and Returns." Working paper, University of Michigan, 2005.

SPANOS, Y. E.; G. ZARALIS; AND S. LIOUKAS. "Strategy and Industry Effects on Profitability: Evidence from Greece." *Strategic Management Journal* 25 (2004): 139–65.
STIGLER, G. J. *Capital and Rates of Return in Manufacturing Industries*. Princeton, NJ: Princeton University Press, 1963.
VUONG, Q. H. "Likelihood Ratio Tests for Model Selection and Non-nested Hypotheses." *Econometrica* 57 (1989): 307–33.
WARING, G. "Industry Differences in the Persistence of Firm-Specific Returns." *The American Economic Review* 85 (1996): 1253–65.
WILLIAMS, J. T. "Financial and Industrial Structure with Agency." *Review of Financial Studies* 8 (1995): 431–74.