Industry Information and Forecasts of Long-Term Earnings Growth

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Abstract

Forecasts of long-term earnings growth (LTG) are important for valuation. Prior research has employed firm-level models to forecast LTG. However, research in economics, management, and accounting is unclear as to whether industry-level models would be more useful. Therefore, I study the relative accuracy of LTG forecasts derived from firm- and industry-level financial statement information and whether the information contained in these forecasts is incorporated into analyst forecasts and market prices. I find that industry-based forecasts of LTG are more accurate than firm-based forecasts. The industry-level financial statement based LTG forecast is more accurate than the median I/B/E/S consensus analyst long-term growth forecast, a zero growth forecast, a forecast combining industry and firm information and forecasts from the Hou et al. (2011) model. I document evidence consistent with analysts not fully incorporating industry-level financial statement information in their LTG forecasts. Finally, I find that abnormal returns are earned by trading on the industry-based forecast, suggesting that market prices do not fully incorporate the implications of industry-level financial statement information for long-term earnings growth.

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1. *Introduction*

Forecasts of accounting profitability are key inputs to equity valuation models (Ohlson 1995; Feltham and Ohlson 1995). Long-term profitability forecasts are especially important because of their influence on valuation-related estimates (Bradshaw et al. 2011)[1]. Prior research generally relies on analysts' forecasts of long-term earnings growth because analysts enjoy an information and timing advantage over model-based forecasts (Bradshaw et al. 2011; Brown et al. 1987; Kothari 2001, p145).[2] The literature on analysts' long-term earnings growth (LTG) forecasts, however, finds they are on average inaccurate, optimistically biased, of limited usefulness for valuation and subject to various incentives (La Porta 1996; Chan et al. 2003; Harris 1999; Szakmary et al. 2008; Dechow et al. 2000).[3]

Recent studies re-examine the accuracy of model-based forecasts relative to analysts' forecasts. Bradshaw et al. (2011) find that a naïve random walk time-series earnings per share (EPS) forecast is more accurate than analysts' annual EPS forecasts over a three-year horizon. Similarly, cross-sectional earnings forecasting models developed by Hou et al. (2011) and Evans et al. (2010) generate earnings forecasts that are more accurate and/or less biased than analysts' forecasts.[4]

While economy, industry and firm-level factors all impact future earnings, existing forecast models (i.e. Fama and French 2000, Hou et al. 2011, Evans et al. 2010) project future earnings (or profitability) solely as a function of firm-level characteristics. The use of firm-level models is

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[1] Accuracy of earnings forecasts is important because more accurate forecasts lead to better investment decisions. Loh and Mian (2006) and Ertimur et al. (2007) find that trading strategies based on recommendations from more accurate equity analysts earn abnormal returns. Abarbanell and Bushee (1998) find that the abnormal returns to their fundamental analysis trading strategy are driven by earnings forecasts that are more accurate than the earnings expectations embedded in market prices.

[2] Analysts typically make point estimates of earnings for only one- and two- years ahead, and then provide a growth rate for the following three to five years. Although these growth rates are referred to as "long-run" rates they apply to only five years at most. Long-term growth rates beyond five years are rarely made (Penman 2004, p 498). Analysts and investors typically assume that earnings grow at a constant rate (i.e. 3 percent) beyond five years into perpetuity.

[3] While LTG forecasts are highly influential on valuation estimates, LTG forecasts produced by analysts do not lead to profitable investment strategies (Szakmary et al. 2008).

[4] Hou et al. (2011) and Evans et al. (2010) study forecasts of earnings up to 5 years in the future.

consistent with prior research which argues that firm-level characteristics are the most useful for forecasting future changes in earnings and profitability. For example, Fama and French (2000) assert that their cross-sectional model based on firm-level characteristics captures "… differences in expected profitability across industries as well as across firms." At the same time, Fama and French (2000, p165) acknowledge potential benefits from exploring the impact of industry effects on their forecasting model, although they leave this to future research. Consistent with the use of an industry-level model, research in economics suggests that the importance of firm characteristics fades over time and that industry characteristics determine future changes in earnings or profitability (Schmalensee 1985). While the issue of the relative usefulness of a firm- or industry-level model has been raised in prior research (Fama and French 2000), the question has not been addressed empirically. In this study, I examine the relative accuracy of firm- versus industry-level financial statement based forecasts of long-term earnings growth.

I develop a LTG forecasting model based on firm-level financial statement information and a model based on industry-level financial statement information. I benchmark the accuracy of the firm- and industry-level forecasts to the median I/B/E/S consensus analyst LTG forecast, a zero growth forecast, and forecasts from the Hou et al. (2011) model. I also examine the accuracy of a model that combines both industry- and firm-level information. Out-of-sample tests reveal that the industry-level forecast is more accurate than the firm-level forecast as well as the benchmark forecasts. Accuracy improvements from the industry-level forecast are positively associated with the absolute difference in the firm- and industry-level forecasts, the firm's market share, the magnitude of industry-level barriers to entry, industry concentration, and industry profitability. The finding that an industry-level model produces more accurate LTG forecasts than a firm-level model contradicts basic assumptions underlying forecasting models used in the extant literature (e.g. Fama and French 2000; Hou et al. 2011) and suggests that an industry-level model should be used to forecast future long-term firm performance.

I also examine whether analysts' LTG forecasts fully incorporate firm- and industry-level financial statement information about long-term earnings growth. Specifically, I examine whether analysts weight the information contained in the firm- and industry-level LTG forecasts in a manner consistent with its actual forecasting ability. I examine the association between the median I/B/E/S forecast of LTG and the industry- and firm-level forecasts. I also examine the association between the analyst forecast errors and the industry- and firm-level forecasts. I document evidence consistent with analysts underweighting the industry and firm forecasts relative to their actual predictive ability.

Finally, I examine whether market prices fully incorporate the information in the firm- and industry-level forecasts of long-term earnings growth. I implement a zero-investment hedge portfolio for the industry, firm and benchmark forecasts by purchasing (selling short) stocks for firm-year observations with high (low) forecasted earnings growth. I find that a trading strategy based on industry-level forecasts earns abnormal returns over holding periods between 24 and 60 months suggesting that market prices do not fully incorporate information contained in the industry-level LTG forecast.

My paper contributes to the extant literature on several dimensions. First, I provide evidence that industry-level, rather than firm-level, financial statement information best predicts future long-term earnings growth. This finding informs both researchers and investors by demonstrating that industry characteristics are the most important determinants of future firm-level, long-term performance. This finding is of interest to researchers relying on forecasts from firm-level models (i.e. Hou et al. 2011; Fama and French 2000).

Second, my paper contributes to the analyst forecasting literature (Frankel and Lee 1998; Dechow et al. 2000) by demonstrating that, on average, analysts' LTG forecasts underweight the information contained in the industry and firm-level forecasts relative to its actual predictive ability.

Third, my paper contributes to the literature on the incorporation of financial statement information into price (Ou and Penman 1989; Abarbanell and Bushee 1998; Piotroski 2000) by providing evidence that market prices do not fully incorporate the implications of industry-level financial statement information. I demonstrate that a trading strategy based on the industry forecast earns abnormal returns.

Finally, I contribute to the earnings forecasting literature by documenting that the industry-level LTG forecast is more accurate than the median I/B/E/S LTG forecast, a zero growth forecast, a forecast combining industry and firm information, and forecasts from the Hou et al. (2011) model. Identification of improved LTG forecasts may improve valuation estimates and increase market efficiency.

The remainder of the paper is organized as follows. Section 2 reviews prior literature and develops the research questions. Section 3 defines LTG and introduces the forecasting models. Section 4 describes the results and Section 5 concludes.

2. Prior Literature and Research Questions

2.1 The relative accuracy of firm- and industry-level information in forecasting LTG

The relative importance of firm and industry effects in explaining profitability has been studied extensively by researchers in the fields of economics and management. On the one hand, a stream of literature suggests that firm effects are more important for explaining a firm's profitability than industry effects. Cubbin and Geroski (1987) find that nearly half the firms in their study show no common, industry-wide response to industry-level profitability shocks. They conclude that the systematic persistence of profitability is a result of firm-specific rather than industry-specific factors. McGahan and Porter (2002) estimate the variance in business-unit profitability attributable to industry effects to be between 8.3 and 19.6 percent, while the variance in business-unit profitability attributable to firm-level effects is between 36.0 and 55.0 percent. These studies conclude that firm effects rather than industry effects best explain the variance in business-unit profitability.

On the other hand, industrial economics research posits that differences in firms are transitory. The research suggests that differences in long-term profitability between firms are the result of industry characteristics and are determined by the ability of established firms to restrict rivalry and establish barriers to new entry (Schmalensee 1985). Therefore, industry characteristics such as the level of competition, barriers to entry and product demand are expected to determine the performance of firms in the industry. The classical tradition suggests that industry characteristics will be most useful in explaining profitability over long time horizons (Mueller and Raunig 1999). Economic theory, therefore, indicates that industry characteristics should be the primary determinant of long-term profitability.

Consistent with this, both prior empirical research and common practices of the investment industry suggest that industry characteristics are useful in predicting future earnings growth. Dechow et al. (1999) find that the persistence of firm-level abnormal earnings is increasing in the historical persistence of abnormal industry earnings.[5] Similarly, Cheng (2005a) documents the usefulness of predicted year-ahead industry abnormal return on equity (ROE) in explaining year-ahead abnormal firm ROE. In practice, financial organizations typically organize research

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[5] In a residual income model, abnormal or residual earnings are defined as earnings in excess of required earnings (book value × cost of equity capital).

personnel by industry and analysts routinely benchmark a firm's performance to its industry, suggesting that industry-level information is useful (Fairfield et al. 2009).

Fairfield et al. (2009) examine the usefulness of industry-level analysis in forecasting long-term, firm-level growth and profitability. Because growth in earnings and profitability is mean reverting (Freeman et al. 1982; Fama and French 2000; Nissim and Penman 2001), prior research generally assumes that firm-level profitability will converge to an industry or economy-wide average over time. Fairfield et al. (2009) evaluate the accuracy of estimating autoregressive forecasting models by industry relative to estimating the same models economy-wide. They find that for forecasts of long-term growth in book value, net operating assets, and sales, a model estimating the mean reversion parameter by industry produces more accurate forecasts than a model estimated economy-wide. However, when forecasting future profitability (i.e. return on equity or return on net operating assets), estimating the mean reversion parameter by industry does not produce more accurate forecasts than an economy-wide model for year-ahead or five-year-ahead forecasts. While the findings of Fairfield et al. (2009) are useful for identifying which financial statement variables regress to an economy versus industry average, the study does not consider measures commonly included in valuation models (i.e. LTG) and does not address the question of whether to use firm- or industry-level variables in a forecasting model.

It is not clear from the prior research whether firm-level or industry-level information produces more accurate forecasts of LTG. Despite this, existing earnings forecasting models rely exclusively on firm-level information. To provide insight into this issue, I investigate the relative accuracy of firm- and industry-level financial statement based forecasts of long-term earnings growth. Stated formally, my first research question is:

RQ1: **What is the relative accuracy of firm- versus industry-level financial statement based forecasts of long-term earnings growth?**

2.2 Analyst forecasts and firm- and industry-level financial statement information about LTG

Analysts' earnings forecasts are commonly used in empirical studies involving accounting-based valuation models. Their forecasts are popular because they capture forward-looking information in a form that can easily be incorporated into a valuation model (Cheng 2005b). However, the prior literature documents inefficiencies in analysts' earnings forecasts related to information contained in financial statements and market prices. Frankel and Lee (1998) document ex-post optimism (pessimism) in LTG forecasts related to high past sales growth (high book-to-price ratios). Analysts' short-horizon forecasts have also been shown to be inefficient with respect to prior earnings information (Abarbanell and Bernard 1992), past price changes (Abarbanell 1991), the persistence of prior earnings forecast errors (Mendenhall 1991), and the effects of conservative accounting and transitory earnings (Cheng 2005b). While prior research suggests that analysts' forecasts do not fully incorporate certain types of public information, there is no evidence on how analysts incorporate the information contained in the industry- and firm-level LTG forecasts.

Although analysts are typically organized by industry and have access to large amounts of information on the firms they cover, it is not clear ex ante whether analysts will accurately incorporate the information contained in the firm and industry LTG forecasts. Fairfield et al. (2009) examine analysts' one-year-ahead sales growth and return on equity forecasts from the Value Line Investment survey and document evidence consistent with analysts using industry (firm) information to forecast firm-level sales growth (profitability). I investigate whether analysts' LTG forecasts weight firm- and industry-level financial statement information in a manner consistent with its predictive ability for future earnings growth. Stated formally, my second research question is:

***RQ2:* Do analysts' LTG forecasts fully incorporate firm- and industry-level financial statement information about long-term earnings growth?**

2.3 Market prices and firm- and industry-level financial statement information

To understand how the market forms expectations of long-term earnings growth, I investigate which forecast of LTG best explains contemporaneous price. The identification of an empirical surrogate for earnings expectations is important for understanding how earnings expectations are formed as well as examining the rationality of the earnings expectations, their use of accounting information, and their consistency with the observed behavior of earnings (Fried and Givoly 1982). Prior research identifies analyst forecasts as the best empirical proxy of the market expectation of near-term earnings (Fried and Givoly 1982). However, prior research has not identified the best proxy for the market expectation of LTG. I investigate which of the LTG forecasts in my study best proxies for the market expectation of LTG and test the ability of each LTG forecast to explain contemporaneous price. Thus, my third research question is:

***RQ3*: Which forecast of LTG best explains contemporaneous price?**

Prior research suggests that equity prices do not fully incorporate firm-level financial statement information (Ou and Penman 1989; Abarbanell and Bushee 1998; Piotroski 2000) and that common industry information is diffused sluggishly into price (Hou 2007). If prices do not fully incorporate information contained in the industry- and firm-based LTG forecasts, then a trading strategy can be designed to exploit this information. I test whether a hedge strategy purchasing (selling short) stocks of firms with high (low) forecasted LTG earns abnormal returns. The realization of abnormal returns would suggest that market prices systematically fail to incorporate information in the LTG forecast. Thus, my fourth research question is:

***RQ4*: Do market prices fully incorporate the information in the firm- and industry-level forecasts of long-term earnings growth?**

3. Variable Definitions and Forecast Models

3.1 Definition of LTG

I define LTG as annual growth in earnings per share over a five-year period ($GEPS_{t+5}$), consistent with the I/B/E/S definition of LTG.[6] Because analysts forecast earnings purged of transitory or special items, I use I/B/E/S actual earnings per share to calculate $GEPS_{t+5}$. $GEPS_{t+5}$ is computed following Dechow and Sloan (1997) by fitting a least squares growth line through the logarithm of the six annual earnings observations from year t through year $t + 5$. If I/B/E/S actual earnings per share are missing or negative for year t or year $t + 5$, then a growth rate is not calculated for that observation. I use continuous compounding rather than discrete compounding to avoid extreme outliers when the base year is close to zero. Fitting a least squares regression line avoids placing excessive weight on the first and last observations in the growth period.[7]

3.2 Firm-level model

Existing cross-sectional, firm-level earnings forecasting models (i.e. Hou et al. 2011; Evans et al. 2010) forecast the *level* of earnings and rely on market prices in creating the forecast. While these studies choose to forecast the level of earnings, the construct of interest is earnings growth. Therefore, I choose to forecast earnings growth directly. The firm-level model incorporates the primary drivers of LTG identified in Li (2003). The firm-level model relies entirely on historical financial statement information (market prices are not used in generating the forecasts) and is grounded in the extant financial statement analysis literature:

$$GEPS_{i,t+5} = \alpha_0 + \alpha_{1.}GNOA_{i,t} + \alpha_{2.}GEPS_{i,t} + \alpha_{3.}GSALES_{i,t} + \alpha_{4.}RNOA_{i,t} + \alpha_{5.}CPX_{i,t} + \varepsilon_{i,t+5}. \quad (1)$$

Where, for firm i and fiscal year t the variables are defined as (see Appendix for variable

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[6] The Thomson Reuters (2009) *Methodology for Estimates* manual states "The long term growth rate represents an expected annual increase in operating earnings over the company's next full business cycle. These forecasts refer to a period between three and five years [in length], and are expressed as a percentage." While I believe the use of I/B/E/S actuals better captures the earnings amount that analysts forecast, robustness checks using Compustat earnings per share and operating income growth are discussed in Section 8.2.

[7] In untabulated analyses I find that inferences are unchanged when $GEPS_{t+5}$ is measured as the geometric mean or percentage change in EPS_t from year t to year $t + 5$, using the beginning and ending years only.

definitions):

$GEPS_{i,t+5}$ = Five-year annualized growth in I/B/E/S actual earnings per share calculated from a least squares growth line fitted through the logarithms of the six annual I/B/E/S EPS observations from year t through year $t + 5$.

$GNOA_{i,t}$ = Growth in net operating assets calculated as $NOA_{t} / NOA_{t-1} - 1$.

$GEPS_{i,t}$ = Growth in earnings per share calculated as $(EPSPX_t/AJEX_t) / (EPSPX_{t-1}/AJEX_{t-1}) - 1$. *AJEX* is an adjustment factor to control for stock splits and stock dividends.

$GSALES_{i,t}$ = Growth in sales calculated as $SALE_t / SALE_{t-1} - 1$.

$RNOA_{i,t}$ = Return on net operating assets calculated as $OI_t / ((NOA_t + NOA_{t-1}) / 2)$.

$CPX_{i,t}$ = Scaled capital expenditure calculated as $CAPX_t / PPENT_{t-1}$.

Prior research documents that growth in assets, earnings and sales is mean reverting (Nissim and Penman 2001; Fairfield et al. 2009; Li 2003). Growth in net operating assets (*GNOA*), growth in earnings per share (*GEPS*), and growth in sales (*GSALES*) are included in the model to capture information contained in past growth relevant for predicting future earnings growth. The expected sign on the coefficient estimates of *GNOA*, *GEPS,* and *GSALES* is negative. Prior research demonstrates that because of mean reversion in profitability, current profitability is informative about future earnings (Freeman et al. 1982; Fama and French 2000; Nissim and Penman 2001). Return on net operating assets (*RNOA*) captures current firm profitability and the expected sign on *RNOA* is negative consistent with mean reversion. Finally, *CPX* is included in the model as capital expenditure by the firm reflects physical investment and is indicative of managers' beliefs about investment opportunities. The expected sign on *CPX* is positive because high investment in physical assets in the current period is expected to predict future earnings growth.

3.3 Industry-level model

To capture industry-level financial statement information useful for forecasting future firm-level earnings growth, I estimate a regression similar to equation (1) using industry medians rather than firm-level values as the independent variables.

$$GEPS_{i,t+5} = \alpha_0 + \alpha_1.INDGNOA_{i,t} + \alpha_2.INDGEPS_{i,t} + \alpha_3.INDGSALES_{i,t} + \alpha_4.INDRNOA_{i,t} + \alpha_5.INDCPX_{i,t} + \varepsilon_{i,t+5}. \qquad (2)$$

Where, for firm *i* and fiscal year *t*, the variables are defined as:

$GEPS_{i,t+5}$ =	Five-year annualized growth in I/B/E/S actual earnings per share calculated from a least squares growth line fitted through the logarithms of the six annual I/B/E/S EPS observations from year *t* through year $t + 5$.
$INDGNOA_{i,t}$ =	Median $GNOA_t$ for the 3-digit SIC code.
$INDGEPS_{i,t}$ =	Median $GEPS_t$ for the 3-digit SIC code.
$INDGSALES_{i,t}$ =	Median $GSALES_t$ for the 3-digit SIC code.
$INDRNOA_{i,t}$ =	Median $RNOA_t$ for the 3-digit SIC code.
$INDCPX_{i,t}$ =	Median CPX_t for the 3-digit SIC code.

$GEPS_{t+5}$ is regressed on the industry median values of *GNOA*, *GEPS, GSALES*, *RNOA*, and *CPX* in year *t*. Historical growth, profitability and capital investment of the average firm in the industry is used to forecast future LTG for all firms in the industry. I define industry at the 3-digit Standard Industrial Classification (SIC) code level.[8] I expect negative coefficient estimates for *INDGNOA*, *INDGEPS, INDGSALES* and *INDRNOA* consistent with mean reversion. I expect a positive coefficient estimate for *INDCPX* as higher average industry-level capital investment is expected to predict firm-level earnings growth.

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[8] While the SIC code industry definition may not fully reflect the economic relatedness of firms (i.e. firms may have operations covering multiple industries), prior research using SIC codes documents the usefulness of industry information in explaining short-term profitability (Dechow et al. 1999; Cheng 2005a; McGahan and Porter 2002).

3.4 Combined model

The *COMBINED* model exploits information contained in fundamentals at both the firm and industry levels. This model is included in the study to evaluate the characteristics of forecasts incorporating both industry and firm-level variables.

$$GEPS_{i,t+5} = \alpha_0 + \alpha_{1.}GNOA_{i,t} + \alpha_{2.}GEPS_{i,t} + \alpha_{3.}GSALES_{i,t} + \alpha_{4.}RNOA_{i,t} + \alpha_{5.}CPX_{i,t} + \alpha_{6.}INDGNOA_{i,t} + \alpha_{7.}INDGEPS_{i,t} + \alpha_{8.}INDGSALES_{i,t} + \alpha_{9.}INDRNOA_{i,t} + \alpha_{10.}INDCPX_{i,t} + \varepsilon_{i,t+5}\,. \quad (3)$$

3.5 Benchmark Models

Analyst forecast

Prior research typically uses analysts' LTG forecasts to predict long-term earnings growth. However, the quality of analyst forecasts of LTG is generally poor. Analysts' LTG forecasts are optimistically biased, lacking in accuracy and of limited usefulness for valuation (e.g. La Porta 1996; Harris 1999; Chan et al. 2003; Szakmary et al. 2008). *ANALYST* is defined as the first median consensus forecast of LTG on I/B/E/S available at least three months after the fiscal year-end, allowing information in the financial statements to be incorporated into analysts' forecasts.

Zero growth

Bradshaw et al. (2011) find that the *ZERO GROWTH* forecast of three-year-ahead earnings is significantly more accurate than the analyst consensus forecast.[9] The *ZERO GROWTH* forecast assumes that earnings follow a random walk and that the dollar amount of earnings today is the best predictor of five-year-ahead earnings, thereby implying earnings growth of zero.

$$E[GEPS_{i,t+5}] = 0. \quad (4)$$

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[9] While Bradshaw et al. (2011) use the term random walk forecast in their paper, I refer to this as a *ZERO GROWTH* forecast.

Prior research typically finds that sophisticated time-series models of annual earnings are no more accurate than a simple random walk model (Bradshaw et al. 2011).[10]

4. Empirical Tests

The in-sample estimation includes all nonfinancial firms with sufficient data available on Compustat and I/B/E/S to compute the independent and dependent variables.[11] In-sample data span the fiscal years 1971 to 1999 and are used to forecast $GEPS_{t+5}$ realized in 1976 through 2004. Beginning and ending values of *EPSPX*, *EPS_IBES, NOA* and *SALE* must be greater than zero for the calculation of growth rates. To avoid the effect of small denominators and growth due to acquisitions, I exclude firm-years with $GEPS_t$, $GNOA_t$ and $GSALES_t$ greater than 3 from the in-sample estimation. All dependent and independent variables used in the in-sample estimation are truncated at 1 percent and 99 percent. A sample of 21,151 firm-year observations is used in the in-sample estimation.

For the out-of-sample tests, all non-financial firms with sufficient Compustat and I/B/E/S data are included in the sample. Firm-year observations with *EPSPX*, *EPS_IBES*, *NOA,* and *SALE* in periods t and $t-1$ (and *EPS_IBES* in $t + 5$) less than or equal to zero are excluded from the tests for the calculation of growth rates. A sample of 20,642 firm-year observations is used in the out-of-sample tests of *RQ1* and *RQ2* with $GEPS_{t+5}$ realized over 25 years from 1986 to 2010.[12] Sample selection procedures are detailed in Panels A and B of Table 1.

4.1 In-sample estimation

In Panel A of Table 2, I report in-sample coefficient estimates for the *FIRM*, *INDUSTRY* and *COMBINED* models. For each year *t,* I estimate rolling regression models using data from the

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[10] In untabulated analyses I employ an alternative random walk assumption and use earnings growth in period t as the forecast of $GEPS_{t+5}$. This random walk forecast does not perform as well as the *ZERO GROWTH* forecast.

[11] I exclude financial firms with SIC codes from 6000 to 6999 because separation of their financial and operating activities is artificial.

[12] The out-of-sample tests start in 1986 because analyst forecasts of LTG are not available broadly on I/B/E/S until 1981.

preceding 10 years (minimum of 5 years).[13] I then forecast earnings growth from year t through year $t + 5$ by multiplying the independent variables as of year t with the coefficients from the in-sample regressions using the previous 10 years (minimum of 5 years) of data. For example, to calculate the in-sample coefficients applied to the out-of-sample data for the year 2000, the regression models use ten years of data with $GEPS_{t+5}$ realized from 1990 to 1999. The coefficient from the ten year rolling regressions ending in 1999 is then applied to data from 2000 to produce out-of-sample forecasts of $GEPS_{t+5}$ realized from 2001 to 2005.

I report results for both annual and pooled regressions in Panel A; however, my discussion focuses on the pooled regressions. The signs of the slope coefficient estimates of $GNOA_t$, $GEPS_t$, and $RNOA_t$ in the *COMBINED* and *FIRM* regressions are negative as expected, consistent with mean reversion. While the coefficient estimate for $GSALES_t$ is positive in the *COMBINED* regression, it is not significantly different from zero in the *FIRM* regression. The slope coefficient of CPX_t in the *COMBINED* and *FIRM* regressions is positive consistent with capital investment being positively associated with future earnings growth.

$INDGNOA_t$ and $INDRNOA_t$ in the *INDUSTRY* and *COMBINED* regressions have negative coefficient estimates, which is consistent with mean reversion. The coefficient estimates for $INDGEPS_t$ and $INDGSALES_t$ in the *INDUSTRY* and *COMBINED* regressions are not significantly different from zero. Finally, the coefficient estimate for $INDCPX_t$ is positive in the *INDUSTRY* and *COMBINED* regressions, indicating that industry-level capital investment is positively associated with future firm-level earnings growth. While I do not formally test the explanatory power of the models in-sample, the *COMBINED* model has the highest adjusted R^2,

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[13] I/B/E/S actuals are not available broadly until 1976.

followed by the *FIRM* and *INDUSTRY* models.[14] I report the correlation matrix for the in-sample variables in Panel B of Table 2.[15]

4.2 Descriptive statistics for out-of-sample forecasts

Panel A of Table 3 reports descriptive statistics for the $GEPS_{t+5}$ forecasts and *ACTUAL* (where *ACTUAL* equals realized $GEPS_{t+5}$). The mean (median) *ACTUAL* in the out-of-sample period is 5.0 percent (6.5 percent). The mean (median) *FIRM* forecast is 3.9 percent (5.0 percent), while the mean (median) *INDUSTRY* forecast is 6.8 percent (5.9 percent). The mean (median) benchmark $GEPS_{t+5}$ forecasts vary between 0 (0) for the *ZERO GROWTH* forecast and 13.7 (13.0) percent for the *ANALYST* forecast.

Panel B of Table 3 presents the correlation matrix for the $GEPS_{t+5}$ forecasts and *ACTUAL*. Based on Spearman correlation coefficients, the *ANALYST, COMBINED, FIRM,* and *INDUSTRY* forecasts are significantly positively correlated with *ACTUAL*. The *ANALYST* forecast has the highest correlation with *ACTUAL* (0.15), while the *FIRM* forecast has the lowest correlation with *ACTUAL* (0.04). Based on Pearson correlation coefficients, the *ANALYST* and *INDUSTRY* forecasts are significantly positively correlated with *ACTUAL* (0.08 and 0.03 respectively).

4.3 What is the relative accuracy of firm- versus industry-level financial statement based forecasts of long-term earnings growth (RQ1)?

I compare the out-of-sample accuracy of the $GEPS_{t+5}$ forecasts from the *INDUSTRY* and *FIRM* models to address my first research question. The *ANALYST*, *COMBINED* and *ZERO GROWTH* forecasts are included in the analysis as benchmarks. All models are estimated using the same sample of firms and all formal tests of accuracy are conducted using a holdout sample (i.e. all information required to forecast earnings growth from year *t* through year *t+5* is

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[14] The R^2s for the in-sample regressions appear reasonable when compared to those reported in prior studies. Although smaller than the R^2s reported in Li (2003), my models do not include level variables (only changes) and I employ fewer independent variables.

[15] The in-sample estimation does not appear to be impacted by collinearity in the in-sample variables.

available in year *t*). Differences in accuracy between forecasts are measured through a matched-pair comparison of the absolute value of prediction errors from the two forecasts. I calculate the firm-specific absolute forecast error annually from 1986 to 2010 for each of the models. For example, the *INDUSTRY* absolute forecast error is calculated as:

$$AFE_{INDUSTRY} = |GEPS_{i,t+5} - E_{INDUSTRY}(GEPS_{i,t+5})|. \qquad (5)$$

For each firm-year observation, I calculate paired forecast improvements to compare the accuracy of competing models. For example, to compare the *INDUSTRY* and *FIRM* forecasts I calculate $AFE_{FIRM} - AFE_{INDUSTRY}$. A positive (negative) value indicates that the *INDUSTRY* forecasts is more (less) accurate than the *FIRM* forecast.

Panels A and B of Table 4 present descriptive statistics for the out-of-sample tests of signed forecast error (bias) and absolute forecast error (accuracy). In Panel A, signed forecast error is defined as forecasted $GEPS_{t+5}$ less actual $GEPS_{t+5}$. The mean (median) signed forecast error for the *FIRM* forecast is -0.010 (-0.013) consistent with forecasts from the *FIRM* model being pessimistic on average. The mean (median) signed forecast error for the *INDUSTRY* forecast is 0.018 (0.000) consistent with forecasts from the *INDUSTRY* model being slightly optimistic (unbiased) on average. I assess the economic significance of the bias relative to the average earnings growth realized during the sample period. The mean (median) bias for the *FIRM* forecast of -0.010 (-0.013) represents 20 percent (20 percent) of the sample-wide mean (median) realized earnings growth of 0.050 (0.065). Similarly, the mean (median) bias for the *INDUSTRY* forecast of 0.018 (0.000) represents 36 percent (0 percent) of the mean (median) realized earnings growth. Mean (median) signed forecast error for the benchmark models varies between -0.050 (-0.065) for the *ZERO GROWTH* forecast and 0.088 (0.057) for the *ANALYST* forecast, which is consistent with the *ZERO GROWTH* forecasts being the most pessimistic and the *ANALYST* forecasts being the most optimistic of the forecasts.

In Panel B, absolute forecast error is defined as the absolute value of the difference between forecasted $GEPS_{t+5}$ and actual $GEPS_{t+5}$. All mean and median absolute forecast errors are significantly different from zero at the one percent level. Mean (median) absolute forecast error is 0.143 (0.093) for the *FIRM* forecast and 0.131 (0.090) for the *INDUSTRY* forecast. The mean (median) absolute forecast error for the *FIRM* forecast represents 286 percent (143 percent) of the mean (median) realized earnings growth. The mean (median) absolute forecast error for the *INDUSTRY* forecast represents 262 percent (138 percent) of the mean (median) realized earnings growth. Mean absolute forecast error for the benchmark models falls between 0.138 for the *ZERO GROWTH* forecast (most accurate) and 0.146 for the *COMBINED* forecast (least accurate). Median absolute forecast error for the benchmark models varies between 0.091 for the *ANALYST* forecast (most accurate) and 0.108 for the *ZERO GROWTH* forecast (least accurate).

Formal tests of differences in out-of-sample absolute forecast error are reported in Panel C of Table 4. Mean (median) matched-pair differences in absolute forecast error and associated *p*-values are reported for the 25 year out-of-sample period.[16] The number of years that the yearly mean (median) difference in forecast error is significantly different from zero at the 10 percent significance level is reported. Positive (negative) values indicate that the first model is more (less) accurate than the second model. The results presented in Panel C of Table 4 indicate that the *INDUSTRY* forecast is significantly more accurate than the *FIRM* forecast in terms of mean absolute forecast error, with no difference in median absolute forecast error. The *INDUSTRY* forecast is significantly more (less) accurate in 12 (1) years based on mean absolute forecast

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[16] I use the average absolute value of forecast error to measure ex-post forecast accuracy. According to Kennedy (2008), this measure is appropriate when the cost of forecast errors is proportional to the absolute size of the forecast error. There are many other potential measures of forecast accuracy and the choice of the appropriate measure depends primarily on the specification of the loss function (Kennedy 2008). Use of the average absolute value of forecast error is consistent with the prior literature (Fairfield et al. 2009, Hou et al. 2011, and Evans et al 2010).

error and is significantly more (less) accurate than the *FIRM* forecast in 14 (6) years based on median absolute forecast error.[17] The mean difference in absolute forecast error between the *INDUSTRY* and *FIRM* forecasts represents an accuracy improvement of 22.80 percent relative to the mean realized $GEPS_{t+5}$.

Panel C documents that the *INDUSTRY* forecast is more accurate than the *COMBINED* forecast in terms of both mean and median absolute forecast errors. The *INDUSTRY* forecast is more accurate than the *ANALYST* forecast in terms of mean absolute forecast errors, with no difference in median absolute forecast errors. The *INDUSTRY* forecast is more (less) accurate than the *ANALYST* forecast in terms of median absolute forecast errors in 14 (5) years. The *INDUSTRY* forecast is more accurate than the *ZERO GROWTH* forecast in terms of median absolute forecast error, with no difference in mean absolute forecast errors. The *INDUSTRY* forecast is more (less) accurate than the *ZERO GROWTH* forecast in terms of mean absolute forecast error in 17 (3) years. In sum, the *INDUSTRY* forecast is the most accurate of the $GEPS_{t+5}$ forecasts.

Panel D of Table 4 reports tests of the incremental and relative information content of the *FIRM* and *INDUSTRY* forecasts. Panel D reports results of the following pooled regression with *t*-statistics reported based on robust standard errors clustered by firm and by year (Petersen 2009):

$$ACTUAL_{i,t+5} = \alpha_0 + \alpha_1 . FIRM_{i,t} + \alpha_2 . INDUSTRY_{i,t} + \varepsilon_{i,t+5}. \quad (6)$$

The *INDUSTRY* forecast is significant in explaining *ACTUAL*, while the *FIRM* forecast is not, indicating that the *INDUSTRY* forecast captures unique information about future earnings growth

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[17] While the overall median difference between the *INDUSTRY* and *FIRM* forecasts is not significant, I interpret the annual results as being consistent with the *INDUSTRY* forecast being more accurate than the *FIRM* forecast in terms of median absolute forecast errors.

incremental to the information contained in the *FIRM* forecast. The results of the relative information content tests are consistent with this finding.

Panel E of Table 4 reports accuracy by quintile of forecast difference between the *INDUSTRY* and *FIRM* forecasts. Forecast difference is defined as the absolute value of the difference in the *INDUSTRY* and *FIRM* forecasts. The estimation of the *INDUSTRY* forecast results in the median firm in an industry having the same value for both the *INDUSTRY* and *FIRM* forecasts. Therefore, I examine the relative accuracy of the two forecasts when the difference in forecasts is large. In Panel E, there is no significant difference in accuracy between the *FIRM* and *INDUSTRY* forecasts for quintiles 1 through 4. In quintile 5, where the forecast difference is largest, the *INDUSTRY* forecast is significantly more accurate than the *FIRM* forecast in terms of both mean and median absolute forecast error. In quintile 5 the *INDUSTRY* forecast is more (less) accurate than the *FIRM* forecast in 12 (0) years in terms of differences in mean absolute forecast error and is more (less) accurate in 13 (3) years in terms of median absolute forecast error.

Panel F of Table 4 investigates potential determinants of forecast improvement from the *INDUSTRY* forecast relative to the *FIRM* forecast. The *INDUSTRY* forecast may be more accurate because industry characteristics are less extreme than firm-level characteristics and extreme firm-year observations reduce the overall accuracy of the *FIRM* forecast. I therefore include *Extreme Observation* in the analysis. The improvement in forecast accuracy could also be related to the volatility of earnings such that firms with volatile earnings may be more accurately forecasted at the industry level rather than firm level. Accuracy improvements from the *INDUSTRY* forecast could be related to industry characteristics or the firm's position within the industry. For example, industry-level forecasts may be more accurate for firms operating in concentrated industries, for firms operating in industries with high barriers to entry, or for firms with large market shares. To test these potential explanations, I regress the improvement in forecast accuracy from the *INDUSTRY* forecast relative to the *FIRM* forecast on proxies for the potential determinants. Panel F reports the results of the following pooled regression estimated with industry and year fixed effects and with *t*-statistics reported based on robust standard errors clustered by firm:

$$\begin{aligned} \mathit{Forecast\ Improvement}_{i,t+5} = {} & \alpha_{0} + \alpha_{1.}\mathit{Extreme\ Observation}_{i,t} + \alpha_{2.}\mathit{Earnings\ Variability}_{i,t} + \\ & \alpha_{3.}\mathit{Forecast\ Difference}_{i,t} + \alpha_{4.}\mathit{Market\ Share}_{i,t} + \alpha_{5.}\mathit{Industry\ R\&D}_{i,t} + \\ & \alpha_{6.}\mathit{Industry\ Number}_{i,t} + \alpha_{7.}\mathit{Industry\ ROA}_{i,t} + \varepsilon_{i,t+5}. \end{aligned} \tag{7}$$

Extreme Observation is an indicator variable equal to 1 for extreme firm-year observations in year *t*. *Earnings Variability* measures the variance of I/B/E/S actual EPS for the years *t-3* to *t*. *Forecast Difference* is defined as the absolute difference between the *INDUSTRY* and *FIRM* forecasts. *Market Share* equals the firm's sales divided by industry sales. To capture the impact of industry characteristics on forecast improvement I include *Industry R&D*, *Industry Number* and *Industry ROA*. *Industry R&D* measures industry-level research and development expense and is a proxy for competition from potential entrants. *Industry Number*, defined as the number of firms operating in the industry, proxies for competition from existing rivals. *Industry ROA* measures industry profitability and reflects the effects of product differentiation or the lack of substitute products in an industry (Li 2010).

Panel F of Table 4 documents positive (negative) relations between improvements in forecast accuracy from the *INDUSTRY* forecast relative to the *FIRM* forecast and *Forecast Difference*, *Market Share*, *Industry R&D* and *Industry ROA* (*Extreme Observation* and *Industry Number*). *INDUSTRY* is more accurate for firms with large differences between the *INDUSTRY* and *FIRM* forecasts, large market shares, firms operating in more profitable industries and firms in industries with higher barriers to entry. *Forecast Improvement* is negatively related to *Extreme Observation* and *Industry Number*, consistent with the *FIRM* forecast being more accurate for extreme firm-year observations and the *INDUSTRY* forecast being more accurate for firms operating in more concentrated industries. *Forecast Improvement* is unrelated to *Earnings Variability*.

Table 4 provides evidence consistent with the *INDUSTRY* forecast being on average more accurate than the *FIRM* forecast. *INDUSTRY* is more accurate than *FIRM* for firms with large differences in *INDUSTRY* and *FIRM*, firms with large market shares, and firms operating in profitable and concentrated industries with high barriers to entry. The *INDUSTRY* forecast is on average more accurate than the *FIRM*, *COMBINED*, *ANALYST* and *ZERO GROWTH* forecasts.

4.4 Do analysts' LTG forecasts fully incorporate firm- and industry-level financial statement information about long-term earnings growth (RQ2)?

Analysts' forecasts of future earnings are important determinants of market expectations (Fried and Givoly 1982). Analysts' forecasts are also interesting to the extent that analysts proxy for other market participants (Richardson et al. 2010). I study analysts' five-year ahead earnings per share growth forecasts to determine whether analysts weight the information contained in *INDUSTRY* and *FIRM* in a manner consistent with the actual predictive ability of the forecasts. If analysts' forecasts incorporate firm- and industry-level financial statement information about growth, *ANALYST* will be significantly associated with *FIRM* and *INDUSTRY*.

Panel A of Table 5 reports results from a pooled regression of equation (8):

$$ANALYST_{i,t} = \alpha_0 + \alpha_{1.} Forecasted\ LTG_{i,t} + \varepsilon_{i,t}. \qquad (8)$$

I find that *INDUSTRY* is not significantly associated with *ANALYST*. While *FIRM* is significantly associated with *ANALYST*, the sign of the coefficient estimate for *FIRM* is not in the expected direction. The negative coefficient estimate for *FIRM* indicates that as the *FIRM* forecast increases, the *ANALYST* forecast decreases.

Examining analyst forecast error is also useful in understanding how analysts incorporate information into their forecasts. If analysts do not correctly incorporate information in a variable that is useful for predicting actual earnings, the variable will explain analyst forecast error and the coefficient and *t*-statistic will indicate whether analysts over- or under-react to the information (Cheng 2005b).

Panel B of Table 5 reports results from estimating the following equation:

$$AFE_{i,t+5} = \alpha_0 + \alpha_1 . \, Forecasted\ LTG_{i,t} + \varepsilon_{i,t+5}. \qquad (9)$$

Analyst forecast error ($AFE_{i,t+5}$) is defined as *ACTUAL* less *ANALYST*. If analysts correctly interpret the implication of information contained in the *INDUSTRY* or *FIRM* forecast for future earnings growth, the coefficient on *INDUSTRY* or *FIRM* in equation (9) will be zero. Panel B reports a positive and significant coefficient on *FIRM*, consistent with analysts on average underweighting the information in *FIRM* when forecasting $GEPS_{t+5}$.[18] The coefficient on *INDUSTRY* in Panel B is also significant and positive consistent with analysts on average underweighting information in the *INDUSTRY* forecast.[19] In sum, Table 5 presents evidence consistent with analysts underweighting the information contained in *FIRM* and *INDUSTRY* relative to its actual predictive ability in forming their LTG forecasts.

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[18] The coefficient on *FIRM* in Panel B of Table 5 can be imputed using information from Panel D of Table 4 and Panel A of Table 5. The coefficient on *FIRM* in explaining actual $GEPS_{t+5}$ is 0.0038 (from Panel D of Table 4). The coefficient on *FIRM* in explaining *ANALYST* is -0.0101 (from Panel A of Table 5). It follows then from the definition of analyst forecast error (*ACTUAL* less *ANALYST*) that the coefficient on *FIRM* in explaining analyst forecast error is 0.0139 [0.0038 – (-0.0101)]. Therefore, while the actual weighting on *FIRM* for predicting $GEPS_{t+5}$ is 0.0038, analysts' forecasts reflect a weighting of -0.0101.

[19] The coefficient on *INDUSTRY* in Panel B of Table 5 can be imputed using information from Panel D of Table 4 and Panel A of Table 5. The coefficient on *INDUSTRY* in explaining actual $GEPS_{t+5}$ is 0.0545 (from Panel D of Table 4). The coefficient on *INDUSTRY* in explaining *ANALYST* is 0.0218 (from Panel A of Table 5). It follows then from the definition of analyst forecast error (*ACTUAL* less *ANALYST*) that the coefficient on *INDUSTRY* in explaining analyst forecast error is 0.0327 (0.0545 – 0.0218). Therefore, while the actual weighting on *INDUSTRY* for predicting $GEPS_{t+5}$ is 0.0545, analysts' forecasts reflect a weighting of 0.0218.

4.5 Which forecast of LTG best explains contemporaneous price (RQ3)?

I identify the long-run earnings expectations embedded in market prices by following Dechow et al. (1999) and testing the usefulness of the LTG forecasts in explaining contemporaneous stock price. The regression equation estimated in Panel A of Table 6 is a simplification of the residual-income model (Ohlson 1995). I estimate the following equation:

$$P_{i,t} = \alpha_0 + \alpha_{1.}BV_{\mathrm{i,t}} + \alpha_{2.}E_{\mathrm{i,t}} + \alpha_{3.}\ Forecasted\ E_{i,t} + \varepsilon_{\mathrm{i,t}}. \qquad (10)$$

Where $P_{\mathrm{i,t}}$ equals firm *i*'s stock price measured three months after the fiscal year end, $BV_{\mathrm{i,t}}$ denotes book value per share, $E_{\mathrm{i,t}}$ denotes I/B/E/S actual earnings per share, and *Forecasted* $E_{i,t}$ denotes the level of expected $EPS_{i,t+5}$ computed using the $GEPS_{t+5}$ forecasts. While the residual income model specifies that abnormal earnings be used, this simplified expression reflects the explanatory power of the information variables without making assumptions about the firm's cost of capital (Dechow et al. 1999).[20]

The *t*-statistics reported in Panel A of Table 6 are based on robust standard errors clustered by firm and by year (Petersen 2009). Panel A reports that the *ANALYST, COMBINED* and *FIRM* forecasts of EPS_{t+5} are significantly associated with contemporaneous price.[21] However, the sign of the coefficient estimates for the *COMBINED* and *FIRM* forecasts is not in the expected direction. The negative coefficient estimates for *COMBINED* and *FIRM* indicate that as forecasted earnings increase, controlling for book value and current earnings, prices decline. Untabulated Vuong (1989) tests find that the *ANALYST* forecast best explains variation in contemporaneous price.

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[20] Abnormal earnings refer to earnings in excess of required earnings calculated as: book value × cost of equity capital.

[21] A realization of earnings in years *t* through $t + 5$ is not required. The number of firm-year observations used in the out-of-sample returns tests more than doubles from 20,642 observations for tests of *RQ1* and *RQ2* to 42,218 used in Table 6.

To determine whether *FIRM* or *INDUSTRY* is incrementally informative over *ANALYST* in explaining contemporaneous price, I estimate the following regression with results reported in Panel B of Table 6:

$$P_{i,t} = \alpha_0 + \alpha_1 . BV_{i,t} + \alpha_2 . E_{i,t} + \alpha_3 . E\_ANALYST_{i,t+5} + \alpha_4 . E\_FIRM_{i,t+5} + \alpha_5 . E\_INDUSTRY_{i,t+5} + \varepsilon_{i,t}. \tag{11}$$

E_ANALYST, *E_FIRM* and *E_INDUSTRY* represent the levels of EPS_{t+5} calculated using the respective $GEPS_{t+5}$ forecast and all other variables are as defined in equation (10). Similar to the results in Panel A, the coefficient estimate for *E_ANALYST* is positive and significant, the coefficient estimate for *E_FIRM* is negative and significant, and the coefficient estimate for *E_INDUSTRY* is not significantly different from zero. I conclude that the *ANALYST* forecast best represents the market expectation of long-term earnings growth embedded in price. Market prices do not have the expected relationship with *FIRM* and do not rely on the information contained in *INDUSTRY* about long-term earnings growth.

4.6 Do market prices fully incorporate the information in the firm- and industry-level forecasts of long-term earnings growth *(RQ4)*?

Table 7 provides evidence on whether market prices fully incorporate information contained in the *INDUSTRY, FIRM* and benchmark forecasts. If market prices do not fully incorporate the implications of the industry and firm information, then a hedge strategy based on purchasing (selling short) stock of firms with high (low) forecasted $GEPS_{t+5}$ will yield positive abnormal returns. Because the strategy is based on long-term growth forecasts, I expect abnormal returns to be earned in holding periods between three and five years.

In Table 7, I report buy-and-hold abnormal returns to trading strategies based on the $GEPS_{t+5}$ forecasts. Firms are sorted into terciles at the portfolio formation date by forecasted $GEPS_{t+5}$, where tercile 1 (3) is composed of firms with the lowest (highest) forecasted $GEPS_{t+5.}$ A zero-investment hedge portfolio is formed by taking long positions in the high $GEPS_{t+5}$ stocks against equally weighted short positions in the low $GEPS_{t+5}$ stocks. Trading portfolios are formed at the conclusion of June each year based on the forecasts available prior to portfolio formation. Buy-and-hold size-adjusted returns are calculated as the raw cumulative return minus the size-matched decile portfolio return over the same holding period based on the firm's prior year ending market value of equity. Returns are cumulated from the portfolio formation date until the end of June 36 to 60 months later. Delisting returns are calculated following the methodology of Beaver et al. (2007) and delisting proceeds are assumed to be invested in the corresponding size-decile portfolio.

The reported mean is the mean return over the 25 period time-series. The *t*-statistics for the time-series mean are computed using Newey-West Heteroskedasticity and Autocorrelation-consistent (HAC) standard errors (Newey and West 1987). The *t*-statistics for the 36, 48, and 60 month returns are computed with 2 year, 3 year, and 4 year lags, respectively. The number of times over the 25 period time-series that the hedge return is significantly greater (less) than zero at the ten percent significance level is reported.

The *p*-values for the annual hedge returns are calculated using a bootstrap technique following Piotroski (2000). I randomly assign firms to the long and short portfolios annually by matching the number of observations in the actual portfolios. I simulate 1,000 annual hedge portfolios and use the distribution of simulated return differences to test the statistical significance of the actual return differences. This approach avoids look-ahead bias, mitigates concerns of skewness bias and alleviates biases in *t*-statistics due to overlapping returns (So 2011).

The *INDUSTRY* hedge portfolio earns positive abnormal size-adjusted returns over holding periods of 48 and 60 months.[22] Size-adjusted returns increase monotonically for *INDUSTRY* across terciles in every holding period. The *INDUSTRY* zero-investment hedge portfolio earns an 8.62 percent and 10.15 percent size-adjusted abnormal return over holding periods of 48 and 60 months, respectively. The *INDUSTRY* hedge return is significantly greater (less) than zero 13 (5) and 13 (4) times over the 25 period time-series for the 48 and 60 month holding periods, respectively. The abnormal hedge returns for *INDUSTRY* are earned entirely on the long position. Table 7 presents evidence consistent with market prices not fully incorporating industry financial statement information about future growth.

To control for known predictors of returns, I follow prior research (Beneish and Vargus 2002; Wahlen and Wieland 2011) and estimate the following pooled regression with results presented in Table 8:[23]

$$AR_{i,t+j} = \alpha_0 + \alpha_1 . BM_{i,t} + \alpha_2 . BETA_{i,t} + \alpha_3 . MOMENT_{i,t} + \alpha_4 . ACCRUAL_{i,t} + \alpha_5 . PE_{i,t} + \alpha_6 . HEDGE_{i,t} + \varepsilon_{i,t+j}. \tag{12}$$

$AR_{i,t+j}$ equals the size-adjusted return, $BM_{i,t}$ equals the book value of equity divided by market value of equity, $BETA_{i,t}$ is the slope coefficient from the regression of the firm's return on the return to the equally weighted CRSP index estimated using daily returns over year *t*, $MOMENT_{i,t}$ equals the cumulative market-adjusted return for the six months prior to the portfolio formation date, $ACCRUAL_{i,t}$ equals operating accruals, $PE_{i,t}$ equals price per share divided by basic earnings per share before extraordinary and discontinued items, and $HEDGE_{i,t}$ is an indicator variable equal to 1 (0) for the long (short) trading portfolio. All independent variables except

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[22] In untabulated results I find that the hedge portfolio returns for the *INDUSTRY* forecast over holding periods of 12 and 24 months are not significantly different than zero.

[23] The choice of control variables is based on evidence from (1) Fama and French (1992) that beta and the book-to-market ratio explain future returns, (2) Jegadeesh (1990) and Jegadeesh and Titman (1993) that short-run returns tend to persist in the subsequent year, (3) Haugen and Baker (1996) that low P/E ratio firms outperform high P/E ratio firms on a risk-adjusted basis, and (4) Sloan (1996) that trading strategies based on extreme accruals generate abnormal returns.

$HEDGE_{i,t}$ are mean-adjusted. Table 8 reports pooled regressions with *t*-statistics based on robust standard errors clustered by firm and by portfolio year (Petersen 2009). Because the *HEDGE* variable only takes values of zero and one, I interpret the slope coefficient estimate in the regression equation as the return to a zero-investment hedge portfolio in the hedge factor after controlling for the effects of the other variables. Similarly, I interpret the intercept (α_0) as the return to the short position in the hedge portfolio and the sum of α_0 and α_6 as the return to the long position in the portfolio after controlling for the effect of the other variables.

The coefficient on *HEDGE* for the *INDUSTRY* forecast is positive and significant for holding periods between 36 and 60 months. Hedge strategies based on the other $GEPS_{t+5}$ forecasts do not earn abnormal returns. The coefficient of 0.0932 on *HEDGE* for the 60 month holding period indicates that an investor earns an abnormal return of 9.32 percent by trading on the *INDUSTRY* forecast over 60 months after controlling for BM, beta, momentum, accruals, and PE. The abnormal return is earned entirely on the long-position (the return to the short position α_0 is not significantly different than zero) and no portfolio rebalancing is required. Although not large, the abnormal returns to the trading strategy provide evidence that information about long-term earnings growth contained in *INDUSTRY* is not fully incorporated into market prices. I argue, consistent with Lewellen (2010), that while the magnitude of abnormal returns are indicative of how important an anomaly is, the presence of even modest abnormal returns helps in understanding the price-setting process and how the market processes information.

4.7 Additional Analyses

Hou et al. (2011) model

Researchers are rapidly adopting the Hou et al. (2011) model as a source of earnings forecasts because the *HOU* forecasts are superior to analyst forecasts in terms of coverage, forecast bias, and earnings response coefficient (see Richardson et al. 2010; Christensen et al. 2011; Lee et al. 2010; Wang and Wang 2010; So 2011).[24] I compare the accuracy of the *INDUSTRY* forecast to forecasts from the Hou et al. (2011) model. In untabulated analyses I find that the *INDUSTRY* forecast is more accurate than the *HOU* forecast in terms of both mean and median absolute forecast errors. *INDUSTRY* is more (less) accurate than *HOU* in terms of mean absolute forecast errors in 21 (1) years and 20 (1) years for median absolute forecast errors.

Robustness Checks

In untabulated analyses I replicate the accuracy tests in terms of *level* of earnings per share, rather than *growth* in earnings per share. Inferences are unchanged when I measure accuracy in terms of the level of earnings per share. I also investigate the sensitivity of the findings to the definition of earnings growth employed. I repeat the analyses forecasting growth in net operating income and growth in earnings-per-share using Compustat data rather than I/B/E/S actuals. I find that inferences are unchanged when Compustat, rather than I/B/E/S data are used to calculate actual earnings growth. Finally, I replicate the analyses using Compustat data without requiring an analyst forecast of LTG and find that inferences are unchanged.

While my methodology uses industry-level financial statement information to forecast $GEPS_{t+5}$, it is possible that estimating the *FIRM* or *HOU* models by industry may produce forecast improvements similar to the *INDUSTRY* model. In untabulated analyses I find that estimating the *FIRM* and *HOU* models by industry does not improve the performance of these models relative to the *INDUSTRY* forecast.

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[24] $EPS_{i,t+5} = \alpha_0 + \alpha_{1.}V_{i,t} + \alpha_{2.}A_{i,t} + \alpha_{3.}D_{i,t} + \alpha_{4.}DD_{i,t} + \alpha_{5.}EPS_{i,t} + \alpha_{6.}AC_{i,t} + \varepsilon_{i,\, t+5}$.

Hou et al. (2011) regress earnings of the firm ($E_{i,t+j}$), on market value ($V_{i,t}$), total book assets ($A_{i,t}$), dividend payment ($D_{i,t}$), a dummy variable equal to 0 for dividend payers and 1 for non-payers ($DD_{i,t}$), earnings ($E_{i,t}$), a dummy variable equal to 1 for firms with negative earnings and 0 otherwise ($Neg\ E_{i,t}$) and operating accruals ($AC_{i,t}$). These coefficient estimates are then used in forecasting future dollar earnings. Because my research design excludes firms with negative earnings in the base year, the dummy variable used by Hou et al. (2011) for firms with negative earnings, $Neg\ E_{i,t}$, is omitted. Hou et al. (2011) forecast net income before extraordinary items, while I use the *HOU* model to forecast I/B/E/S actual earnings per share. After forecasting the dollar amount of EPS_{t+5}, I calculate the implied earnings per share growth ($GEPS_{t+5}$) used in my analyses.

5. Conclusion

Prior academic work focuses on firm-level attributes in forecasting long-term earnings. In this study, I investigate the relative accuracy of LTG forecasts derived from firm- and industry-level financial statement information. I examine whether analysts' LTG forecasts fully incorporate firm and industry financial statement information about LTG. Finally, I analyze returns to trading strategies based on the *INDUSTRY, FIRM* and benchmark forecasts to determine whether prices fully incorporate firm- and industry-level financial statement information about long-term growth.

I find that an industry-based forecast of long-term earnings growth is more accurate than a firm-based forecast. Accuracy improvements from *INDUSTRY* relative to *FIRM* are positively associated with the absolute difference between the *FIRM* and *INDUSTRY* forecasts, market share, industry profitability, industry barriers to entry and industry concentration. The industry-based financial statement forecast is more accurate than the median consensus analyst forecast of LTG, the zero growth forecast, a forecast combining industry and firm information and forecasts from the Hou et al. (2011) model. Analysts' LTG forecasts do not fully incorporate the implications of industry information in forecasting long-term earnings growth. Finally, I document evidence consistent with market prices not fully incorporating the implications of industry-level financial statement information about LTG.

Several caveats are needed when drawing inferences from my study. The data requirements and methodology employed may limit the generalizability of the findings and impose a survivorship bias. The calculation of growth requires positive beginning and ending values of *EPS*, so my findings may not apply to loss firms. The tests of *RQ1* and *RQ2* require that firms have realizations of earnings in periods t through $t + 5$. Therefore, my findings may not be applicable to firms in financial distress, firms likely to be acquired, or firms likely to go private in the near future.

My study contributes to the academic literature on several dimensions. First, I provide evidence demonstrating that industry-level, rather than firm-level, financial statement information should be used to forecast long-term firm performance. Second, my paper contributes to the analyst forecasting literature demonstrating that analysts' LTG forecasts do not fully incorporate industry-level financial statement information. Finally, my paper contributes to the literature on the incorporation of financial statement information into price, demonstrating that market prices do not fully incorporate the implications of industry-level financial statement information about long-term earnings growth.

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Appendix: Variable Definitions

All variables are from Compustat unless otherwise noted. The financial statement-based variables are defined following Nissim and Penman (2001).

Variable Name	Description	Computation
$AJEX_t$	Cumulative adjustment factor for all stock splits and stock dividends	
$CAPX_t$	Capital expenditures	
CEQ_t	Common equity	
CHE_t	Cash and short-term investments	
DLC_t	Debt in current liabilities	
$DLTT_t$	Long-term debt	
DVP_t	Dividends preferred	
$DVPA_t$	Dividends preferred in arrears	
EPS_IBES_t	I/B/E/S actual earnings per share	
$EPSPX_t$	Basic earnings per share before extraordinary items and discontinued operations	
$IDIT_t$	Interest and related income	
$IVAO_t$	Other investments and advances	
MIB_t	Redeemable noncontrolling interest (balance sheet)	
MII_t	Noncontrolling interest (income account)	
MSA_t	Marketable securities adjustment	
MTR_t	Marginal tax rate assumed to be the top statutory federal tax rate plus 2% average state tax rate	
NI_t	Net income (loss)	
$PPENT_t$	Net property, plant and equipment	
$PSTK_t$	Preferred stock (capital)	
$RECTA_t$	Accumulated other comprehensive income cumulative translation adjustment	
$SALE_t$	Sales	
$TSTKP_t$	Preferred treasury stock	
$XINT_t$	Interest and related expense	
CNI_t	Comprehensive net income	$NI_t - DVP_t + MSA_t - MSA_{t-1} + RECTA_t - RECTA_{t-1}$
CSE_t	Common shareholders' equity	$CEQ_t + TSTKP_t - DVPA_t$
FA_t	Financial assets	$CHE_t + IVAO_t$
FO_t	Financial obligations	$DLC_t + DLTT_t + PSTK_t - TSTKP_t + DVPA_t$
NFE_t	Net financial expense	$XINT_t \times (1-MTR_t) + DVP_t - IDIT_t \times (1-MTR_t) + MSA_{t-1} - MSA_t$
NOA_t	Net operating assets	$FO_t - FA_t + CSE_t + MIB_t$
OI_t	Comprehensive operating income	$NFE_t + CNI_t + MII_t$
CPX_t	Scaled capital expenditure	$CAPX_t/PPENT_{t-1}$
$GEPS_t$	Growth in earnings per share	$(EPSPX_t/AJEX_t)/(EPSPX_{t-1}/AJEX_{t-1}) - 1$
$GEPS_{t+5}$	Annual growth in I/B/E/S actual earnings per share from year t to year $t + 5$	From a least squares growth line fitted through the logarithms of the six annual EPS_IBES observations from year t through year $t + 5$
$GNOA_t$	Growth in net operating assets	$NOA_t/NOA_{t-1} - 1$
$GSALES_t$	Growth in sales	$SALE_t/SALE_{t-1} - 1$
$RNOA_t$	Return on net operating assets	$OI_t / ((NOA_t + NOA_{t-1}) / 2)$
$INDCPX_t$	Median CPX_t for 3-digit SIC code	
$INDGEPS_t$	Median $GEPS_t$ for 3-digit SIC code	
$INDGNOA_t$	Median $GNOA_t$ for 3-digit SIC code	
$INDGSALES_t$	Median $GSALES_t$ for 3-digit SIC code	
$INDRNOA_t$	Median $RNOA_t$ for 3-digit SIC code	

Table 1: Sample Selection and Model Definitions

This table presents the sample selection process for the in-sample estimation and the out-of-sample tests. In-sample model definitions are provided.

Panel A: Sample selection for in-sample estimation

Firm-year observations with Compustat data to calculate independent and dependent variables (financial firms excluded)	77,890
Firm-year observations with I/B/E/S actuals	29,714
Firm-year observations with positive values in beginning and ending years for calculation of $GEPS_t$, $GEPS_{t+5}$, $GNOA_t$ and $GSALES_t$.	25,709
Firm-year observations after removal of firms with $GEPS_t$, $GNOA_t$ and $GSALES_t$ greater than 3.	24,938
Firm-year observations after removal of extreme observations for all dependent and independent variables (truncation at 1% and 99%)	21,151

Panel B: Sample selection for out-of-sample tests

Firm-year observations with Compustat data to calculate independent and dependent variables (financial firms excluded)	69,290
Firm-year observations with I/B/E/S median LTG forecasts and corresponding I/B/E/S actuals	24,334
Firm-year observations with positive values in beginning and ending years for calculation of $GEPS_t$, $GEPS_{t+5}$, $GNOA_t$, and $GSALES_{t,}$	20,642

Panel C: Model definitions

See Appendix for the *COMBINED, FIRM*, and *INDUSTRY* variable definitions.

ANALYST	$E[GEPS_{i,t+5}] =$	median consensus forecast of LTG from I/B/E/S at least 3 months after the fiscal year-end
COMBINED	$GEPS_{i,t+5} =$	$\alpha_0 + \alpha_1 . GNOA_{i,t} + \alpha_2 . GEPS_{i,t} + \alpha_3 . GSALES_{i,t} + \alpha_4 . RNOA_{i,t} + \alpha_5 . CPX_{i,t} + \alpha_6 . INDGNOA_{i,t} + \alpha_7 . INDGEPS_{i,t} + \alpha_8 . INDGSALES_{i,t} + \alpha_9 . INDRNOA_{i,t} + \alpha_{10} . INDCPX_{i,t} + \varepsilon_{i,t+5}$
FIRM	$GEPS_{i,t+5} =$	$\alpha_0 + \alpha_1 . GNOA_{i,t} + \alpha_2 . GEPS_{i,t} + \alpha_3 . GSALES_{i,t} + \alpha_4 . RNOA_{i,t} + \alpha_5 . CPX_{i,t} + \varepsilon_{i,t+5}$
INDUSTRY	$GEPS_{i,t+5} =$	$\alpha_0 + \alpha_1 . INDGNOA_{i,t} + \alpha_2 . INDGEPS_{i,t} + \alpha_3 . INDGSALES_{i,t} + \alpha_4 . INDRNOA_{i,t} + \alpha_5 . INDCPX_{i,t} + \varepsilon_{i,t+5}$
ZERO GROWTH	$E[GEPS_{i,t+5}] = 0$	

Table 2: In-Sample Estimation

This table presents the in-sample rolling regressions and the correlation table for the in-sample variables.

Panel A: *COMBINED, FIRM* and *INDUSTRY* in-sample estimation

The dependent variable is $GEPS_{t+5}$. The reported coefficient for the annual regressions is the mean coefficient of the 25 rolling regressions with $GEPS_{t+5}$ realized from 1976 to 2004. The *t*-statistics for the annual regressions are computed using the Fama and MacBeth (1973) approach. The *t*-statistics for the pooled regressions are reported with robust standard errors clustered by firm and by year (Petersen 2009). ***, **, and * indicate two-tailed significance at the 1%, 5%, and 10% levels, respectively. See Appendix for variable definitions. 21,151 firm-year observations are used in the in-sample estimation.

	Expected	Annual Regressions			Pooled Regressions		
	Sign	*COMBINED*	*FIRM*	*INDUSTRY*	*COMBINED*	*FIRM*	*INDUSTRY*
Intercept		0.071 ***	0.067 ***	0.063 ***	0.061 ***	0.055 ***	0.052 ***
		(14.43)	(14.12)	(12.64)	(6.37)	(7.26)	(5.83)
GNOA	-	-0.029 ***	-0.040 ***		-0.036 ***	-0.044 ***	
		-(4.77)	-(7.50)		-(5.37)	-(6.06)	
GEPS	-	-0.029 ***	-0.031 ***		-0.023 ***	-0.024 ***	
		-(15.76)	-(15.92)		-(5.02)	-(4.07)	
GSALES	-	0.003	-0.009		0.030 **	0.025	
		(0.16)	-(0.59)		(2.04)	(1.46)	
RNOA	-	-0.088 ***	-0.079 ***		-0.082 ***	-0.077 ***	
		-(10.34)	-(9.69)		-(3.68)	-(3.43)	
CPX	+	0.028 ***	0.048 ***		0.021 *	0.038 ***	
		(3.10)	(7.10)		(1.73)	(3.10)	
INDGNOA	-	-0.104 ***		-0.111 ***	-0.151 ***		-0.170 ***
		-(4.68)		-(4.00)	-(2.83)		-(3.21)
INDGEPS	-	-0.015		-0.035 **	0.002		-0.015
		-(1.01)		-(2.55)	(0.16)		-(1.00)
INDGSALES	-	-0.049		-0.062 *	0.009		0.024
		-(1.08)		-(1.78)	(0.15)		(0.41)
INDRNOA	-	-0.020		-0.040	-0.201 ***		-0.190 ***
		-(0.17)		-(0.31)	-(3.71)		-(3.54)
INDCPX	+	0.083		0.082	0.130 ***		0.117 ***
		(1.28)		(1.41)	(4.00)		(3.94)
Adj. R^2		3.13%	1.73%	1.63%	1.55%	0.86%	0.81%

Panel B: Correlation table for in-sample variables

Spearman (Pearson) correlations are presented below (above) the diagonal. All correlations are significant at the 1% significance level unless in bold and italics.

	$GEPS_{t+5}$	$GNOA_t$	$GEPS_t$	$GSALES_t$	$RNOA_t$	CPX_t	$INDGNOA_t$	$INDGEPS_t$	$INDGSALES_t$	$INDRNOA_t$	$INDCPX_t$
$GEPS_{t+5}$		-0.04	-0.07	-0.02	-0.06	***0.00***	-0.04	-0.04	-0.02	-0.06	0.02
$GNOA_t$	-0.04		***0.01***	0.41	0.17	0.45	0.26	0.03	0.16	0.02	0.19
$GEPS_t$	-0.04	0.05		0.31	0.23	0.05	0.07	0.29	0.19	0.06	0.07
$GSALES_t$	***0.00***	0.42	0.40		0.19	0.30	0.22	0.21	0.39	0.07	0.19
$RNOA_t$	-0.07	0.21	0.35	0.24		0.30	0.17	0.11	0.14	0.08	0.26
CPX_t	0.03	0.49	0.10	0.31	0.36		0.28	0.04	0.22	0.06	0.46
$INDGNOA_t$	-0.03	0.32	0.11	0.27	0.20	0.33		0.18	0.57	0.19	0.62
$INDGEPS_t$	-0.02	0.07	0.35	0.26	0.17	0.09	0.21		0.49	0.37	0.08
$INDGSALES_t$	***0.01***	0.21	0.23	0.45	0.16	0.24	0.59	0.50		0.18	0.46
$INDRNOA_t$	-0.06	0.06	0.12	0.12	0.24	0.12	0.26	0.44	0.24		0.10
$INDCPX_t$	0.06	0.23	0.11	0.21	0.32	0.53	0.62	0.13	0.45	0.19	

Table 3: Descriptive Statistics and Correlation Matrix for Out-of-Sample Forecasts

This table provides descriptive statistics and the correlation matrix for the out-of-sample forecasts. 20,642 firm-year observations are used in the out-of-sample tests spanning 25 years with $GEPS_{t+5}$ realized from 1986 to 2010. The forecasts are of annual *I/B/E/S* actual *EPS* growth over a 5 year horizon. See Table 1, Panel C for model definitions. *ACTUAL* is realized I/B/E/S annual earnings growth *(GEPS)* from year *t* to year *t + 5*.

Panel A: Descriptive statistics

	Mean	**Median**	**Std Dev**	**First Quartile**	**Third Quartile**	**5%**	**95%**
ANALYST	0.137	0.130	0.067	0.100	0.170	0.040	0.250
COMBINED	0.048	0.055	0.271	0.030	0.085	-0.032	0.160
FIRM	0.039	0.050	0.273	0.033	0.071	-0.028	0.131
INDUSTRY	0.068	0.059	0.089	0.042	0.082	0.019	0.153
ZERO GROWTH	0.000	0.000	0.000	0.000	0.000	0.000	0.000
ACTUAL	0.050	0.065	0.180	-0.025	0.147	-0.270	0.302

Panel B: Correlation matrix

This panel presents the correlation matrix for the $GEPS_{t+5}$ forecasts and actual earnings growth. Spearman (Pearson) correlations are presented below (above) the diagonal. All correlations are significant at the 1% significance level unless in bold and italics.

	ANALYST	***COMBINED***	***FIRM***	***INDUSTRY***	***ACTUAL***
ANALYST		-0.03	-0.04	0.03	0.08
COMBINED	-0.08		0.90	0.40	***0.01***
FIRM	-0.17	0.80		0.06	***0.01***
INDUSTRY	0.08	0.78	0.44		0.03
ACTUAL	0.15	0.07	0.04	0.07	

Table 4: Out-of-Sample Forecast Error

This table presents analyses of the bias and accuracy of the $GEPS_{t+5}$ forecasts. 20,642 firm-year observations are used in the out-of-sample tests spanning 25 years with $GEPS_{t+5}$ realized from 1986 to 2010.

Panel A: Signed forecast error (bias)

Signed forecast error equals forecasted $GEPS_{t+5}$ less actual $GEPS_{t+5}$. All mean and median signed forecast errors are significantly different than zero at the 1% level unless in bold and italics.

	Mean	Median	Std Dev	First Quartile	Third Quartile	5%	95%
ANALYST	0.088	0.057	0.187	-0.013	0.164	-0.157	0.437
COMBINED	***-0.001***	***-0.007***	0.324	-0.095	0.094	-0.274	0.345
FIRM	-0.010	-0.013	0.326	-0.102	0.083	-0.283	0.327
INDUSTRY	0.018	***0.000***	0.198	-0.083	0.099	-0.238	0.351
ZERO GROWTH	-0.050	-0.065	0.180	-0.147	0.025	-0.302	0.270

Panel B: Absolute forecast error (accuracy)

Absolute forecast error equals the absolute value of forecasted $GEPS_{t+5}$ less actual $GEPS_{t+5}$. All mean and median absolute forecast errors are significantly different than zero at the 1% level.

	Mean	Median	Std Dev	First Quartile	Third Quartile	5%	95%
ANALYST	0.140	0.091	0.151	0.037	0.190	0.007	0.448
COMBINED	0.146	0.095	0.289	0.044	0.183	0.009	0.417
FIRM	0.143	0.093	0.293	0.043	0.177	0.009	0.412
INDUSTRY	0.131	0.090	0.150	0.041	0.175	0.008	0.396
ZERO GROWTH	0.138	0.108	0.125	0.052	0.185	0.010	0.376

Panel C: Matched-pair comparison of absolute forecast error

Difference in accuracy is measured through a matched-pair comparison of the absolute value of prediction errors from the two models. The mean (median) difference in accuracy is computed annually and the reported difference is the mean (median) of the 25 annual mean (median) differences. Positive (negative) values indicate that the first model is more (less) accurate than the second model. Number of years is the number of years out of 25 that the annual mean (median) difference is significantly positive / negative at the 10% significance level. Tests of means are based on Fama-MacBeth *t*-statistics computed from the annual mean forecast differences. Tests of medians are based on Wilcoxon signed ranks tests of the annual median forecast differences. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Mean Difference		Number of years	Median Difference		Number of years
	Value	*p*-Value		Value	*p*-Value	
INDUSTRY vs. FIRM	0.0114 ***	0.001	12 / 1	0.0017	0.131	14 / 6
INDUSTRY vs. COMBINED	0.0145 ***	0.000	21 / 0	0.0015 ***	0.000	18 / 0
INDUSTRY vs. ANALYST	0.0090 **	0.040	16 / 3	0.0028	0.154	14 / 5
INDUSTRY vs. ZERO GROWTH	0.0070	0.113	17 / 3	0.0242 ***	0.000	18 / 3
FIRM vs. COMBINED	0.0031	0.324	8 / 7	-0.0003	0.927	9 / 8
FIRM vs. ANALYST	-0.0024	0.500	6 / 6	0.0020	0.273	13 / 7
FIRM vs. ZERO GROWTH	-0.0044	0.167	5 / 5	0.0176 ***	0.000	16 / 2
COMBINED vs. ANALYST	-0.0055	0.268	5 / 6	-0.0007	0.378	11 / 7
COMBINED vs. ZERO GROWTH	-0.0075	0.163	6 / 6	0.0150 ***	0.001	15 / 3
ANALYST vs. ZERO GROWTH	-0.0021	0.678	8 / 10	0.0091	0.647	9 / 9

Table 4 (Continued): Out-of-Sample Forecast Error

Panel D: Incremental and Relative information content

This panel reports the results of estimating the following pooled regressions:

$$ACTUAL_{i,t+5} = \alpha_0 + \alpha_1 . FIRM_{i,t} + \alpha_2 . INDUSTRY_{i,t} + \varepsilon_{i,t+5}$$
$$ACTUAL_{i,t+5} = \alpha_0 + \alpha_1 . FIRM_{i,t} + \varepsilon_{i,t+5}$$
$$ACTUAL_{i,t+5} = \alpha_0 + \alpha_1 . INDUSTRY_{i,t} + \varepsilon_{i,t+5}$$

ACTUAL is realized I/B/E/S annual earnings growth *(GEPS)* from year *t* to year *t + 5*. *FIRM* and *INDUSTRY* represent out-of-sample forecasts of $GEPS_{t+5}$ made as of 1981 through 2005. The *t*-statistics are reported based on robust standard errors clustered by firm and by year (Petersen 2009). ***, **, and * indicate two-tailed significance at the 1%, 5%, and 10% levels, respectively.

	Intercept		***FIRM***	***INDUSTRY***		**Adj. R^2**
Coef. Est.	0.0458	***	0.0028	0.0540	**	0.07%
t-Statistic	(5.81)		(0.50)	(2.27)		
Coef. Est.	0.0495	***	0.0038			0.00%
t-Statistic	(6.58)		(0.69)			
Coef. Est.	0.0459	***		0.0545	**	0.07%
t-Statistic	(5.86)			(2.27)		

Panel E: Matched-pair comparison of absolute forecast error by quintile of difference between the *INDUSTRY* and *FIRM* forecasts

Forecast difference is calculated as the absolute value of the difference in the *INDUSTRY* and *FIRM* forecasts. Firm-year observations are sorted into quintiles annually based on forecast difference. Quintile 1 (quintile 5) represents firm-years with forecast difference of the lowest (highest) magnitude. The reported means and medians are for paired differences between the absolute forecast errors. Positive (negative) values indicate that the first model is more (less) accurate than the second model. The number of years out of 25 that the annual mean (median) difference is significantly positive / negative at the 10% significance level is reported.

		INDUSTRY* vs. *FIRM		
Quintile 1	Mean	0.0001		2 / 1
	Median	0.0001		2 / 1
Quintile 2	Mean	-0.0003		6 / 2
	Median	0.0033		6 / 4
Quintile 3	Mean	-0.0010		8 / 4
	Median	0.0099		6 / 4
Quintile 4	Mean	-0.0015		8 / 4
	Median	0.0117		9 / 4
Quintile 5	Mean	0.0601	***	12 / 0
	Median	0.0302	*	13 / 3

Table 4 (Continued): Out-of-Sample Forecast Error

Panel F: Determinants of the usefulness of the *INDUSTRY* forecast

This panel reports the results of estimating the following pooled regression:

$$\begin{aligned} \textit{Forecast Improvement}_{i,t+5} = {} & \alpha_0 + \alpha_{1.}\textit{Extreme Observation}_{i,t} + \alpha_{2.}\textit{Earnings Variability}_{i,t} + \alpha_{3.}\textit{Forecast Difference}_{i,t} \\ & + \alpha_{4.}\textit{Market Share}_{i,t} + \alpha_{5.}\textit{Industry R\&D}_{i,t} + \alpha_{6.}\textit{Industry Number}_{i,t} + \alpha_{7.}\textit{Industry ROA}_{i,t} \\ & + \varepsilon_{i,t+5}. \end{aligned}$$

Forecast Improvement is defined as *FIRM* absolute forecast error less *INDUSTRY* absolute forecast error. *Extreme Observation* is an indicator variable set equal to 1 if any of the variables used in creating the *FIRM* forecast are in the 1st or 99th percentile of the out-of-sample observations by year and zero otherwise. *Earnings Variability* equals the variance of firm-level I/B/E/S earnings-per-share amounts for the three years from *t-3* to *t*. *Forecast Difference* equals the absolute value of the difference in the *INDUSTRY* and *FIRM* forecasts. *Market Share* is defined as the firm's sales divided by industry sales. *Industry R&D* equals the weighted average of research and development expense of all firms in an industry. A firm's market share, calculated as the ratio of the firm's sales to industry sales, is used as the weight. *Industry Number* equals the total number of firms in the industry. *Industry ROA* is measured as industry aggregate operating profit before depreciation divided by industry aggregate total assets. This analysis is conducted using 19,570 out-of-sample forecasts of $GEPS_{t+5}$ made as of 1981 through 2005. The regressions are estimated with industry and year fixed effects. The *t*-statistics are reported based on robust standard errors clustered by firm. ***, **, and * indicate two-tailed significance at the 1%, 5%, and 10% levels, respectively.

	Expected Sign	Coefficient Estimate		t-Statistic	p-Value
Intercept		-0.10146	***	-3.22	0.001
Extreme Observation	+	-0.03339	***	-6.74	0.000
Earnings Variability	+	0.00000		-0.31	0.758
Forecast Difference	+	0.99801	***	787.97	0.000
Market Share	+	0.02310	**	1.99	0.047
Industry R&D	+	0.00001	***	2.95	0.003
Industry Number	-	-0.00010	***	-4.60	0.000
Industry ROA	+	0.14989	***	3.30	0.001
Adjusted R^2					0.997

Table 5: Analyst Forecasts

This table presents regressions of the *ANALYST* forecast and analyst forecast error on the *FIRM* and *INDUSTRY* forecasts. The results of pooled regressions are reported using 20,642 firm-year out-of-sample forecasts of $GEPS_{t+5}$ made as of 1981 through 2005. The *t*-statistics are reported based on robust standard errors clustered by firm and by year (Petersen 2009). ***, **, and * indicate two-tailed significance at the 1%, 5%, and 10% levels, respectively.

Panel A: *ANALYST* forecast regressed on *FIRM* and *INDUSTRY* forecasts

This panel reports the results of estimating the following pooled regression:

$$ANALYST_{i,t} = \alpha_0 + \alpha_{1.}Forecasted\ LTG_{i,t} + \varepsilon_{i,t}.$$

		Intercept		Forecast		Adj. R^2
FIRM	Coef. Est.	0.1378	***	-0.0101	***	0.17%
	t-Statistic	(58.38)		(-3.40)		
INDUSTRY	Coef. Est.	0.1359	***	0.0218		0.08%
	t-Statistic	(57.82)		(1.19)		

Panel B: Analyst forecast error regressed on *FIRM* and *INDUSTRY* forecasts

This panel reports the results of estimating the following pooled regression:

$$AFE_{i,t+5} = \alpha_0 + \alpha_{1.}Forecasted\ LTG_{i,t} + \varepsilon_{i,t+5}.$$

where *AFE* equals *ACTUAL* less *ANALYST*.

		Intercept		Forecast		Adj. R^2
FIRM	Coef. Est.	-0.0884	***	0.0139	***	0.04%
	t-Statistic	(-11.09)		(2.85)		
INDUSTRY	Coef. Est.	-0.0900	***	0.0327	*	0.02%
	t-Statistic	(-10.85)		(1.66)		

Table 6: Explanatory Power for Contemporaneous Stock Prices

Panel A: All forecasts

This panel reports the results of estimating the following equation:

$$P_{i,t} = \alpha_0 + \alpha_{1.}BV_{i,t} + \alpha_{2.}E_{i,t} + \alpha_{3.}\mathit{Forecasted}\ E_{i,t} + \varepsilon_{i,t}.$$

Pooled regressions are estimated with 42,218 out-of-sample firm-year observations from 1981 to 2005. The *t*-statistics are reported based on robust standard errors clustered by firm and by year (Petersen 2009). *P* denotes stock price measured three months after the fiscal year end, *BV* denotes book value per share (*CEQ*/*CSHO*), *E* denotes actual I/B/E/S earnings per share and *Forecasted E* denotes forecasted EPS_{t+5} using the $GEPS_{t+5}$ forecast from the respective model. ***, **, and * indicate two-tailed significance at the 1%, 5%, and 10% levels, respectively.

		Intercept	**_BV_**	**_E_**	**_Forecasted E_**	**Adj. R^2**
ANALYST	Coeff. Est.	4.8435	1.3144 ***	-0.0001 ***	30.2228 ***	29.99%
	t-Statistic	(1.29)	(5.84)	(-12.48)	(3.09)	
COMBINED	Coeff. Est.	11.0206 ***	1.2326 ***	-0.0001 ***	-4.6349 ***	29.33%
	t-Statistic	(5.24)	(6.05)	(-9.13)	(-2.73)	
FIRM	Coeff. Est.	10.9706 ***	1.2315 ***	-0.0001 ***	-3.8438 ***	29.29%
	t-Statistic	(5.21)	(6.03)	(-9.72)	(-2.97)	
INDUSTRY	Coeff. Est.	12.0828 ***	1.2322 ***	-0.0001 ***	-18.5310	29.37%
	t-Statistic	(5.42)	(6.11)	(-10.35)	(-1.42)	
ZERO GROWTH	Coeff. Est.	10.9265 ***	1.2265 ***	-0.0001 ***		29.06%
	t-Statistic	(5.17)	(5.99)	(-11.42)		

Panel B: Incremental explanatory power for contemporaneous stock prices

This panel reports the results of estimating the following equation:

$$P_{i,t} = \alpha_0 + \alpha_{1.}BV_{i,t} + \alpha_{2.}E_{i,t} + \alpha_{3.}E\_ANALYST_{i,t} + \alpha_{4.}E\_FIRM_{i,t} + \alpha_{5.}E\_INDUSTRY_{i,t} + \varepsilon_{i,t}.$$

Pooled regressions are estimated with 42,218 out-of-sample firm-year observations from 1981 to 2005. The *t*-statistics are reported based on robust standard errors clustered by firm and by year (Petersen 2009). *P* denotes stock price measured three months after the fiscal year end, *BV* denotes book value per share (*CEQ*/*CSHO*), *E* denotes actual I/B/E/S earnings per share and *E_ANALYST, E_FIRM,* and *E_INDUSTRY* denote forecasted EPS_{t+5} calculated using the $GEPS_{t+5}$ forecast from the respective model. ***, **, and * indicate two-tailed significance at the 1%, 5%, and 10% levels, respectively.

	Intercept	**_BV_**	**_E_**	**_E_ANALYST_**	**_E_FIRM_**	**_E_INDUSTRY_**	**Adj. R^2**
Coeff. Est.	6.0169	1.3263 ***	-0.0001 ***	30.7620 ***	-3.2521 ***	-19.9473	30.52%
t-Statistic	(1.57)	(6.01)	(-9.99)	(3.16)	(-2.98)	(-1.58)	

Table 7: Buy-and-Hold Size-Adjusted Portfolio Returns

This table presents future buy-and-hold size-adjusted returns by tercile of forecasted $GEPS_{t+5}$ where tercile 1 (tercile 3) contains firm-year observations with the lowest (highest) forecasted *EPS* growth. Size-adjusted returns are calculated as the raw cumulative return minus the size-matched decile portfolio return over the same holding period based on firm *i*'s prior year ending market value of equity. Portfolios are formed at the conclusion of June each year based on the $GEPS_{t+5}$ forecasts available prior to portfolio formation. The sample used in this analysis consists of 40,138 firm-year observations with portfolios formed annually between 1981 and 2005. The reported mean is the mean return over the 25 period time-series. The *t*-statistics are shown in parentheses below the corresponding return and are computed using Newey-West Heteroskedasticity and Autocorrelation-Consistent (HAC) standard errors (Newey and West 1987). The *t*-statistics for the 36, 48 and 60 month returns are computed with 2 year, 3 year and 4 year lags, respectively. Two-tailed significance levels are indicated by *, **, and *** for 10%, 5%, and 1%. Delisting returns are estimated following Beaver et al. (2007) and delisting proceeds are assumed to be invested in the corresponding size decile portfolio. # of Times is the number of times over the 25 period time-series that the hedge return is significantly greater than / less than zero at the 10% significance level with *p*-values calculated using bootstrapping procedures based on 1,000 iterations.

36 Months:

Model		***Tercile 1***	***Tercile 2***	***Tercile 3***	***Hedge Portfolio***	***# of Times***
ANALYST	Mean	0.0585	0.0657 ***	0.0177	-0.0408	7 / 12
	t-Statistic	(1.48)	(2.99)	(0.59)	(-0.66)	
COMBINED	Mean	0.0382 *	0.0388	0.0589 ***	0.0206	7 / 6
	t-Statistic	(1.90)	(1.47)	(3.87)	(1.08)	
FIRM	Mean	0.0509 ***	0.0458 *	0.0391	-0.0118	4 / 8
	t-Statistic	(3.64)	(1.80)	(1.59)	(-0.45)	
INDUSTRY	Mean	0.0123	0.0505 **	0.0737 ***	0.0614	13 / 6
	t-Statistic	(0.37)	(2.38)	(5.85)	(1.64)	

48 Months:

Model		***Tercile 1***	***Tercile 2***	***Tercile 3***	***Hedge Portfolio***	***# of Times***
ANALYST	Mean	0.0678	0.0828 ***	0.0209	-0.0470	9 / 11
	t-Statistic	(1.30)	(3.07)	(0.56)	(-0.59)	
COMBINED	Mean	0.0473 **	0.0489	0.0709 ***	0.0235	9 / 5
	t-Statistic	(2.12)	(1.55)	(3.60)	(1.27)	
FIRM	Mean	0.0680 ***	0.0534	0.0458	-0.0222	3 / 7
	t-Statistic	(4.60)	(1.71)	(1.34)	(-0.65)	
INDUSTRY	Mean	0.0126	0.0564	0.0988 ***	0.0862 **	13 / 5
	t-Statistic	(0.36)	(1.65)	(9.12)	(2.17)	

60 Months:

Model		***Tercile 1***	***Tercile 2***	***Tercile 3***	***Hedge Portfolio***	***# of Times***
ANALYST	Mean	0.0795	0.0985 ***	0.0382	-0.0413	10 / 12
	t-Statistic	(1.22)	(3.02)	(0.95)	(-0.44)	
COMBINED	Mean	0.0630 ***	0.0564	0.0924 ***	0.0294 **	7 / 5
	t-Statistic	(2.99)	(1.44)	(3.82)	(2.26)	
FIRM	Mean	0.0896 ***	0.0621	0.0601	-0.0294	4 / 6
	t-Statistic	(6.07)	(1.57)	(1.44)	(-0.68)	
INDUSTRY	Mean	0.0163	0.0790 *	0.1178 ***	0.1015 **	13 / 4
	t-Statistic	(0.42)	(1.84)	(10.58)	(2.47)	

Table 8: Cross-Sectional Regression Controlling for Predictors of Returns

This table presents coefficients from the following pooled regression:

$$AR_{i,t+j} = \alpha_0 + \alpha_{1.}BM_{i,t} + \alpha_{2.}BETA_{i,t} + \alpha_{3.}MOMENT_{i,t} + \alpha_{4.}ACCRUAL_{i,t} + \alpha_{5.}PE_{i,t} + \alpha_{6.}HEDGE_{i,t} + \varepsilon_{i,t+j}.$$

The *t*-statistics based on robust standard errors clustered by firm and by portfolio year (Petersen 2009) are reported below the coefficient estimate. Two-tailed significance levels are indicated by *, **, and *** for 10%, 5%, and 1% respectively. $AR_{i,t+j}$ equals the size-adjusted return for firm *i* calculated as the raw cumulative return minus the size-matched decile portfolio return over the same holding period based on firm *i*'s prior year ending market value of equity. $BM_{i,t}$ equals the book value of equity divided by market value of equity [*CEQ*/(*PRCC_F***CSHO*+*AT*-*CEQ*)]. $BETA_{i,t}$ is the slope coefficient from a regression of the firm's return on the return to the equally weighted CRSP index, estimated using daily returns over year *t* (approximately 250 trading days). $MOMENT_{i,t}$ equals the cumulative market-adjusted return for the six months prior to portfolio formation. $ACCRUAL_{i,t}$ equals operating accruals calculated using the indirect balance sheet method as the change in non-cash current assets less the change in current liabilities excluding the change in short-term debt and the change in taxes payable minus depreciation and amortization (ΔACT-ΔCHE-ΔLCT+ΔDLC+ΔTXP-DP). $PE_{i,t}$ equals price per share at the end of the prior fiscal year divided by basic earnings per share before extraordinary and discontinued items (*PRCC_F*/*EPSPX*). $HEDGE_{i,t}$ is an indicator variable equal to 1 (0) for the long (short) portfolio. Trading portfolios are formed by sorting firm-year observations into terciles annually based on the magnitude of the $GEPS_{t+5}$ forecast where tercile 3 (tercile 1) is composed of firm-year observations with the highest (lowest) $GEPS_{t+5}$ forecast. Firm-year observations in tercile 3 (tercile 1) form the long (short) portfolio. The sample used in this analysis consists of 40,138 firm-year observations with portfolios formed annually from 1981 to 2005. Delisting returns are estimated following Beaver et al. (2007) and delisting proceeds are assumed to be invested in the corresponding size decile portfolio.

36 Months:

Model		Intercept	*BM*	*BETA*	*MOMENT*	*ACCRUAL*	*PE*	*HEDGE*	Adj. R^2
ANALYST	Coeff. Est.	0.0319	0.2025 ***	-0.0120	0.2232 ***	0.0000	0.0001	0.0148	0.73%
	t-Statistic	(1.40)	(4.17)	(-0.27)	(5.36)	(-1.07)	(0.50)	(0.56)	
COMBINED	Coeff. Est.	0.0468 *	0.1859 ***	-0.0053	0.2570 ***	0.0000	0.0001	0.0099	0.82%
	t-Statistic	(1.77)	(3.64)	(-0.10)	(6.19)	(-0.70)	(0.50)	(0.39)	
FIRM	Coeff. Est.	0.0570 ***	0.2156 ***	-0.0007	0.2481 ***	0.0000	0.0001	-0.0215	0.79%
	t-Statistic	(2.79)	(4.21)	(-0.01)	(6.44)	(0.16)	(0.53)	(-1.01)	
INDUSTRY	Coeff. Est.	0.0103	0.1585 ***	-0.0146	0.2464 ***	0.0000	0.0002	0.0668 **	0.94%
	t-Statistic	(0.34)	(3.03)	(-0.34)	(6.99)	(-1.31)	(0.63)	(2.06)	

48 Months:

Model		Intercept	*BM*	*BETA*	*MOMENT*	*ACCRUAL*	*PE*	*HEDGE*	Adj. R^2
ANALYST	Coeff. Est.	0.0416	0.2032 ***	-0.0079	0.2456 ***	0.0000	0.0000	0.0158	0.52%
	t-Statistic	(1.63)	(3.78)	(-0.14)	(5.01)	(-1.09)	(-0.29)	(0.64)	
COMBINED	Coeff. Est.	0.0553 *	0.1755 ***	0.0013	0.2578 ***	0.0000	0.0000	0.0149	0.62%
	t-Statistic	(1.79)	(2.91)	(0.02)	(5.15)	(-0.61)	(-0.27)	(0.53)	
FIRM	Coeff. Est.	0.0728 ***	0.1991 ***	0.0051	0.2634 ***	0.0000	0.0000	-0.0229	0.55%
	t-Statistic	(3.03)	(3.32)	(0.08)	(5.78)	(0.24)	(-0.12)	(-1.08)	
INDUSTRY	Coeff. Est.	0.0199	0.1576 **	-0.0026	0.2672 ***	0.0000	0.0000	0.0816 **	0.66%
	t-Statistic	(0.65)	(2.52)	(-0.04)	(5.84)	(-1.53)	(-0.29)	(2.53)	

60 Months:

Model		Intercept	*BM*	*BETA*	*MOMENT*	*ACCRUAL*	*PE*	*HEDGE*	Adj. R^2
ANALYST	Coeff. Est.	0.0463	0.2402 ***	-0.0273	0.2491 ***	0.0000	0.0000	0.0353	0.39%
	t-Statistic	(1.54)	(3.52)	(-0.60)	(3.61)	(-0.79)	(-0.13)	(1.18)	
COMBINED	Coeff. Est.	0.0678 **	0.1964 **	-0.0147	0.2434 ***	0.0000	0.0000	0.0213	0.47%
	t-Statistic	(1.98)	(2.55)	(-0.28)	(4.60)	(0.27)	(-0.40)	(0.63)	
FIRM	Coeff. Est.	0.0910 ***	0.2274 ***	-0.0085	0.2665 ***	0.0000	0.0000	-0.0276	0.39%
	t-Statistic	(3.67)	(3.03)	(-0.16)	(4.50)	(0.53)	(0.10)	(-1.07)	
INDUSTRY	Coeff. Est.	0.0265	0.1611 **	-0.0236	0.2793 ***	0.0000	0.0000	0.0932 **	0.51%
	t-Statistic	(0.76)	(2.12)	(-0.46)	(4.48)	(-1.34)	(0.02)	(2.27)	