

Intangible Assets, Information Complexity, and Analysts' Earnings Forecasts

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Abstract: We examine the relation between analysts' earnings forecasts and firms' intangible assets, including technology-based intangibles, brand names, and recognized intangibles. We predict that high information complexity of intangible assets increases the difficulty for analysts to assimilate information and increases analysts' forecast error of intangibles-intensive firms. We find a positive association between analysts' forecast error and the firm's intangible intensity that deviates from the industry norm. We also find that analysts' forecast errors are greater for firms with diverse and innovative technologies. In contrast, analysts' forecast errors are smaller for biotech/pharmaceutical and medical equipment firms that are subject to intangibles-related regulation.

Keywords: intangible assets, information complexity, analysts' earnings forecasts

1. INTRODUCTION

The rise of intangible assets in size and contribution to corporate growth over the last two decades poses an interesting dilemma for analysts. Most intangible assets are not recognized in financial statements, and current accounting rules do not require firms to report separate performance measures for intangibles. The increasing importance of intangible assets and

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the absence of explicit information about the contribution of intangibles to earnings imply strong market incentives for analysts to provide value-added information (e.g., accurate earnings forecasts) for high-intangibles firms. Indeed, Barth et al. (2001) find that analyst coverage and effort are greater for firms with more intangible assets. On the other hand, intangible assets are also associated with more complex information than other types of corporate assets (e.g., physical and financial assets), due to the high uncertainty in the value of intangibles, fuzzy property rights on the asset, and lack of active markets and reliable value estimates for most intangibles.¹ High information complexity of intangibles thus may likely increase the difficulty of assimilating intangible information and complicate analysts' task of earnings forecast. To date, there is little evidence on how well analysts are tackling intangibles. In this study, we investigate the effect of information complexity of intangible assets on analysts' forecast error. We focus our analysis on forecast error, which is a meaningful quality indicator of analysts' earnings forecasts and an important determinant of the usefulness of analysts' research.

We argue that the information complexity of intangible assets is primarily attributable to firm-specific intangibles—intangible investment in excess of the industry average. Firms tend to outspend their industry peers when they are engaged in highly differentiated, pioneering innovations that are aimed at creating new products or services fundamentally different from the existing ones (Barney, 1991; and Lev, 2001). Compared to intangible investment that conforms to industry norms, or industry-average intangibles, firm-specific intangibles are highly idiosyncratic investment with greater uncertainty in value and greater nontradability.² The performance of the firm's industry-average intangibles, however, is closely aligned with commonly observed industry-wide trends (e.g., wide-spread adoption of information technologies) and is not expected to complicate considerably analysts' task of earnings forecast. Thus, we predict a positive

1 See Lev (2001) for a detailed discussion of these unique economic characteristics of intangibles.

2 By definition, idiosyncratic assets are transaction-specific assets that have little value in their next best use. Hence, idiosyncratic assets have high uncertainty in value and low tradability.

relation between analysts' forecast error and the amount of firms' intangibles that are above the industry norm.

We also expect the information complexity of technology-based intangibles (R&D) to increase with the diversity and innovativeness of the firm's technology portfolio. Diversity increases the time, effort, and skills required on the part of analysts for assimilating intangible information. Technologies of a more innovative nature tend to be associated with more uncertain prospects and are more difficult for analysts to evaluate because they are fundamentally different from the *status quo*. In contrast, we expect intangibles-related regulation (e.g., product filing with the FDA) in the biotech/drug and medical equipment industries to decrease such information complexity, due to increased information transparency of the firm's intangibles (e.g., prospects of new drugs under development). Hence, we predict a positive (negative) relation between analysts' forecast error and the diversity and innovativeness (regulation) pertaining to the firm's technology-based intangibles.

Consistent with our prediction, we find a significantly positive association between analysts' forecast error and the amount of the firm's intangible assets—technology-based intangibles, brand names, and recognized intangibles—that deviate from the industry average. We also find, consistent with our prediction, that the diversity and innovativeness of the firm's technology portfolio are positively associated with analysts' forecast error. The innovativeness of the firm's technology also enhances the positive association between analysts' forecast error and the firm's technology-based intangibles. In contrast, we find a negative association between analysts' forecast errors and intangibles-related regulation that biotech, pharmaceutical, and medical equipment firms are subject to. Regulation that increases the transparency of the firm's innovation process and facilitates the valuation of intangibles also mitigates the positive association between analysts' forecast error and the firm's technology-based intangibles. Taken together, our evidence suggests that the information complexity of intangible assets increases the difficulty of forecasting earnings of intangibles-intensive firms.

This study contributes to our understanding of the information attributes of intangible assets and their impact on users' processing of intangible information. Recent studies focus on

the role of accounting for intangibles and suggest that expensing (vs. capitalizing) intangibles decreases the usefulness of intangible information (Lev and Zarowin, 1999; and Luft and Shields, 2001). We find evidence that holding the accounting treatment constant—uniform expensing of intangible expenditures (e.g., R&D) across all firms—the inherent information complexity of intangibles adversely affects analysts' use of intangible information in forecasting earnings.

Our research is also related to the literature examining the determinants of analysts' forecast error. Prior research finds that analysts' forecast errors are positively related to the complexity of the forecasting task (e.g., Brown, 1993; and Plumlee, 2003). We contribute to this literature by identifying intangibles-related financial and nonfinancial factors as a significant source of information complexity that adversely affects analysts' forecasts. Our results indicate that the level of the firm's intangibles in excess of the industry average and the diversity and innovativeness of the firm's technology-based intangibles complicate analysts' forecasting task, whereas intangibles-related regulation in the biotech/drug and medical equipment industries mitigates intangibles-related information complexity.

The remainder of this paper is organized as follows. Section 2 motivates our hypotheses. In Section 3, we explain the empirical measures and statistical models used in this study. Section 4 describes the sample and data. We report the empirical results in Section 5. Section 6 concludes our study.

2. HYPOTHESIS DEVELOPMENT

We assume that while performing their task analysts face the constraints of economic resources available to them. Accordingly, analysts' earnings forecasts are adversely affected by the cost of information processing and analysis. The cost incurred by analysts (e.g., time and effort required for the forecasting task) is likely higher when analysts process and analyze more complex information relating to the firm's future earnings. Research of decision-making also finds that increased complexity of a task adversely affects judgment quality (e.g., Payne et al., 1988). Therefore, greater errors are expected in

analysts' earnings forecasts for firms that are associated with more complex information.

Compared to tangible (physical and financial) assets, intangible assets are associated with more complex information, due to the high uncertainty in the value of intangibles (will a newly invented technology contribute to future profit?) and fuzzy property rights on the asset (who owns the value of employee training—employer or employee?). The inherently high risk of technology-based intangibles (e.g., R&D) and the difficulty of defining and enforcing property rights of patents are well documented by research.³ The benefits of advertising—a major type of investment in creating valuable brands—are also subject to uncertainty relating to complex internal and external factors (e.g., Picconi, 1977; Aaker and Carman, 1982; and Lilien et al., 1992). Research also finds that, due to the public goods nature of advertising, advertising spending by the firm may strengthen the brands of its competitors (Cabral, 2000), and truthful advertising by the firm can be rendered implausible and useless when advertising by others is deemed false (Hansen and Law, 2004). This externality implies considerable difficulty for advertisers to effectively secure the benefits of advertising.

Many intangibles are also rarely traded on active and transparent markets. Assuming observable and reliable market prices of assets can aid analysts in estimating the future earnings power of the firm, nontradability of intangibles further complicates the task of forecasting earnings for intangibles-intensive firms. This is consistent with accountants' contention that the economic value of intangibles (i.e., ability to generate future earnings) cannot be reliably estimated.⁴ High information complexity of intangibles thus increases the difficulty for analysts to assess the contribution of intangibles to the firm's future earnings. *Ceteris paribus*, the higher the firm's intangible intensity is, the greater the difficulty of forecasting the firm's future earnings.

3 See Lev (2001) for a summary of case and empirical studies on the higher risk of R&D investment than other corporate activities, such as production. Firms investing in technological innovation are also plagued by the difficulty of defining and enforcing property rights of patents, as evidenced by the large number of patent infringement lawsuits and the growing tendency for firms to rely on means other than patenting to protect the value of intangibles (Cohen et al., 2000).

4 For this argument, see FASB (1974).

Intangible assets at the firm level, however, are not all alike. Prior research finds that firms invest in intangible assets with two purposes: to develop new knowledge and to learn about and benefit from the innovation of others (Mowery, 1983; and Cohen and Levinthal, 1989). The need to keep up with the innovation of others dictates that firms spend at levels similar to their industry peers. Homogeneity of the industry-level investment renders the performance of industry-average intangibles similar across firms. Plans to develop idiosyncratic (unique) and strategic intangibles that give firms distinctive competencies, however, call for investment at a rate higher than the industry average (Barney, 1991). This link between the relative intangible intensity and idiosyncrasy is widely recognized in economics research. For example, Titman and Wessels (1988) observe 'firms that sell products with close substitutes are likely to do less research and development since their innovations can be more easily duplicated.' This relation between the lack of idiosyncrasy and differentiation in innovation and below-average R&D intensity is consistent with the rule of intangible investment: basic (radical), highly differentiated research represents early-stage innovation and requires greater outlays with above-average intangible intensity than late-stage, applied research, such as process reengineering (Lev, 2001).⁵

Pioneering innovations are, by nature, highly idiosyncratic activities that command greater initial investment than innovations involving the modification of existing technologies. Due to the lack of readily available benchmarks and other useful information for comparison, this idiosyncrasy likely increases the time and effort on the part of analysts to adequately comprehend the implications of firm-specific intangibles for future earnings. The idiosyncratic nature of firms' above-norm

5 Research on the pattern of R&D spending confirms that firms pursuing competitive strategies of high product and technology differentiation invest more in intangibles, such as specialized R&D projects or technology alliances leading to new products or services (Granstrand, 1998; Cumming and MacIntosh, 2000; Liao and Cheung, 2002; and Giarratana, 2004). Firms introducing new products also tend to use more expensive advertising campaigns (e.g., national television advertising) and innovative promotion approaches (e.g., computerized product demonstrators) and incur substantially higher advertising expenses and R&D expenditures (Dugas, 1984; Fitzgerald, 1989; and Baron, 2004).

intangibles also implies higher risk in value, greater nontradability of such assets, and greater nonavailability of reliable value estimates, thereby further complicating analysts' forecasting task. Thus, we expect that the information complexity of intangible assets is primarily attributable to firms' industry-adjusted intangibles as opposed to industry-average intangibles. Accordingly, we predict a positive association between analysts' forecast error and the firm's intangible intensity in excess of the industry average. This is our first hypothesis (in alternate form):

H₁: Analysts' forecast errors with respect to future earnings are greater for firms that have higher intangible intensity than industry peers.

For firms investing in technology-based intangibles (e.g., research and development of new drugs or software), we expect information complexity to increase with the diversity of the firm's technology. To the extent that investments in intangibles in different technological fields differ in risk and contribution to the firm's future earnings, information complexity is likely greater when firms invest in a more diverse set of technologies.⁶ Because analysts are constrained by time, effort, and expertise, diversity is expected to increase the difficulty of information processing and thus the cost of performing the forecasting task. Hence, we expect a positive association between analysts' forecast error and the degree of diversity in the firm's technology investment portfolio.

Although one may expect diversity to reduce earnings volatility due to a portfolio effect and decrease the difficulty of earnings forecast, this result may not necessarily obtain for technological innovation because, with an objective to increase growth potential, firms do not always intentionally invest in

6 Prior research indicates that the return to technological innovation varies substantially among industries and firms. Lev and Sougiannis (1996) find that the effect of R&D expenditures on future earnings varies considerably by industry, in terms of cumulative effect and the distribution of the effect over time. For example, their analysis shows that the total value-enhancing effect of R&D expenditures for chemical and pharmaceutical firms (with two-digit SIC of 28) is about 35% stronger and also lasts longer (nine years vs. five years) than those for scientific instruments firms (with two-digit SIC code of 38). Confirming the large cross-sectional variation in the economic return to technological innovation, Scherer et al. (1998) find that the reward to innovation process is highly skewed, as success is concentrated in a few firms or products.

technologies with uncorrelated risks—a condition required for the diversification effect to occur.⁷ This is consistent with prior evidence that diversity, along other dimensions of the firm's operation, does not reduce analysts' forecast error. For example, Duru and Reeb (2002) find that international diversity in firms' operations increases analysts' forecast error, due to greater exposure to international economic factors that increase earnings volatility and analysts' unfamiliarity with these factors. Similarly, Haw et al. (1994) find no evidence that industry diversification reduces forecast errors. Therefore, we predict that analysts' forecast errors are greater for firms investing in more diverse technologies. This is our second hypothesis (in alternate form):

H₂: There is a positive association between analysts' forecast errors and the diversity of the firm's technology investment portfolio.

We also expect information complexity to be higher for firms investing in newer technologies or more original innovations. This is consistent with the findings of prior research that newer innovations tend to be associated with more uncertain prospects (e.g., Mansfield and Wagner, 1977). Original or radical innovations also depart more dramatically from existing and matured technologies and industries because they are often aimed at creating fundamental changes in science and technology.⁸ As such, when compared with existing technologies, the lack of useful and applicable benchmarks with respect to customer, competitor, and regulation—and the difficulty in applying conventional tools to evaluate these factors—substantially increases the complexity of projecting the future success of new innovations.⁹ Thus, we predict a positive association between analysts' forecast errors and the extent to which the

7 Firms with more diverse technologies are also likely more active in acquiring new technologies. Because new innovations tend to have more uncertain prospects and are more difficult to assess (as explained more fully in hypothesis 3), diversity is expected to increase forecast error.

8 Economists characterize radical or basic innovations as 'disruptive technologies' or 'discontinuous innovations' as they often enable entire industries or markets to transform, emerge, or disappear (e.g., Christensen, 1997).

9 For corporate examples of how the process of understanding markets for radical innovations is vastly different than the conventional process, see Lynn et al. (1996) and Kaplan (1999).

firm invests in cutting-edge technology-based intangibles, measured by the originality of the firm's ongoing innovation and change in the speed of its innovation. This is our third hypothesis (in alternate form):

H₃: Analysts' forecast errors are greater for firms investing in more original technologies and firms with an increasing speed of innovation.

Information complexity of intangible assets may also vary by the firm's regulatory environment. We expect less complex information relating to the intangibles of biotech and pharmaceutical firms and firms manufacturing equipment used in medical treatment, due to the highly stringent and comprehensive regulatory overview at virtually every stage of new product development of these firms (e.g., FDA approval of new drugs and new medical equipment).¹⁰ Because the research process of these firms is more regulated and more transparent, the progress of innovation and the changes in the value of intangibles are likely more identifiable. Consistent with this, firm-specific data on the drug development phase is found to be useful to investors in assessing the value-relevance of financial statement information (e.g., R&D expenditures) of biotech and pharmaceutical firms (e.g., Shortridge, 2001; and Ely et al., 2002).¹¹ Therefore, we expect that the regulatory overview of product development decreases the information complexity of intangible assets for firms from the biotech, pharmaceutical, and medical equipment industries. Hence, our fourth hypothesis is (in alternate form):

10 For instance, in the biotech and pharmaceutical industry, current regulation defines for all firms four general stages associated with the development of a new drug: discovery, safety tests in animals, human trials, and filing of marketing applications with the FDA. During the stage of human trials of a new drug, an increasingly rigorous FDA approval process is required for each of the three phases of clinical tests on humans. As new drugs move through the testing and approval process, the likelihood of eventual success increases (Siegfried, 1998). Once a new drug is advanced to the commercialization stage subsequent to FDA approval, lower uncertainty is expected concerning factors relevant for future revenue, such as market size (patient population), pricing environment, patent expiration, and arrival of competing products.

11 Prior studies also find that biotech and drug companies are more likely to apply for patents than firms from other industries (Levin et al., 1987; and Cohen et al., 2000). Given the extensive and detailed documentation required in patent applications, this practice is expected to further decrease the information complexity for the intangibles of biotech and drug companies.

H₄: Analysts' forecast errors are significantly smaller for firms from the biotech, pharmaceutical, and medical equipment industries, which are subject to regulatory review of product development.

Hypotheses 2–4 concern the relation between analysts' forecast error and certain nonfinancial characteristics of the firm's technology-based intangibles. It is also possible that these characteristics are related to analysts' forecast error through their interaction with the level of the firm's investment in intangibles. Thus, in addition to the stand-alone measures of these characteristics (diversity of technology, originality of innovation, and regulatory environment), we examine in the test of hypotheses 2–4 the interaction between these nonfinancial factors and the firm's technology-based intangibles or R&D expenditures. Consistent with the hypothesized effect of these factors, we predict that the diversity and innovativeness of the firm's technology increase the positive association between analysts' forecast error and technology-based intangibles, whereas intangibles-related regulation in biotech, pharmaceutical, and medical equipment industries mitigates this association.

3. RESEARCH DESIGN

We study three accounting-based measures of intangible assets: R&D expenditures (RD), advertising expenses (AD), and intangibles recognized on the firm's balance sheet (BI). To examine the association between analysts' forecast error and these measures of intangible assets, we estimate the following regression model:

$$\begin{aligned} AFE_{it+1} = & \alpha_0 + \alpha_1 RD_{it} + \alpha_2 AD_{it} + \alpha_3 BI_{it} + \alpha_4 STDE_{it} \\ & + \alpha_5 LOSS_{it} + \alpha_6 MV_{it} + \alpha_7 COV_{it} + u_{it}, \end{aligned} \quad (1)$$

where AFE_{it+1} is analysts' forecast error for year $t + 1$, defined as the absolute difference between actual future earnings per share of year $t + 1$ ($AEPS_{it+1}$) and median analysts' forecast of earnings per share for that year ($FEPS_{it+1}$), issued six months

after the end of fiscal year t .^{12,13} RD, AD, BI are the firm's intangibles relating to investment in technological innovation (R&D), brand promotion (advertising), and acquisition of intangibles, respectively. Analysts' forecast errors (AFE_{it+1}) are deflated by the stock price as of one month before the release of analysts' earnings forecasts. Similarly, measures of intangible assets are deflated by the firm's market value as of the same date.

Control variables in this model (STDE, LOSS, MV and COV) generally follow prior studies on firm characteristics associated with analysts' forecast error. Prior research finds that forecast errors are greater for firms with more volatile earnings (e.g., Lang and Lundholm, 1996). Following Lang and Lundholm (1996), we use the standard deviation of return on equity computed over the preceding ten years (STDE) to control for the relation between the firm's earnings volatility and analysts' forecast errors. Hwang et al. (1996) find that analysts' forecasts are more biased for loss firms than profitable firms, suggesting greater forecast errors for loss firms. To control for this difference, we include in the model a dummy variable that equals 1 for firms that report negative net income before extraordinary items and 0 otherwise (LOSS). We also include firm size (MV), measured by the logarithm of the firm's market value one month before the release of analysts' earnings forecasts. Analyst coverage (COV) is the number of analysts issuing forecasts used in calculating median forecast. Prior research finds that forecast errors are smaller for larger firms and firms followed by more analysts.

Hypothesis 1 predicts that analysts' forecast errors are greater for firms with intangible intensity above the industry norm. To examine this, we estimate equation (1) while measuring all variables in the equation as deviations from the three-digit SIC industry medians.¹⁴ Thus, coefficient estimates of the

12 To ensure consistency in the definition and measurement of earnings per share (EPS), we use actual earnings per share (AEPS) provided by I/B/E/S.

13 In all tests, we also use analysts' forecast error of year $t + 2$ as the dependent variable of equation (1). Our results are very similar to those based on forecast error of year $t + 1$. Therefore, our conclusions are robust to the horizon of analysts' forecast.

14 For example, the intangibles measures are defined as the firm's reported intangibles minus the industry-average intangibles, where industry-average intangibles are defined as the three-digit SIC industry median value.

intangibles variables (RD, AD and BI) inform whether within industry forecast errors are related to a firm's intangible intensity relative to its industry. This estimation approach is similar to the use of an industry fixed effects model except that industry medians rather than means are used as a benchmark. Our results, however, are not sensitive to the use of industry means as the benchmark in equation (1). We predict positive coefficients on RD, AD and BI (hypothesis 1).

Hypotheses 2–4 predict a positive association between analysts' forecast errors and other complexity-related characteristics of firms' technology-based intangibles (i.e., diversity, innovativeness, and regulatory environment). To test these predictions, we estimate the following regression:

$$\begin{aligned} AFE_{it+1} = & \beta_0 + \beta_1 RD_{it} + \beta_2 AD_{it} + \beta_3 BI_{it} + \beta_4 DIV_{it} + \beta_5 NEW_{it} \\ & + \beta_6 SOI_{it} + \beta_7 REG_{it} + \beta_8 DIV \times RD_{it} + \beta_9 NEW \times RD_{it} \\ & + \beta_{10} SOI \times RD_{it} + \beta_{11} REG \times RD_{it} + \beta_{12} STDE_{it} \\ & + \beta_{13} LOSS_{it} + \beta_{14} MV_{it} + \beta_{15} COV_{it} + v_{it}, \end{aligned} \quad (2)$$

where AFE, RD, AD, BI, STDE, LOSS, MV and COV are defined in the same way as in equation (1). DIV (NEW and SOI) captures the diversity (innovativeness) of the firm's technology-based intangibles, whereas REG indicates whether the firm is subject to regulatory review of product development. The definition and measurement of these proxies are explained below.

Our proxies for the diversity and innovativeness of the firm's technology-based intangibles are based on the characteristics of the firm's patent portfolio. We measure the diversity of the firm's technology (DIV) by the number of technological fields to which the firm's patents belong using the patent classification system of Hall et al. (2001). They aggregate the highly detailed patent classification system developed by the US Patent and Trademark Office (USPTO) into 36 technological categories.¹⁵ We expect greater information complexity for firms with

15 For description purposes, these 36 categories are further aggregated into six main categories: chemical, computers and communications, drugs and medical, electrical and electronic, mechanical, and others. See Appendix 1 of Hall et al. (2001) for a detailed list of the 36 fields and the patent classes they comprise.

greater technological diversity and, therefore, predict a positive coefficient on DIV and its interaction with firm-specific investment in R&D ($DIV \times RD$) (hypothesis 2).

To measure the relative innovativeness of the firm's technology, we employ two indicators based on information of citations made in patent applications. Patent applications contain extensive and detailed documentation of the sources or antecedents of the invention applied for protection and, therefore, provide useful information on the relation between firms' technologies and early inventions.¹⁶ Following Trajtenberg et al. (1997), we use citation data found in patent applications to measure the originality of patented inventions (NEW). Patents citing previous patents that belong to a broader (narrower) set of technologies are expected to be more (less) innovative or of a more original (derivative) nature than those citing early patents from a narrow (broader) set of technologies. Thus, the originality of a patent is calculated as $1 - \sum_j^{n_i} s_{ij}^2$, where s_{ij} denotes the percentage of citations made to patents in class j , out of n_i patent classes. Higher values of NEW denote more innovative or original inventions. For each firm-year, we calculate the average originality measure across all patents applied for by the firm in that year. We predict a positive coefficient on NEW and its interaction with RD ($NEW \times RD$) (hypothesis 3).

Our second proxy for the innovativeness of the firm's technology-based intangibles is based on the technology cycle reflected by the average age of early patents cited in the firm's patent applications, or citation lags. Shorter citation lags suggest that the patent applied by firms is linked to more recent technologies and newer innovation, hence greater speed of innovation. To capture this, we include in equation (2) a measure of the firm's speed of innovation (SOI) computed as $1 - \text{mean citation lags}$ pertaining to patents applied by the firm in year t . Higher values of SOI indicate greater speed of innovation. Hypothesis 3 predicts a positive coefficient on SOI and its interaction with RD ($SOI \times RD$).

16 Prior research finds that analysis of patent citations is a useful way to track the spillover of knowledge in science and technology over time and across different fields (e.g., Jaffe et al., 1993).

We use a dummy variable (REG) to capture the regulatory environment that reduces the information complexity associated with the intangibles of biotech and pharmaceutical firms and firms making medical equipment. REG is set to equal 1 for firms with three-digit SIC of 283 and 384 and 0 otherwise. Hypothesis 4 predicts a negative coefficient on REG and its interaction with RD (REG \times RD).

4. SAMPLE DATA

The test of this study requires sample firms to have data from two sources: the 1999 COMPUSTAT merged annual files and analyst earnings forecasts provided by I/B/E/S. Our analysis of the relation between analysts' forecast errors and firm-specific and industry-average intangibles (hypothesis 1) covers the period 1981–1998 and includes a total of 18,803 firm-years that have the required financial data available from these two sources.¹⁷

Sample firms included in our examination of technology-based intangibles (hypotheses 2–4) are from the patent and citations database compiled by the National Bureau of Economic Research (NBER). This database covers all utility patents granted by USPTO during the period 1963–1999 and provides information on patent applications and citations made and received by each patent. For details on variable definition and measurement concerning the NBER patent database, see Hall et al. (2001). We include in our analysis a total of 6,167 firm-years (752 firms) identified in the NBER database that also have the required data from COMPUSTAT and I/B/E/S for the period 1981–1998. Thus, by construction, this sample is a subset of the sample used in the test of hypothesis 1.

In Table 1, we report descriptive statistics for the variables of interest. The mean (median) analysts' forecast errors relative to stock price are 0.026 (0.007).¹⁸ The mean values of firms' intangibles (RD, AD and BI) are all higher than their medians, indicating substantial concentration in a subset of firms' spending on intangibles. The measures of firms' technology diversity

17 Our sample period started from 1981 because prior to 1981 I/B/E/S covered only a relatively small number of firms.

18 The mean and median forecast errors are both significantly different from zero at the 0.001 level.

Table 1
Descriptive Statistics of Sample Data

<i>Variable</i>	<i>No. Obs.</i>	<i>Mean</i>	<i>Standard Deviation</i>	<i>25%</i>	<i>Median</i>	<i>75%</i>
AFE	18,803	0.026	0.125	0.002	0.007	0.028
RD	18,803	0.047	0.082	0.008	0.026	0.061
AD	18,803	0.035	0.057	0.004	0.024	0.047
BI	18,803	0.053	0.112	0.000	0.001	0.059
STDE	18,803	0.214	0.565	0.038	0.071	0.142
LOSS	18,803	0.129	0.335	0.000	0.000	0.000
MV	18,803	6.113	1.783	4.796	6.047	7.379
COV	18,803	3.105	3.401	1.000	2.000	4.000
DIV	6,167	5.858	5.914	2.000	4.000	8.000
NEW	6,167	1.111	0.451	0.897	1.117	1.358
SOI	6,167	-0.026	0.406	-0.170	0.031	0.197
REG	6,167	0.063	0.254	0.000	0.000	0.000

Notes:

Variable definitions are as follows. AFE is analysts' forecast errors with respect to earnings of year $t + 1$, defined as the absolute difference between analyst earnings forecast and actual earnings of year $t + 1$. We use analysts' forecast of earnings per share issued six months after the end of fiscal year t . Analysts' forecast errors are deflated by stock price per share one month before the release of analysts' forecast. RD is the firm's reported R&D expenditures. AD is the firm's reported advertising expenses. BI is the firm's recognized intangible assets. The measures of intangibles are deflated by market value one month before the release of analysts' forecast. STDE is the standard deviation of historical earnings. LOSS is a dummy variable equal to 1 for loss firms, and 0 otherwise. MV is the natural logarithm of market value one month before the release of analysts' forecast. COV is the number of analysts issuing forecasts used in calculating AFE_{t+1} . DIV is the number of technological fields to which the firm's patents applied in year t belong. NEW is the originality score of the firm's patents applied in year t , computed as $1 - \sum_j^m s_{ij}^2$, where s_{ij} denotes the percentage of citations made to patents in class j , out of n_i patent classes. SOI is the firm's speed of innovation, computed as $1 - \text{mean citation lags in patents applied in year } t$. REG is a dummy variable equal to 1 for biotech and pharmaceutical firms (with three-digit SIC of 283) and firms manufacturing medical equipment (3-digit SIC of 384), and 0 otherwise.

and innovativeness all exhibit considerable cross-sectional variation during the sample period. Firms have a mean (median) number of technological fields (DIV) of 5.858 (4.000), with standard deviation of 5.914. The mean (median) originality score for sample firms' technology innovation (NEW) is 1.111 (1.117), with a standard deviation of 0.451. The mean (median) value of firms' speed of innovation (SOI) is -0.026 (0.031), with standard deviation of 0.406.

Table 2 reports the Pearson and Spearman correlation coefficients among the variables of interest. It shows that analysts' forecast errors with respect to future earnings are positively correlated with the amount of firms' investment in R&D (RD),

Table 2
Correlation Coefficients of Key Variables

<i>AFE</i>	<i>RD</i>	<i>AD</i>	<i>BI</i>	<i>STDE</i>	<i>LOSS</i>	<i>MV</i>	<i>COV</i>	<i>DIV</i>	<i>NEW</i>	<i>SOI</i>	<i>REG</i>
<i>AFE</i>	0.16	0.05	0.07	0.12	0.25	-0.21	-0.12	-0.08	-0.04	0.02	-0.08
<i>RD</i>	0.13	0.12	0.06	0.04	0.31	-0.18	-0.07	0.17	-0.01	0.06	-0.03
<i>AD</i>	0.08	0.08	0.16	0.01	0.08	-0.07	-0.05	-0.01	0.01	-0.01	0.04
<i>BI</i>	0.03	0.01	0.14	0.05	0.06	0.01	0.01	0.03	-0.01	0.02	0.01
<i>STDE</i>	0.33	0.22	-0.07	-0.03	0.14	-0.15	-0.06	-0.06	-0.02	0.01	0.08
<i>LOSS</i>	0.29	0.23	0.03	0.01	0.33	-0.22	-0.08	-0.04	0.00	0.03	0.04
<i>MV</i>	-0.35	-0.11	-0.06	-0.30	-0.22	0.68	0.63	0.66	-0.01	-0.04	0.20
<i>COV</i>	-0.24	-0.06	0.10	-0.10	-0.10	0.68	0.40	0.36	-0.01	-0.03	0.29
<i>DIV</i>	-0.13	0.16	0.03	-0.09	-0.05	0.55	0.40	0.01	0.02	-0.07	0.04
<i>NEW</i>	-0.02	0.01	-0.01	-0.02	-0.01	-0.03	-0.03	-0.04	-0.01	-0.01	-0.01
<i>SOI</i>	0.03	0.05	-0.04	0.04	0.04	-0.03	-0.02	-0.04	-0.06	-0.01	-0.06
<i>REG</i>	-0.18	-0.05	-0.06	0.03	0.04	0.18	0.18	0.08	-0.01	-0.09	

Notes:

Pearson (Spearman) correlation coefficients are reported above (below) the diagonal. Coefficients significantly different from zero at β -values less than 1% (two-tailed test) are in boldface type. Variable definitions are as follows: AFE_{t+1} is analysts' forecast errors with respect to earnings of year $t+1$, defined as the absolute difference between analyst earnings forecast and actual earnings of year $t+1$. We use analysts' forecast of earnings per share issued six months after the end of fiscal year t . Analysts' forecast errors are deflated by stock price per share one month before the release of analysts' forecast. *RD* is the firm's reported R&D expenditures. *AD* is the firm's reported advertising expenses. *BI* is the firm's recognized intangible assets. The measures of intangibles are deflated by market value one month before the release of analysts' forecast. *STDE* is the standard deviation of historical earnings. *LOSS* is a dummy variable equal to 1 for loss firms, and 0 otherwise. *MV* is the natural logarithm of market value one month before the release of analysts' forecast. *COV* is the number of analysts issuing forecasts used in calculating AFE_{t+1} . *DIV* is the number of technology fields to which the firm's patents applied in year t belong. *NEW* is the originality score of the firm's patents applied in year t , computed as $1 - \frac{\sum_{j=1}^{m_t} s_{ij}^2}{m_t}$, where s_{ij} denotes the percentage of citations made to patents in class j , out of m_t patent classes. *SOI* is the firm's speed of innovation, computed as $1 - \text{mean citation lags in patents applied in year } t$. *REG* is a dummy variable equal to 1 for biotech and pharmaceutical firms (with three-digit SIC of 283) and firms manufacturing medical equipment (3-digit SIC of 384), and 0 otherwise.

advertising (AD), and recognized intangible assets (BI). The correlation coefficients are statistically significant at the 0.01 level. We also find that analysts' forecast errors are greater for smaller firms, firms with relatively more volatile past earnings, firms followed by fewer analysts, and firms that report losses. These patterns are consistent with the results of prior research. Table 2 also shows, as expected, that larger firms are likely to have more diverse technology portfolios, but smaller firms are more likely to invest in more innovative technologies and have higher speed of innovation. Correlation between these nonfinancial measures and financial variables other than firm size is generally small.

5. EMPIRICAL RESULTS

Table 3 reports summary statistics from the regression of equation (1). All regression variables are measured as deviations from the three-digit SIC industry medians. Thus, this model regresses within industry forecast errors on firms' intangible intensity that deviates from the industry medians (RD, AD and BI) and industry-adjusted control variables (earnings variability (STDE), status of loss firms (LOSS), firm size (MV), and analyst coverage (COV)). A total of 18,803 firm-years with the required data available are included in this regression. Following the approach of Fama and MacBeth (1973), we estimate the model separately for each sample year and report the mean value and *t*-statistics based on coefficient estimates obtained from 18 separate annual regressions. Since a firm's intangible intensity and thus the absolute magnitude of its forecast errors are likely to be stable from year to year, we follow the procedure employed in Abarbanell and Bernard (2000) to adjust for time-series dependence when computing the standard error and *t*-statistics of the coefficient estimates obtained from the annual regression.¹⁹

19 The Abarbanell-Bernard procedure (Abarbanell and Bernard, 2000) adjusts the standard errors used in the Fama-MacBeth calculations for serial correlation in the coefficient estimates obtained from cross-sectional regressions. This procedure assumes that serial correlation is first-order autoregressive and hence multiplies the unadjusted standard errors by the square root of $\{(1 + \phi)/(1 - \phi) - [2\phi(1 - \phi^n)/n(1 - \phi)^2]\}$, where ϕ is the estimated first-order autocorrelation in the yearly coefficients and $n = 18$ (years). This correction is not applied when the estimated autocorrelation is negative.

Table 3

Mean Coefficient Estimates for Annual Regressions of Analysts' Forecast Error on Firms' Industry-adjusted

Intangible Intensity (*t*-statistics in parenthesis)

$$AFE_{it+1} = \alpha_0 + \alpha_1 RD_{it} + \alpha_2 AD_{it} + \alpha_3 BI_{it} + \alpha_4 STDE_{it} + \alpha_5 LOSS_{it} + \alpha_6 MV_{it} + \alpha_7 COV_{it} + e_{it} \quad (1)$$

<i>Variable</i>	<i>Exp. Sign</i>	<i>Model 1</i>	<i>Model 2</i>	<i>Model 3</i>	<i>Model 4</i>	<i>Model 5</i>
Intercept	+/-	0.019 (8.99)	0.018 (8.89)	0.019 (9.78)	0.016 (7.16)	0.014 (6.76)
RD	+	-	0.281*** (5.37)	-	-	0.275*** (5.13)
AD	+	-	-	0.089*** (2.97)	-	0.072*** (1.87)
BI	+	-	-	-	0.095*** (3.83)	0.091*** (3.51)
STDE	+	0.033*** (3.16)	0.033*** (3.21)	0.033*** (3.15)	0.033*** (3.12)	0.033*** (3.16)
LOSS	+	0.088*** (5.70)	0.076*** (5.52)	0.088*** (5.68)	0.087*** (4.71)	0.075*** (4.52)
MV	-	-0.008*** (-6.97)	-0.008*** (-6.14)	-0.008*** (-6.64)	-0.009*** (-7.14)	-0.008*** (-6.91)

COV	—	0.001 (1.21)	-0.001 (-0.91)	0.001 (1.19)	0.001 (1.24)	-0.001 (-0.99)
No. Obs.		18,803	18,803	18,803	18,803	18,803
Adj. R^2		10.1%	12.9%	11.9%	12.4%	14.2%

Notes:

***, **, * indicate one-tailed statistical significance at the 0.01, 0.05 and 0.1 level, respectively when predicted sign is either '+' or '-' and two-tailed significance otherwise.

Variable definitions are as follows. AFE_{t+1} is analysts' forecast errors with respect to earnings of year $t + 1$, defined as the absolute difference between analyst earnings forecast and actual earnings of year $t + 1$. We use analysts' forecast of earnings per share issued six months after the end of fiscal year t . Analysts' forecast errors are deflated by stock price per share one month before the release of analysts' forecast. RD is the firm's reported R&D expenditures. AD is the firm's reported advertising expenses. BI is the firm's recognized intangible assets. The measures of intangibles are deflated by market value one month before the release of analysts' forecast. STDE is the standard deviation of returns on equity computed over the preceding ten years. LOSS is a dummy variable equal to 1 for loss firms, and 0 otherwise. MV is the natural logarithm of market value one month before the release of analysts' forecast. COV is the number of analysts issuing forecasts used in calculating AFE_{t+1} . All regression variables are measured as deviations from the three-digit SIC industry median value. The standard errors and t -statistics of the coefficient estimates obtained from the annual cross-sectional regressions are adjusted for time-series dependence following the procedure of Abarbanell and Bernard (2000). This procedure assumes that serial correlation is first-order autoregressive and hence multiplies the unadjusted standard errors by the square root of $\{[(1 + \phi)/(1 - \phi)] - [2\phi(1 - \phi^n)/(1 - \phi)^2]\}$, where ϕ is the estimated first-order autocorrelation in the yearly coefficients and $n = 18$ (years). This correction is not applied when the estimated autocorrelation is negative.

As a benchmark for comparison, we first report results from the regression that includes only the control variables (Model 1). We find that, consistent with prior evidence, analysts' forecast errors are positively associated with the volatility of historical earnings (STDE) and the status of loss firms (LOSS), but negatively associated with firm size (MV). The coefficients on these firm characteristics are statistically significant at less than the 0.01 level. The coefficient on analyst coverage (COV), however, is not statistically significant at the conventional level.²⁰ The adjusted R^2 of the model is 10.1%, suggesting that the model explains a meaningful portion of the variation in analysts' forecast errors of the sample firms.

In the remaining regressions of Table 3, we include measures for firms' industry-adjusted intangible intensity relating to R&D, brand names, and recognized intangibles. These measures indicate the extent to which firms' intangible intensity deviates from the industry norm. Model 2 shows that the coefficient on firms' industry-adjusted investment in R&D (RD) is positive (0.281) and statistically significant at the 0.01 level (adjusted t -statistics = 5.37), after controlling for the effect of earnings volatility, status of loss firms, firm size, and analyst coverage. This result is consistent with our prediction that firms' intangibles that are above the industry norm increase analysts' forecast error. Similarly, we find in Model 3 that the coefficient on firms' industry-adjusted intangibles relating to brand names (AD) is positive (0.089) and statistically significant at the 0.01 level (adjusted t -statistics = 2.97). Model 4 also shows a similar result for firms' recognized intangibles that deviate from the industry median level: the coefficient on BI is positive (0.095) and statistically significant at the 0.01 level (adjusted t -statistics = 3.83). Thus, the results based on each individual category of intangibles are consistent with our prediction of a positive association between firms' industry-adjusted intangible intensity and analysts' forecast error (hypothesis 1).

In Model 5, we include all three intangible measures together to assess their joint explanatory power. Consistent with the

20 The insignificant result for COV may be due to the high correlation between firm size and the number of analysts following the firm (higher than 0.60 as reported in Table 2).

results from the individual regressions, the coefficients on the firms' industry-adjusted intangible investment (RD, AD and BI) are positive and statistically significant at the 0.05 level or higher (adjusted *t*-statistics ranging from 1.87 to 5.13). The magnitude of the coefficient estimate does not change appreciably relative to the individual regressions (Model 2–4). These results thus indicate that the errors in analysts' forecast of future earnings are greater for firms that have higher intangible intensity than their industry peers in the areas of technology, brand names, and recognized intangibles.²¹ The evidence is consistent with our hypothesis that the high information complexity associated with the firm's idiosyncratic investment in intangibles increases the difficulty of forecasting earnings. Among the three intangibles examined, the coefficient on R&D expenditures is substantially larger than advertising expenses and recognized intangibles (0.275 vs. 0.072 and 0.091, respectively).²²

A comparison of Model 1 and Model 5 also indicates that including measures of intangible intensity increases the adjusted R^2 of the regression from 10.1% to 14.2%. Thus, information on intangible intensity adds considerably to the explanatory power of the model, suggesting that intangibles are important determinants of analysts' forecast error or accuracy. An implication of this result is that future studies examining analysts' forecast error or accuracy should consider explicitly controlling for the effect of intangible intensity.

Having established the positive association between analysts' forecast errors and firms' intangible intensity that deviate from the industry norm, we now turn to the examination of whether

21 To complement our evidence on the relation between firms' idiosyncratic intangible intensity and analysts' forecast error, we examine whether industries with higher intangible intensity have greater forecast errors than industries with lower intangible intensity. We run a regression similar to equation (1), except that all variables are measured as the three-digit SIC industry median value, and the regression includes one observation per three-digit SIC industry per year. We find that the coefficient on all variables of intangible intensity is statistically insignificant at the conventional level, whereas the coefficient on the control variables is statistically significant at the 0.05 level or higher, except for analyst coverage (COV). We obtain substantively similar results when the three-digit SIC industry mean values are used in estimating this regression. The insignificance of the intangible intensity in these regressions indicates that mean and median forecast errors across industries do not vary significantly with the industry's intangible intensity.

22 The mean and median difference of the coefficient on R&D vs. advertising and recognized intangibles is statistically significant at the 0.001 level.

the diversity, innovativeness, and regulation concerning the firm's technology-based intangibles (R&D) are also associated with analysts' forecast error. We predict that the diversity and innovativeness of the firm's technology increase analysts' forecast error and its association with the level of technology-based intangibles (hypotheses 2 and 3), whereas intangibles-related regulation in the biotech, pharmaceutical, and medical equipment industries has the opposite effect (hypothesis 4). To test these predictions, we estimate the regression of equation (2) and assess the significance of these nonfinancial factors and their interaction with the level of the firm's technology-based intangibles (RD), while controlling for firms' intangible investment (RD, AD and BI), as well as other firm characteristics (earnings volatility, incidence of loss, firm size, and analyst coverage).

Table 4 reports the time-series mean coefficient estimates and associated *t*-statistics from the year-by-year regression of equation (2) for 6,167 firm-years that have the required data available from the NBER database on patents, COMPUSTAT, and I/B/E/S. The standard errors and *t*-statistics of the coefficient estimates are adjusted for time-series dependence following the procedure of Abarbanell and Bernard (2000). We first report coefficient estimates from the regression that includes firms' intangibles (RD, AD and BI) and control variables (STDE, LOSS, MV and COV) (Model 1). This serves as our benchmark regression for this analysis. Model 1 shows that analysts' forecast errors are greater for firms with greater intangible intensity, after controlling for the effects of earnings volatility, the difference between loss and profitable firms, firm size, and analyst coverage. The adjusted R^2 of the regression is 23.4%. In unreported analysis, we find that the adjusted R^2 of the regression without the three intangible variables is 17.3%. Thus, including the intangible measures for this subset of the sample firms also increases the explanatory power of the model.

The remaining regressions of Table 4 examine various nonfinancial factors that are expected to increase the information complexity of technology-based intangibles and hence increase analysts' forecast error. Model 2 focuses on the diversity of the firm's technology portfolio (DIV), measured by the number of technological fields to which the firm's patents belong. Consistent with the prediction of hypothesis 2, the coefficient on DIV is positive

Table 4

Mean Coefficient Estimates for Annual Regressions of Analysts' Forecast Error on Information Complexity of Technology-based Intangibles (*t*-statistics in parenthesis)

$$\begin{aligned}
 AFE_{i,t+1} = & \beta_0 + \beta_1 RD_{it} + \beta_2 AD_{it} + \beta_3 BI_{it} + \beta_4 DIV_{it} + \beta_5 NEW_{it} + \beta_6 SOI_{it} + \beta_7 REG_{it} \\
 & + \beta_8 DIV \times RD_{it} + \beta_9 NEW \times RD_{it} + \beta_{10} SOI \times RD_{it} + \beta_{11} REG \times RD_{it} \\
 & + \beta_{12} STDE_{it} + \beta_{13} LOSS_{it} + \beta_{14} MV_{it} + \beta_{15} COV_{it} + u_{it}
 \end{aligned}
 \tag{2}$$

Variable	Exp. Sign	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Intercept	+/-	0.049 (4.76)	0.049 (4.38)	0.047 (4.27)	0.049 (5.05)	0.050 (5.49)	0.052 (5.53)
RD	+	0.175*** (4.83)	0.147*** (4.15)	0.108*** (4.09)	0.153*** (4.49)	0.171*** (5.68)	0.086*** (2.69)
AD	+	0.015* (1.63)	0.016* (1.69)	0.015* (1.65)	0.015* (1.68)	0.015* (1.60)	0.013* (1.59)
BI	+	0.044** (2.17)	0.047** (2.21)	0.049** (2.30)	0.034** (1.93)	0.047** (2.25)	0.040** (2.14)
DIV	+	-	0.008*** (2.89)	-	-	-	0.006** (2.35)
DIV × RD	+	-	0.003 (1.03)	-	-	-	0.001 (0.85)
NEW	+	-	-	0.003 (0.45)	-	-	0.003 (0.73)
NEW × RD	+	-	-	0.026** (2.09)	-	-	0.030** (2.31)
SOI	+	-	-	-	0.004** (2.07)	-	0.004** (2.18)
SOI × RD	+	-	-	-	0.014* (1.64)	-	0.006* (1.36)

Table 4 (Continued)

Variable	Exp. Sign	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
REG	-	-	-	-	-	-0.009*** (-5.12)	-0.009*** (-5.03)
REG × RD	-	-	-	-	-	-0.024** (-2.13)	-0.025** (-2.20)
STDE	+	0.018*** (2.90)	0.018*** (2.83)	0.018*** (2.82)	0.018** (2.42)	0.018** (2.48)	0.018** (2.41)
LOSS	+	0.036*** (5.44)	0.036*** (5.31)	0.035*** (5.09)	0.036*** (5.39)	0.036*** (5.23)	0.036*** (5.14)
MV	-	-0.005*** (-8.57)	-0.005*** (-8.72)	-0.005*** (-8.89)	-0.005*** (-8.84)	-0.004*** (-8.08)	-0.004*** (-8.03)
COV	-	-0.001 (-0.44)	-0.001 (-0.41)	-0.001 (-0.41)	-0.001 (-0.42)	-0.001 (-0.22)	-0.001 (-0.37)
No. Obs.		6,167	6,167	6,167	6,167	6,167	6,167
Adj. R ²		23.4%	23.7%	24.3%	23.9%	24.2%	24.7%

Notes:

***, **, * indicate one-tailed statistical significance at the 0.01, 0.05 and 0.1 level, respectively when predicted sign is either '+' or '-' and two-tailed significance otherwise.

Variable definitions are as follows. AFE_{t+1} is analysts' forecast errors with respect to earnings of year $t+1$, defined as the absolute difference between analyst earnings forecast and actual earnings of year $t+1$. We use analysts' forecast of earnings per share issued six months after the end of fiscal year t . Analysts' forecast errors are deflated by stock price per share one month before the release of analysts' forecast. RD is the firm's reported R&D expenditures. AD is the firm's reported advertising expenses. BI is the firm's recognized intangible assets. The measures of intangibles are deflated by market value one month before the release of analysts' forecast. DIV is the number of technology fields to which the firm's patents applied in year t belong. NEW is the originality score of the firm's patents applied in year t , computed as $1 - \sum_{j=1}^n s_{jt}^2$, where s_{jt} denotes the percentage of citations made to patents in class j , out of n_j patent classes. SOI is the firm's speed of innovation, computed as $1 - \text{mean citation lags pertaining to patents applied by the firm in year } t$. REG is a dummy variable equal to 1 for biotech and pharmaceutical firms (with three-digit SIC of 283) and firms manufacturing medical equipment (3-digit SIC of 384), and 0 otherwise. DIV × RD equals to DIV times RD. NEW × RD equals to NEW times RD. SOI × RD equals to SOI times RD. REG × RD equals to REG times RD. STDE is the standard deviation of historical earnings. LOSS is a dummy variable equal to 1 for loss firms, and 0 otherwise. MV is the natural logarithm of market value one month before the release of analysts' forecast. COV is the number of analysts issuing forecasts used in calculating AFE_{t+1} . The standard errors and t -statistics of the coefficient estimates obtained from the annual cross-sectional regressions are adjusted for time-series dependence following the procedure of Abarbanell and Bernard (2000). This procedure assumes that serial correlation is first-order autoregressive and hence multiplies the unadjusted standard errors by the square root of $\{[(1 + \phi)/(1 - \phi)] - [2\phi(1 - \phi^n)/n(1 - \phi^2)]\}$, where ϕ is the estimated first-order autocorrelation in the yearly coefficients and $n = 18$ (years). This correction is not applied when the estimated autocorrelation is negative.

(0.008) and statistically significant at the 0.01 level. The coefficient on the interaction of DIV and RD ($DIV \times RD$), while positive (0.003), is not statistically significant at the conventional level.

Model 3 examines whether analysts' forecast errors are positively associated with the originality of the firm's technology (NEW) and its interaction with the level of firm-specific R&D ($NEW \times RD$). The results show that, while the coefficient on NEW is not statistically significant, the coefficient on the interaction term $NEW \times RD$ is positive (0.026) and statistically significant at the 0.05 level. The originality or innovativeness of the firm's technology thus increases the association between analysts' forecast error and the firm's investment in R&D. In the regression of Model 4, we focus on our second indicator for the innovativeness of the firm's technology, the speed of innovation (SOI) computed as $1 - \text{mean citation lags}$ pertaining to patents applied for by the firm in year t , and its interaction with firms' R&D expenditure ($SOI \times RD$). We find a positive coefficient on SOI (0.004) and $SOI \times RD$ (0.014) that is statistically significant at the 0.05 and 0.1 level, respectively. This evidence is consistent with the prediction of hypothesis 3 that the innovativeness of the firm's technology increases analysts' forecast error and its association with the firm's technology-based intangibles.

In Model 5, we provide evidence on the effect of intangibles-related regulation in the biotech, pharmaceutical, and medical equipment industries (REG). Consistent with the prediction of hypothesis 4, the coefficient on REG is negative (-0.009) and statistically significant at the 0.01 level. The coefficient on the interaction term $REG \times RD$ is also negative (-0.024) and statistically significant at the 0.01 level. Thus, analysts' forecast errors are smaller for firms in the biotech, pharmaceutical, and medical equipment industries, due to regulations that increase the transparency of firms' innovation process and facilitate the valuation of firms' intangibles.²³

23 While our evidence on the effect of the regulation factor (REG) is based on 6,167 firm-years with patent-related data available, we expect this to occur for the general population of biotech, pharmaceutical, and medical equipment firms. To confirm this, we expand the regression reported in Table 3 to include REG and its interaction with firm-specific investment in R&D (RD). In unreported analyses, we find a negative and statistically significant coefficient on REG (-0.023 , t -statistics = -4.80) and the interaction term $REG \times RD$ (-0.036 , t -statistics = -3.93).

Our final regression (Model 6) includes all four indicators for the information complexity of technology-based intangibles (DIV, NEW, SOI and REG) and their interaction with the level of firms' investment in R&D (RD). The results are consistent with earlier regressions: the diversity and innovativeness of the firm's technology increase analysts' forecast error, whereas intangibles-related regulation decreases analysts' forecast error. There is also a positive (negative) interactive effect between innovativeness (regulation) and the level of firm-specific investment in R&D. Taken together, our evidence indicates, consistent with our predictions, that these nonfinancial characteristics of the firm's technology-based intangibles are associated with the difficulty of earnings forecast.

6. SUMMARY AND CONCLUSIONS

In this study, we examine the relation between analysts' earnings forecast error and the firm's intangible intensity, including technology-based intangibles, brand names, and recognized intangibles. Because information on intangible assets is more complex, we expect analysts' forecast error to be greater for firms with higher intangible intensity relative to the industry's average value. Consistent with this prediction, we find a positive association between analysts' forecast error and the firm's intangible intensity that deviates from the industry's median value. Industries with greater intangible intensity, however, do not have greater forecast errors than industries with lower intangible intensity. We also find that the diversity and innovativeness of the firm's technology increase analysts' forecast error and its association with the firm's technology-based intangibles, whereas intangibles-related regulation in the biotech, pharmaceutical, and medical equipment industries decreases analysts' forecast error and its association with technology-based intangibles. Taken together, the results of this research suggest that the level of firm-specific investment in intangibles that deviates from the industry norm, the diversity and innovativeness of the firm's technology, and intangibles-related regulation are associated with the information complexity of intangible assets that affects analysts' abilities to assimilate the information.

Like other types of investment, firms' investment in intangibles is an endogenous decision likely driven by fundamental characteristics of firms' operating environment such as expected profitability and growth opportunities. Because analysts' forecast errors are also likely affected by these same characteristics, a simultaneous equation model is theoretically appropriate for examining the relation between intangible investment and analysts' forecast errors. This approach calls for the use of reliable instruments in the first stage regression. However, because even the best available instruments, such as expected profitability and growth prospects, are largely unobservable to researchers, the first stage regression would have low explanatory power, thus substantially limiting what can be learned from the test. Hence, a caveat to this study is that we do not formally correct for endogeneity in our statistical tests. This endeavor may be attempted by future research. Nevertheless, this study can be a first useful step towards a more comprehensive understanding of the effect of intangibles-related information complexity on analysts' processing of intangible information.

Because intangible assets are taking an increasingly larger share of firm value and current accounting rules do not require separate reporting about their performance, analysts are expected to play an important role as information intermediaries between high-intangibles firms and investors. We find that the information complexity of intangible assets adversely affects earnings forecasts of analysts. Complex information on intangibles thus imposes a cost on even expert users. Our evidence suggests that current efforts by regulators and standard-setters to improve disclosure about intangible assets may need to consider differential information complexity associated with different types of intangible assets.

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