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Do financial analysts get intangibles?

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ABSTRACT

It is widely agreed that corporate financial reports provide deficient information about intangible assets. However, investors are exposed to substantial information beyond financial reports, such as managers' direct communications to capital markets and analysts' reports. We ask: To what extent do these non-financial report sources compensate for the intangibles-related deficiencies of financial statements?

To address this question we assume that analysts' forecasts of earnings reflect, among other things, the beyond-financial-report information we seek, and we use simultaneous equations to estimate the incremental information contribution of earnings forecasts over the information contained in financial reports, thereby isolating value-relevant information not available in financial reports. We focus particularly on intangibles-related information, by comparing analysts' contribution for firms with and without R&D. We find that, to some extent, analysts do compensate for the intangibles-related information deficiencies of financial reports, but definitely not for all the deficiencies. Accordingly, we identify the 'weakest links' – industries in which analysts do not get intangibles.

1. INTRODUCTION

A major theme of research and policy-makers' work on intangible assets concerns the information deficiencies of the financial reports of intangibles-intensive companies (e.g. Lev, 2001). The almost universal expensing of intangible investments (e.g. research and development (R&D) costs, brands, employee training), and the general absence of meaningful footnote disclosure about these investments and their consequences (e.g. revenues from recently

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introduced products, or the impact of training on employee turnover and productivity) are the major factors responsible for these deficiencies in reporting. Given the dominance of intangibles in the assets of modern corporations and the importance of relevant and timely information disclosure to optimal resource allocation in capital markets, it is not surprising that policy-makers and accounting standard-setting bodies (e.g. Financial Accounting Standards Board (FASB) and International Accounting Standards Board (IASB)) are actively considering proposals to enhance information on intangibles in corporate financial reports.

Much of the evidence on the information deficiencies of intangibles-intensive companies comes from an analysis focused on financial reports. For example, Lev *et al.* (2002) provided evidence that by adjusting book values of companies for the capitalization and amortization of R&D (namely, undoing the expensing of R&D), one can both report improved earnings that are better predictors of future earnings and generate profitable investment strategies.

However, a thorough analysis of intangibles-related information deficiencies and the suitable consequent policy actions cannot be restricted to corporate financial reports. Investors in developed economies are exposed to substantial information beyond financial reports. Corporate executives communicate often and directly with investors via conference calls and news releases, and financial analysts provide investors with extensive firm and industry analyses, as well as forecasts of key performance indicators (earnings, sales). The relevant question, therefore, is the following: To what extent do these non-accounting information sources, extending beyond financial reports, compensate for the intangibles-related deficiencies of corporate financial statements? Obviously, the more effective is the non-accounting information in compensating for financial report deficiencies, the less urgent the obligation to reform current accounting and disclosure procedures, and the weaker the need for significant regulatory interventions.

Accordingly, the objective of our study is to assess the contribution of information sources beyond financial reports to investors' decisions concerning intangibles-intensive enterprises. We measure this beyond-financial-report information by the incremental contribution of analysts' earnings forecasts to investors' decisions, relative to that available from financial reports alone. Presumably the information possessed by analysts is derived from both financial reports *and* other sources. We estimate the incremental contribution of analysts to investors' decisions in a novel way. It is widely known that financial analysts not only provide investors with new information, but also learn from past investors' decisions by observing stock prices. That is, analysts observe stock price changes, and incorporate this information in their analyses and forecasts.[1] This information feedback – from analysts to investors and simultaneously from investors (via prices) to analysts – calls for a simultaneous regression approach to isolate analysts' unique contribution to investors from what analysts learn from investors. We perform such a simultaneous analysis.

To address our main research question – Do analysts compensate for the intangibles-related information deficiencies of financial reports? – we compare the extent of analysts' incremental contribution over financial reports between intangibles-intensive companies and those possessing low levels of intangibles. If indeed analysts compensate for financial report deficiencies, then their information contribution to investors should be larger in intangibles-intensive companies than in other companies.

Our findings from a large sample of US companies indicate the following: (a) Analysts' incremental contribution over financial reports is indeed larger in intangibles-intensive companies than in companies with low levels of intangibles, indicating that the much-discussed intangibles-related financial report deficiencies are partially compensated for by other information sources. (b) Analysts' incremental information contribution in the 1990s was significantly larger than that in the 1980s, indicating that analysts increasingly 'get intangibles'. (c) However, while we document that analysts compensate for some intangibles-related financial report deficiencies, it is evident that this compensation is far from complete, particularly in certain important industries that we identify. Specifically, we find that analysts' forecast errors are associated with R&D intensity, indicating that they do not fully account for the impact of R&D on future profitability. This then calls for continued vigilance of researchers and policy-makers concerning accounting deficiencies related to intangibles.

The study proceeds as follows: The next section discusses our empirical design, defines our variables and discloses our data sources. Section 3 presents results for the total sample, while Section 4 focuses on intangibles-intensive companies. Section 5 concludes the study.

2. EMPIRICAL DESIGN AND DEFINITION OF VARIABLES

Studies that examine the value-relevance of accounting information often use a common methodology – tests of the association between accounting numbers and capital market values (e.g. Collins *et al.*, 1997; Lev and Zarowin, 1999). These studies draw conclusions about the relevance of information to investors from contemporaneous and intertemporal regressions. The information set generally associated with stock prices and returns often includes earnings numbers and other relevant variables. We follow this tradition and regress stock returns on three sets of information items: (a) annual earnings; (b) the various fundamental signals identified by Lev and Thiagarajan (1993) as value-relevant to analysts and investors, hereafter the LT signals;[2] and (c) the present value of earnings forecasted by analysts. We list the LT signals used in the present study to capture financial statement information beyond earnings:

1 *INV* – percentage annual change in inventory minus the percentage change in sales. A positive value of this measure generally indicates an unusual inventory build-up, often due to shortfalls in expected sales and

slow-moving inventory, implying high inventory holding costs and lower future earnings.

2 *AR* – percentage annual change in accounts receivable minus the percentage change in sales. A positive value of this measure suggests difficulties in collection from customers, deterioration in the quality of receivables and future losses from customer defaults.

3 *GM* – percentage annual change in sales minus the percentage change in gross margin (sales minus cost of sales). A positive value suggests deteriorating operating efficiency and loss of cost controls, adversely affecting future earnings.

4 *SGA* – percentage annual change in selling and administrative expenses minus the percentage change in sales. A positive value suggests loss of managerial control over general expenses.

5 *ETR* – change in the annual effective tax rate times pretax income. This is a measure of the contribution to earnings of the change in the effective tax rate, which is often temporary.

The two sets of financial statement variables – earnings and the LT signals – define the benchmark against which the contribution of analysts' earnings forecasts is assessed. By adding the present value of earnings forecasts to the financial report variables, we can estimate the incremental contribution of analysts' information (and, by implication, the information beyond financial reports) to securities valuation. The full model is thus:

$$\begin{aligned} ARET_{it} = \alpha_{0t} + \alpha_{1t}EPS_{it} + \alpha_{2t}INV_{it} + \alpha_{3t}AR_{it} + \alpha_{4t}GM_{it} \\ + \alpha_{5t}SGA_{it} + \alpha_{6t}ETR_{it} + \alpha_{7t}PVE_{it} + \varepsilon_{it} \end{aligned} \quad (1)$$

where the following definitions pertain: $ARET_{it}$ denotes firm *i*'s annual abnormal stock return (measured as raw return minus beta (systematic risk) times an average risk premium) during year *t*. The return cumulation period spans the twelve months, ending four months after fiscal year-end (to include in the return the publication of year *t* financials). EPS_{it} is earnings per share deflated by share price at the beginning of the return cumulation period. The five LT signals (INV_{it}, AR_{it}, GM_{it}, SGA_{it} and ETR_{it}), defined above, bear coefficients that are expected to be negative by design (any positive measure implies bad news). Finally, PVE_{it} denotes the present value of analysts' forecasts of earnings, deflated by share price at the beginning of the return cumulation period.[3]

Strictly speaking, equation (1) implies that investors obtain information (represented by the dependent variable – stock return) from both accounting and financial analyst sources. But what if there is a feedback: analysts provide investors with information, and also learn from investors? Specifically, a question frequently discussed in the media is whether analysts recommend stocks solely on the basis of independent research, or whether they adjust their recommendations and earnings forecasts to observed stock price changes.[4] To the extent that analysts learn from stock prices, equation (1) overstates the incremental contribution of analysts' forecasts to investors, since it ignores the information analysts derive from observing stock price behaviour (Lys and Sohn, 1990; Abarbanell, 1991).[5]

To accommodate the information feedback from investors to analysts, we construct the following model of the determinants of analysts' earnings forecasts, which includes our proxies for the financial information available to analysts (earnings and the LT signals) as independent variables, along with the current and lagged stock returns (price changes) – $ARET_{it}$ and $ARET_{i,t-1}$ – from which analysts presumably learn:

$$PVE_{it} = \beta_{0t} + \beta_{1t}ARET_{it} + \beta_{2t}ARET_{i,t-1} + \beta_{3t}EPS_{it} + \beta_{4t}INV_{it} + \beta_{5t}AR_{it} + \beta_{6t}GM_{it} + \beta_{7t}SGA_{it} + \beta_{8t}ETR_{it} + \eta_{it} \quad (2)$$

Equations (1) and (2) are solved *simultaneously* to determine the incremental contribution of analysts' earnings forecasts beyond the financial report information. Given that analysts observe both financial information and stock returns, and investors observe both financial information and analysts' forecasts, the contribution of analysts to investors beyond financial information is ascertained by solving equations (1) and (2) simultaneously. We thus estimate both equations using the two-stage-least-squares (2SLS) technique.

The 2SLS estimation requires identification of the endogenous and instrumental variables in the system. We define the endogenous variables as $ARET_{it}$ and PVE_{it}. The instrumental variables are the following: the annual change in the present value of analysts' forecasts of earnings ($dPVE_{it}$), the firms' book-to-market ratio at the beginning of the return period ($BTM_{i,t-1}$), firm size (logarithm of market value of equity), as well as the current and lagged levels of earnings, the LT signals and stock returns (EPS_{it}, $EPS_{i,t-1}$, INV_{it}, AR_{it}, GM_{it}, SGA_{it}, ETR_{it} and lagged $ARET_{i,t-1}$). In addition, we use yearly dummies (1982–2000) as instruments to account for time effects.

We retrieved stock returns from the CRSP database, financial information from Compustat, and analysts' earnings forecasts from I/B/E/S. We focus on abnormal (excess) stock returns, calculated as follows:

$$ARET_{it} = RAW\ RETURN_{it} - R_{Ft} - (0.03)BETA_{it}$$

where *BETA* is calculated from stock returns from the prior 60 months (minimum 24 observations), the risk-free rate (R_{Ft}) is the return on a 20-year government bond and the equity risk premium is assumed at 3%.[6] Earnings level (EPS_{it}) is measured as earnings per share (Compustat item 58), and the earnings change ($dEPS_{it}$) is measured as the annual change in earnings per share. Both variables are scaled in the various regressions by share price eight months prior to fiscal year-end.

The present value of analysts' forecasted earnings (PVE_{it}) is calculated in three stages: First, we obtain the most recent earnings forecasts made for each firm-year in the sample prior to the end of the fourth month after fiscal year-end (the end of our return cumulation period), to ensure that analysts observed the most recent financial information and stock returns. Then, we calculate for each firm-year the future value of earnings forecasts, assuming a five-year horizon. Analysts' annual earnings forecasts for all future five years are available for only 5% of the sample firms. Generally, analysts provide explicit annual forecasts for the upcoming two to three years and a five-year earnings growth rate forecast. In case of missing annual earnings forecasts for any of the next five years, we substitute for the missing values forecasts derived from analysts' five-year growth rates.

In the second stage, we calculate the future value of dividends, assuming a fixed dividends payout (no change in dividends over the next five years). In the third stage of the computation, we combine the future values of earnings and dividends and discount them back to the present using the firm's estimated cost of capital. Finally, we scale the present value of forecasted earnings by the share price eight months prior to fiscal year-end:

$$PVE_{it} = \rho_{it}^{-5}\{E_t[Future\ Earnings] + E_t[Future\ Dividends]\}/P_{i,t-1} \qquad (3)$$

The discount factor, ρ_{it}, is computed as one plus the firm-specific risk-adjusted cost of equity capital:

$$\rho_{it} = 1 + R_{Ft} + (0.03)BETA_{it}$$

Our tests also involve classifying the sample firms by the size of R&D capital ($RNDCAP_{it}$), which is measured as follows:

$$\begin{aligned} RNDCAP_{it} = {} & (0.9)RND_{it} + (0.7)RND_{i,t-1} + (0.5)RND_{i,t-2} \\ & + (0.3)RND_{i,t-3} + (0.1)RND_{i,t-4} \qquad (4) \end{aligned}$$

This simple and uniform capitalization of R&D assumes a 20% annual amortization rate, implying a five-year useful life of R&D (roughly the industry average estimated in Lev and Sougiannis (1996)), and a straight-line amortization method. (We also assume that R&D is spent in the middle of the year, hence the 10% amortization of current R&D in equation (4).)

3. EMPIRICAL RESULTS: TOTAL SAMPLE

Table 1 presents descriptive statistics for the full sample (Panel A), descriptive statistics by year (Panel B) and a correlation matrix (Panel C) for the variables used in this study. Data are available for 1977–2000. We use the first five years of data to calculate R&D capital, leaving 43,935 firm-year observations during the

Table 1 Descriptive statistics (period: 1982–2000; 26,521 observations with full data)

Variable	*Mean*	*Median*	*Std dev.*	*First quartile*	*Third quartile*	*No. of observations*
Panel A: Descriptive statistics for the full sample						
ARET	0.03	−0.03	0.46	−0.27	0.25	43,935
PVE	0.48	0.45	0.32	0.30	0.62	43,935
dPVE	0.03	0.03	0.34	−0.07	0.12	43,935
EPS	0.05	0.06	0.11	0.03	0.09	43,935
dEPS	0.01	0.01	0.12	−0.02	0.03	43,935
BETA	1.13	1.02	0.53	0.81	1.40	43,935
Rho (ρ)	1.12	1.11	0.03	1.10	1.13	43,935
INV	0.02	−0.02	0.53	−0.19	0.15	34,034
AR	0.01	−0.00	0.30	−0.12	0.12	41,001
GM	−0.01	−0.00	0.19	−0.06	0.06	42,179
SGA	0.01	0.01	0.18	−0.07	0.09	34,070
ETR	−0.00	0.00	0.05	−0.00	0.01	40,127

Panel B: Yearly data

Year	*N*	*SIZE (mean)*	*EPS (median)*	*EPS < 0 (N)*	*RAW RETURN (median)*
1982	946	5.28	0.11	43	−0.10
1983	956	5.44	0.09	104	0.52
1984	1,043	5.64	0.08	112	−0.01
1985	1,103	5.42	0.08	89	0.12
1986	1,120	5.58	0.08	170	0.30
1987	1,137	5.62	0.06	180	0.11
1988	1,089	5.57	0.07	134	−0.04
1989	1,161	5.62	0.09	112	0.15
1990	1,258	5.64	0.08	153	−0.04
1991	1,282	5.42	0.06	166	0.13
1992	1,310	5.83	0.07	217	0.15
1993	1,402	5.96	0.05	235	0.11
1994	1,479	5.98	0.05	247	0.05
1995	1,629	5.92	0.06	205	0.09
1996	1,792	6.00	0.06	268	0.19
1997	1,715	6.02	0.06	260	0.11
1998	1,876	6.27	0.04	404	0.24
1999	2,235	6.20	0.04	447	−0.15
2000	1,988	6.32	0.05	407	−0.07

Table 1 (*continued*)

Panel C: Pearson (above diagonal) and Spearman (below diagonal) correlation coefficients, *r*

Variable	*ARET*	*EPS*	*PVE*	*INV*	*AR*	*GM*	*SGA*	*ETR*
ARET		0.22	0.31	−0.04	0.02	−0.14	−0.13	0.03
EPS	0.29		0.53	−0.02	0.02	−0.24	−0.17	0.16
PVE	0.36	0.69		−0.03	0.01	−0.15	−0.10	0.04
INV	−0.05	−0.05	−0.04		0.11	0.02	0.16	0.01
AR	0.03	0.01	0.01	0.13		−0.01	0.10	0.01
GM	−0.17	−0.24	−0.16	0.05	−0.02		−0.09	−0.03
SGA	−0.12	−0.17	−0.10	0.18	0.10	−0.18		−0.03
ETR	0.02	0.03	0.02	−0.01	0.02	−0.02	−0.03	

Notes:

Variables are defined as follows:

1 *ARET* – abnormal stock return, measured as annual stock returns minus the annual risk-free rate and minus equity beta multiplied by equity risk premium. Stock returns are taken from CRSP. The return period is from eight months prior to fiscal year-end to four months after fiscal year-end (FYE − 8 to FYE + 4). Risk premium is equal to 3%.

2 *PVE* – present value of expected earnings per share (assuming dividends are reinvested) over a five-year horizon, divided by share price eight months prior to fiscal year-end. We use all available analysts' earnings forecasts and forecasted long-term growth (*GR*) in our analysis. Expected earnings per share *n* periods from now are calculated as the median I/B/E/S forecast made four months after fiscal year-end. We discount expected earnings using a firm-specific discount rate (ρ), calculated as risk-free rate plus beta multiplied by a risk premium of 3%.

3 *dPVE* – change in the present value of expected earnings per share (assuming dividends are reinvested) over a five-year horizon, divided by share price eight months prior to fiscal year-end.

4 *EPS* – earnings per share (Compustat item 58) divided by share price eight months prior to FYE.

5 *dEPS* – changes in earnings per share divided by share price eight months prior to FYE.

6 Lev and Thiagarajan (1993) signals (LT) are measured as follows: *INV* – percentage change in inventory minus the percentage change in sales; *AR* – percentage change in accounts receivable minus the percentage change in sales; *GM* – percentage change in sales minus the percentage change in gross margin; *SGA* – percentage change in selling and administration expenses minus the percentage change in sales; *ETR* – change in the effective tax rate relative to the mean effective tax rate in the last three years, multiplied by the change in earnings per share.

7 *BETA* – firm-specific beta calculated from CRSP at the end of the third month following fiscal year-end. Beta values above 3 are set equal to 3.

8 ρ – one plus the firm-specific risk-adjusted cost of equity capital. This variable is calculated as $\rho = 1 + R_F + (0.03)BETA$. R_F is taken from 20-year income bonds.

period examined, 1982–2000. This number of firm-year observations is reduced to the final sample of 26,521 firm-year observations that possess all of the financial, stock return and earnings forecast data used in the study.

Panel A indicates that the mean abnormal stock return is 0.03 (should be zero for a representative sample). This is probably due to a relatively small number of large observations, because the median is negative (−0.03). The positive mean return is consistent with a positive mean value of *BETA* (1.13), although the median *BETA* is, as expected, close to 1. The mean (median) present value of the five-year analysts' forecasts of earnings scaled by price (*PVE*) is 0.48 (0.45), implying that discounted earnings for the upcoming five years account for close to half the share price. Mean (median) earnings per share, *EPS*, accounts for 5% (6%) of lagged share price, indicating a typical price–earnings ratio of about 16.

According to Panel B, the number of sample firms in each year increases almost monotonically. Firm size, measured here as the natural logarithm of market value of equity, increases as well. Median earnings per share scaled by lagged share price, *EPS*, decline during the sample period from a high of 0.11 in 1982 to a low of 0.04 in 1999, reflecting the steady increase in the number of companies in the sample with negative earnings. This indicates the introduction to capital markets of an increasing number of young, intangibles-intensive companies whose reported earnings (after the expensing of intangibles) are negative. Finally, median annual raw return varies significantly during the sample period, ranging from a high of 0.52 to a low of −0.15.

As Panel C reports, the present value of earnings forecasts (*PVE*) has the highest correlation with abnormal stock returns (Pearson's $r = 0.31$, Spearman's $r = 0.36$). The correlation between current and expected earnings, *EPS* and *PVE*, is high (Pearson's $r = 0.53$, Spearman's $r = 0.69$), reflecting the persistence of earnings. The LT signals *INV*, *GM* and *SGA* are negatively correlated with abnormal returns, as expected by construction.

3.1. Analysts' information contribution

Table 2 provides the estimates and statistics from the system of equations (1) and (2) run for the entire sample over the period 1982–2000. The table reports four ordinary-least-squares (OLS) regressions and one system of simultaneous regressions (the two 2SLS equations). The top two regressions in Table 2 report the results of estimating equation (1), with and without the present value of earnings forecasts (*PVE*). Results appear to indicate that the incremental contribution of analysts' forecasts in terms of increased R^2 is substantial: The value of R^2 increases from 0.16 in the second equation to 0.21 in the first – a gain of 31%. As already indicated, however, this 'incremental contribution' is overstated, since it includes the feedback from stock returns to analysts' forecasts. Indeed, the regression summarized in the bottom of Table 2 clearly indicates that both current and lagged stock returns (*ARET* and lag *ARET*) have a positive and very significant effect on analysts' forecasts (the dependent variable). Regression 1 − 2SLS (second from the bottom of Table 2), which accounts for the feedback, yields $R^2 = 0.19$. Thus, the incremental contribution of analysts to investors, beyond the information of financial reports (and accounting for what analysts learn from investors), is estimated by an increase of R^2 from 0.16 (equation 1 − OLS) to 0.19 (1 − 2SLS). This contribution is modest indeed.[7]

The estimates in the first two regressions of Table 2 also highlight the association between abnormal returns and the LT signals. The coefficients on inventory (*INV*), gross margin (*GM*), and sales and administrative expenses (*SGA*) are negative, as expected, and significant at the 0.01 level, indicating that

Table 2 The contribution of analysts' to equity valuation (total sample, 1982–2000)

Model	*Dependent variable*	*ARET*	*Lag ARET*	*EPS*	*INV*	*AR*	*GM*	*SGA*	*ETR*	*PVE*	R^2 *(N)*
1−OLS	*ARET*			0.19	−0.02	0.04	−0.25	−0.28	0.07	0.40	0.21
	t-statistic			6.42	−3.29	4.88	−17.80	−19.13	1.30	40.62	(26,521)
1−OLS	*ARET*			0.75	−0.02	0.04	−0.27	−0.30	−0.05		0.16
	t-statistic			28.92	−4.00	5.02	−18.87	−20.15	−0.84		(26,521)
2−OLS	*PVE*	0.15	0.03	1.29	−0.01	−0.00	−0.01	−0.01	−0.29		0.38
	t-statistic	41.02	9.09	81.91	−2.32	−0.23	−1.08	−0.80	−8.64		(26,521)
2−OLS	*PVE*			1.42	−0.01	0.01	−0.06	−0.06	−0.29		0.34
	t-statistic			90.03	−3.33	1.17	−6.54	−6.52	−8.71		(26,521)
1−2SLS	*ARET*			−0.18	−0.01	0.04	−0.23	−0.26	0.15	0.66	0.19
	t-statistic			−4.80	−2.58	4.55	−16.44	−17.81	2.61	34.20	(26,521)
2−2SLS	*PVE*	1.43	0.09	0.29	0.02	−0.06	0.35	0.39	−0.21		0.13
	t-statistic	35.52	9.95	5.91	2.59	−4.65	15.03	15.92	−2.70		(26,521)

Notes:

Table 2 presents results for the entire sample (26,521 firm-year observations) and for the entire sample period (1982–2000). The first and second models in the table contain ordinary-least-squares (OLS) estimation results for the reduced and full forms of equation (1), respectively. The reduced form of equation (1) forces the coefficient on *PVE* to be zero. The third and fourth models contain OLS estimation results for the full and reduced forms of equation (2), respectively. The reduced form of equation (2) forces the coefficients on *ARET* and Lag *ARET* to be zero. The fifth and sixth models contain two-stage-least-squares (2SLS) estimation results for equation systems (1) and (2). Each model contains year-fixed effects. See Table 1 for variable definitions.

abnormal increases in inventory and *SGA* expenses (relative to sales), and abnormal decreases in gross margin, are viewed negatively by investors. Counter to expectations, however, the coefficient on *AR* is positive and significant at the 0.01 level, and the coefficient on *ETR* is not reliably different from 0.[8] The third and fourth equations in Table 2 (2 – OLS) indicate a strong negative association between *PVE* (present value of analysts' forecasts) and four of the five LT signals. It is clear that both investors and analysts benefit from traditional financial statement analysis, as reflected by the LT signals.

3.2. Sample sub-periods and loss firms

Several recent studies indicated that the value-relevance of financial reports has decreased over the final quarter of the twentieth century (e.g. Lev and Zarowin, 1999). Relating to these studies, we examine changes over time in the contribution of financial analysts to equity valuation by dividing our sample into two sub-periods: 1982–90 and 1991–2000. Also, prior research (Hayn, 1995; Amir and Lev, 1996) indicated that earnings of profitable firms convey relatively more information than those of loss-reporting firms. The reason: reported losses are problematic for valuation purposes since for going-concern enterprises losses are clearly temporary, and no reasonable multiple can be assigned by investors to negative earnings. It is interesting, therefore, to examine whether analysts' information contribution is enhanced when they cover loss-reporting companies. We, accordingly, estimate analysts' contribution for two sample periods along with observations classified to positive and negative earnings. Regression estimates for the two sub-periods, and for firms with positive and negative earnings, are reported in Table 3. For brevity, we omit the estimated regression coefficients and focus on adjusted-R^2 values.

We note in Table 3 that the frequency of loss observations ('percentage loss') has increased from 11% in the 1980s to 17% in the 1990s, reflecting the entry to capital markets of many intangibles-intensive companies (software, biotech, etc.), many of which report losses because of the immediate expensing of intangibles. Consistent with prior evidence (Lev and Zarowin, 1999), the explanatory power (R^2) of equation (1) in a 'reduced form' that regresses returns on earnings and LT signals only decreased from 0.27 in the 1980s to 0.11 in the 1990s (all firms). From the R^2 values of equation (1) in its 'full form' (including earnings forecasts), estimated by 2SLS, it is clear that analysts were not particularly successful in arresting the deterioration that took place in the 1990s in the informativeness of financial information. As indicated by the results of the 2SLS regression shown in the right-most column in Table 3, the value of R^2 for all firms (0.31) in the 1980s decreased to 0.15 in the 1990s, which is a similar rate of decrease to that of the R^2 values without analysts' forecasts: 0.27 to 0.11 (Table 3, second column from right).

Consistent with previous findings, we note that financial statements of profitable firms convey more information to investors than those of loss-reporting firms: The

Table 3 Analysts' contribution to equity valuation: sub-periods and profit versus loss firms

Sample	*N*	*Size*	*Percentage loss*	*R^2, equation (1) (reduced form, OLS)*	*R^2, equation (1) (full form, 2SLS)*	*Percentage analysts' contribution*
Total sample, 1982–2000	26,521	5.84	15%	0.16	0.19	19%
Total sample, Profit firms	22,568	6.01		0.17	0.20	18%
Total sample, Loss firms	3,953	4.90		0.09	0.12	33%
1982–90, All firms	9,813	5.38	11%	0.27	0.31	15%
1982–90, Profit firms	8,716	5.50		0.30	0.32	7%
1982–90, Loss firms	1,097	4.29		0.14	0.19	36%
1991–2000, All firms	16,708	5.84	17%	0.11	0.15	36%
1991–2000, Profit firms	13,852	6.06		0.11	0.14	27%
1991–2000, Loss firms	2,856	4.80		0.08	0.11	38%

Notes:

1 Table 3 presents results for the contribution of analysts' earnings forecasts in explaining abnormal returns. The entire sample period is divided into two sub-periods: early years (1982–90) and recent years (1991–2000). In addition, firm-year observations in each sub-period are divided into two groups: loss observations and profit observations.

2 For each sub-sample, we present (from left to right) the number of observations, median firm size (logarithm of market value), the percentage of loss observations in the sub-sample, R^2 of the reduced form of equation (1) estimated with OLS, R^2 of the full form of equation (1) estimated with 2SLS, and analysts' contribution measured as the percentage change in the previous two columns.

3 See Table 1 for variable definitions and Table 2 for equation specifications.

total-sample R^2 of the OLS regressions is 17% for profitable firms and only 9% for those firms reporting losses. The incremental contribution of analysts to investors in loss firms (the increase from 0.09 to 0.12) is not much larger than their contribution in profit firms (0.17 to 0.20). We thus note that analysts' information contribution both across time and between profit and loss firms is rather modest. We now turn to the main question of this study: Do analysts get intangibles?

4. ANALYSTS' CONTRIBUTION IN R&D VERSUS NO-R&D FIRMS

We examine analysts' ability to value intangibles by estimating the incremental contribution (over financial statement information) of analysts to equity valuation in companies with a large investment in R&D, compared with their contribution in companies having low or no R&D capital.[9] We measure firm-specific R&D intensity as follows:

$$\text{R\&D Intensity} = \frac{(\text{R\&D Capital})}{[(\text{Reported Book Value of Equity}) + (\text{R\&D Capital})]}$$

where R&D capital was defined in equation (4) and is scaled here by book value plus R&D capital, to indicate R&D intensity. We classify the sample into the following categories: (1) companies with zero R&D intensity (15,711 firm-years); (2) companies with low R&D intensity (0–15% intensity; 5,642 firm-years); and (3) companies with high R&D intensity (>15% intensity; 5,168 firm-years). We also separate profit from loss observations and report regression estimates in Table 4, Panel A.

The data on 'size' indicate that firms with R&D are larger, on average, than those that lack R&D, and that the frequency of firms reporting losses is larger in companies with high R&D intensity compared with low-R&D firms, partially due to the immediate expensing of R&D. The R^2 values for equation (1) estimated by OLS – returns on earnings and LT signals (Table 4, Panel A, fourth column from right) – indicate that the informativeness of financial statements is lower in companies with high R&D intensity ($R^2 = 0.14$, all firms) than in companies with low R&D intensity ($R^2 = 0.18$), and no-R&D firms ($R^2 = 0.19$). This confirms the widespread beliefs about the information deficiencies of R&D-intensive companies (and of intangibles-intensive companies in general).

Focusing on the contribution of analysts to equity valuation in R&D versus no-R&D companies – the major objective of this study – we note that this contribution to R^2 is quite significant. As indicated by the data in the second column to the right of Table 4 (percentage analysts' contribution), the percentage increases in the 'explanation' of stock returns brought about by analysts' forecasts (i.e. analysts' contribution *over* financial report information) are 11%, 22% and 43% for the no-R&D, low-R&D and high-R&D companies, respectively. For profitable companies, the corresponding incremental contributions are 10%, 16% and 24%.

Table 4 Analysts' contribution to equity valuation – focus on intensity of R&D capital

Sample	*N*	*Size*	*Percentage loss*	*R^2, equation (1) (reduced form, OLS)*	*R^2, equation (1) (full form, 2SLS)*	*Percentage analysts' contribution*	*R^2, equation (1) (full form, OLS)*
Panel A: Analysis of 1982–2000							
Zero R&D intensity, All firms	15,711	5.38	15%	0.19	0.21	**11%**	0.23
Zero R&D intensity, Profit firms	13,408	5.54		0.20	0.22	**10%**	0.24
Zero R&D intensity, Loss firms	2,303	4.43		0.09	0.11	**22%**	0.12
Low R&D intensity, All firms	5,642	6.16	10%	0.18	0.22	**22%**	0.22
Low R&D intensity, Profit firms	5,106	6.25		0.19	0.22	**16%**	0.23
Low R&D intensity, Loss firms	536	5.16		0.11	0.17	**55%**	0.17
High R&D intensity, All firms	5,168	6.17	21%	0.14	0.20	**43%**	0.21
High R&D intensity, Reported profit	4,069	6.58		0.17	0.21	**24%**	0.22
High R&D intensity, Loss before R&D exp.	680	4.83		0.08	0.11	**38%**	0.12
High R&D intensity, R&D induced losses	419	5.06		0.16	0.24	**50%**	0.26

Panel B: Focus on 1991–2000							
Zero R&D intensity, All firms	10,333	5.57	17%	0.15	0.18	**20%**	0.20
Zero R&D intensity, Profit firms	8,597	5.76		0.15	0.18	**20%**	0.21
Zero R&D intensity, Loss firms	1,736	4.62		0.09	0.11	**22%**	0.12
Low R&D intensity, All firms	2,996	6.49	10%	0.10	0.13	**30%**	0.14
Low R&D intensity, Profit firms	2,688	6.59		0.10	0.13	**30%**	0.13
Low R&D intensity, Loss firms	308	5.16		0.07	0.12	**71%**	0.13
High R&D intensity, All firms	3,379	6.29	24%	0.10	0.16	**60%**	0.17
High R&D intensity, Reported profit	2,567	6.73		0.10	0.15	**50%**	0.16
High R&D intensity, Loss before R&D exp.	506	4.99		0.07	0.11	**57%**	0.11
High R&D intensity, R&D induced losses	306	5.24		0.08	0.15	**87%**	0.16

Notes:

1 Table 4 presents results on the contribution of analysts' earnings forecasts in explaining abnormal returns for different levels of R&D capital. Panel A presents results for the entire period (1982–2000), and Panel B presents results for 1991–2000. The sample is divided into three sub-samples – companies with no R&D capital, companies with low R&D capital (smaller than 15% of book value of equity) and companies with high R&D capital (larger than 15% of book value of equity). In addition, firm-year observations in each sub-sample are divided into two groups: loss observations and profit observations. Loss observations in the high-R&D sub-group are further divided into those with losses before R&D expenses and those with profit before R&D expenses (R&D-induced loss).

2 R&D capital is calculated as $RNDCAP_t = (0.9)RND_t + (0.7)RND_{t-1} + (0.5)RND_{t-2} + (0.3)RND_{t-3} + (0.1)RND_{t-4}$. This assumes that RND (R&D expense) is spent in the middle of the year, that it has a useful life of five years, and that it is amortized using a straight-line method. Amortization of RND: $RNDAMT_t = 0.1(RND_t + RND_{t-5}) + 0.2(RND_{t-1} + RND_{t-2} + RND_{t-3} + RND_{t-4})$.

3 For each sample, we present (from left to right) the number of observations, median firm size (logarithm of market value), the percentage of loss observations in the sub-sample, R^2 of the reduced form of equation (1) estimated with OLS, R^2 of the full form of equation (1) estimated with 2SLS, analysts' contribution measured as the percentage change in the previous two columns, and finally R^2 of the full form of equation (1) estimated with OLS.

4 See Table 1 for variable definitions and Table 2 for equation specifications.

For loss-reporting companies, the corresponding analysts' contributions are substantially higher: 22%, 55% and 38%.

The results in Table 4, Panel A, reflect the entire sample period, 1982–2000. The importance of intangibles in firms' assets constantly increased over that period. If analysts improved their analytical skills and methodologies in analysing intangibles, their contribution to investors should have increased in the 1990s. To check this conjecture, Table 4, Panel B, focuses on the 1991–2000 period. The percentage analyst contributions (second column from right) are indeed larger in Panel B than in Panel A of Table 4, but the R^2 values are smaller. The explanation to these seemingly contradictory results is as follows: As has been indicated earlier (Table 3), the contribution of *all information sources* (financial reports and analysts' forecasts) to the explanation of stock returns was substantially lower in the 1990s than in previous periods. This accounts for the overall lower values of R^2 in Panel B compared with Panel A of Table 4. However, *relative* to financial statement information, analysts' contribution in R&D firms in the 1990s was larger than in the 1980s. For example, for firms with high R&D intensity, analysts increased R^2 from 0.14 to 0.20 (43% improvement) over the entire sample period (Table 4, Panel A), and from 0.10 to 0.16 (60% improvement) over the 1991–2000 period. Once more, a larger contribution but not an overwhelming one.

Finally, concerning loss firms, one should distinguish between companies reporting a loss because of the immediate expensing of R&D (a controversial accounting procedure), and those that lose money even before the R&D expensing ('true losers'). We report on this distinction in the bottom two lines of Panels A and B of Table 4: loss before R&D expensing (true losers) and R&D-induced losses. Interestingly, analysts' contribution is higher for the latter firms – R&D-induced loss – than for the true losers (50% vs 38% in Panel A, and 87% vs 57% in Panel B). Apparently, analysts assist investors in distinguishing between chronic losers and those reporting losses because of dubious accounting procedures.

We conclude from our analysis that analysts' information contribution (and by implication, the relevance of information beyond financial reports) is higher in R&D firms than in firms with little or no R&D, and that this contribution increased in the 1990s relative to the 1980s. However, judging from the rather modest levels of explanatory power (R^2 values), the contribution of analysts, while positive, is somewhat limited.

4.1. A closer look at analysts' forecasts

Overall, our estimates suggest that analysts' efforts compensate for some – but probably not all – of the intangibles-related deficiencies in financial reports. This raises the following question: To what extent are analysts' forecasts of earnings 'contaminated' by intangibles-related factors? If analysts fully compensate for financial report deficiencies, that is if they really 'get intangibles' in their analysis and valuation of business enterprises, then the *quality* of analyst forecasts of earnings should be independent of firms' R&D intensity. We examine this issue by considering two quality indicators: the *bias* and *accuracy* of earnings forecasts. Forecast bias, or error (*FE*) is measured as reported earnings minus consensus analysts' forecasts (made 8 months prior to fiscal year-end), scaled by share price (8 months prior to fiscal year-end). Forecast accuracy (*ABS*(*FE*)) is measured as the absolute value of forecast error (bias). If analysts fully comprehend the implications of R&D concerning future profits, then forecast bias and accuracy should not be affected by R&D intensity.

Table 5 reports median forecast errors (bias) and absolute values of the forecast error (accuracy) for the sample firms. For the entire sample (left panel), we observe that earnings forecasts were optimistic on average (negative forecast errors in every year), and that the forecasts became substantially less accurate (larger absolute errors) in the final years of the study (1998–2000). This latter inaccuracy of analysts is mainly the result of the large increase in recent years in the number of loss firms (see the panel of 'loss observations') for which forecast inaccuracy is generally large. Removing the loss observations, we find (panel showing 'profit observations') that both bias and accuracy did not change significantly during 1982–2000. We further divide the sample of profitable companies into companies without R&D and those with high R&D intensity (right two panels in Table 5), and note that earnings forecasts of companies with high R&D tend to be more optimistic than forecasts of companies without R&D (larger negative *FE* for high-R&D firms). While the bias is larger in the R&D firms, the forecast accuracy of the two groups is similar, on average. The relatively biased forecasts of R&D firms, therefore, suggest that analysts miss some value-relevant information when forecasting the earnings of R&D-intensive companies.

We examine the extent to which R&D intensity affects the attributes of analysts' forecasts with the following regressions, which have firm-specific forecast error (FE_{it}) and accuracy ($ABS(FE_{it})$) as the dependent variable, and the R&D intensity, $PRND_{it}$, as the independent variable. To focus on the incremental effect of R&D on forecast attributes, we add the following three control variables, which were found in previous research (e.g. Brown *et al.*, 1987) to affect forecast bias and accuracy: firm size (*SIZE*) – larger firms have smaller bias and inaccuracy; the variability of earnings (*CVER*), measured as the coefficient of variation of earnings – the higher the variability, the higher the bias and inaccuracy; and the age of the firm (ln(*AGE*)), measured as the natural logarithm of the number of valid monthly return observations on CRSP) – older firms are generally associated with lower bias and inaccuracy:

$$FE_{it} = \gamma_{0t} + \gamma_{1t}PRND_{it} + \gamma_{2t}SIZE_{it} + \gamma_{3t}CVER_{it} + \gamma_{4t}\ \ln(AGE)_{it} + v_{it} \tag{5a}$$

$$ABS(FE_{it}) = \delta_{0t} + \delta_{1t}PRND_{it} + \delta_{2t}SIZE_{it} + \delta_{3t}CVER_{it} + \delta_{4t}\ \ln(AGE)_{it} + \theta_{it} \tag{5b}$$

Table 5 Median analysts' forecast errors (bias) and absolute values of forecast errors (accuracy)

Year	*All observations*			*Loss observations*			*Profit observations*			*Profit – zero R&D intensity*			*Profit – high R&D intensity*		
	N	*FE*	*ABS(FE)*	*N*	*FE*	*ABS(FE)*	*N*	*FE*	*ABS(FE)*	*N*	*FE*	*ABS(FE)*	*N*	*FE*	*ABS(FE)*
1982	1,338	−0.005	0.022	66	−0.201	0.201	1,272	−0.004	0.020	845	−0.003	0.024	110	−0.011	0.017
1983	1,373	−0.018	0.030	137	−0.192	0.192	1,236	−0.014	0.025	783	−0.010	0.024	137	−0.014	0.017
1984	1,513	−0.005	0.024	148	−0.172	0.173	1,365	−0.002	0.020	902	−0.000	0.021	153	−0.002	0.015
1985	1,716	−0.007	0.021	145	−0.144	0.144	1,571	−0.004	0.178	1,083	−0.004	0.021	177	−0.005	0.011
1986	1,770	−0.014	0.026	262	−0.173	0.173	1,508	−0.009	0.019	1,057	−0.007	0.020	168	−0.013	0.019
1987	1,772	−0.010	0.021	294	−0.129	0.130	1,478	−0.005	0.015	1,004	−0.004	0.017	196	−0.006	0.014
1988	1,817	−0.006	0.021	246	−0.134	0.138	1,571	−0.002	0.017	1,060	−0.003	0.019	223	−0.002	0.012
1989	1,969	−0.004	0.022	236	−0.168	0.168	1,733	−0.001	0.017	1,199	−0.000	0.019	240	−0.003	0.015
1990	2,024	−0.008	0.021	255	−0.141	0.142	1,769	−0.004	0.018	1,242	−0.003	0.018	248	−0.007	0.016
1991	2,077	−0.011	0.021	300	−0.155	0.155	1,777	−0.007	0.016	1,241	−0.006	0.018	259	−0.008	0.015
1992	2,124	−0.012	0.025	361	−0.162	0.163	1,763	−0.007	0.018	1,219	−0.007	0.019	262	−0.008	0.019
1993	2,321	−0.006	0.020	421	−0.107	0.107	1,900	−0.002	0.014	1,340	−0.001	0.014	271	−0.005	0.014
1994	2,615	−0.006	0.020	470	−0.105	0.106	2,145	−0.003	0.015	1,547	−0.002	0.016	294	−0.004	0.014
1995	3,038	−0.003	0.019	479	−0.096	0.101	2,559	−0.000	0.014	1,866	−0.001	0.015	355	0.000	0.013
1996	3,290	−0.006	0.023	583	−0.109	0.116	2,707	−0.001	0.016	1,991	−0.001	0.017	351	−0.001	0.015
1997	3,080	−0.004	0.021	620	−0.101	0.104	2,460	0.000	0.014	1,854	0.000	0.015	301	−0.001	0.014
1998	2,995	−0.020	0.033	750	−0.101	0.105	2,245	−0.009	0.025	1,624	−0.008	0.026	298	−0.013	0.025
1999	3,732	−0.008	0.031	924	−0.103	0.110	2,808	0.001	0.022	2,134	0.002	0.023	347	0.004	0.020
2000	3,370	−0.005	0.035	880	−0.121	0.128	2,490	0.005	0.024	1,852	0.005	0.025	333	0.004	0.020
All	43,934	−0.008	0.024	7,577	−0.121	0.125	36,357	−0.003	0.018	25,843	−0.002	0.019	4,723	−0.004	0.016

Notes:

Table 5 presents median forecast errors (*FE*) and median absolute values of forecast errors (*ABS*(*FE*)), by year, for several sub-samples (from left to right): all observations, loss observations, profit observations, profit observations with no R&D capital, and profit observations with high R&D capital (R&D capital above 15% of adjusted book values of equity). Forecast errors are calculated as actual earnings minus forecasted earnings made eight months prior to fiscal year-end (approximately 12 months prior to the release of actual earnings).

Table 6 R&D intensity and the accuracy and bias of analysts' forecasts

Year	*Dep. var. – absolute forecast errors (accuracy)*						*Dep. var. – forecast errors (bias)*					
	Int. *t-stat.*	*PRND* *t-stat.*	*SIZE* *t-stat.*	*CVER* *t-stat.*	*ln(AGE)* *t-stat.*	*Adj-R^2* *(N)*	*Int.* *t-stat.*	*PRND* *t-stat.*	*SIZE* *t-stat.*	*CVER* *t-stat.*	*ln(AGE)* *t-stat.*	*Adj-R^2* *(N)*
All	0.11	0.03	−0.01	0.02	−0.01	0.11	−0.06	−0.04	0.01	−0.02	−0.01	0.06
	29.03	4.64	−31.20	47.87	−1.75	(36,666)	−13.62	−6.59	24.90	−35.25	−2.91	(36,666)
1991–2000	0.11	0.04	−0.01	0.02	−0.01	0.11	−0.06	−0.04	0.01	−0.02	−0.01	0.06
	24.97	5.15	−25.23	36.93	−2.33	(23,339)	−11.37	−5.43	21.15	−25.56	−3.08	(23,339)
1982–90	0.09	−0.00	−0.01	0.02	0.01	0.11	−0.06	−0.04	0.01	−0.02	−0.00	0.07
	13.91	−0.13	−19.03	29.42	2.56	(13,327)	−7.61	−3.68	12.19	−24.60	−0.72	(13,327)

Notes:

1 Table 6 presents pooled regressions for two models: The panel on the right contains regression estimates for equation (5a): $FE_{it} = \gamma_{0t} + \gamma_{1t}PRND_{it} + \gamma_{2t}SIZE_{it} + \gamma_{3t}CVER_{it} + \gamma_{4t}\ \ln(AGE)_{it} + v_{it}$. The panel on the left contains regression estimates for equation (5b): $ABS(FE_{it}) = \delta_{0t} + \delta_{1t}PRND_{it} + \delta_{2t}SIZE_{it} + \delta_{3t}CVER_{it} + \delta_{4t}\ln(AGE)_{it} + \theta_{it}$.

2 The dependent variables are forecast errors (right panel) and absolute forecast errors (left panel). Forecast errors (*FE*) are calculated as actual earnings per share minus earnings per share forecasted eight months prior to fiscal year-end (approximately 12 months prior to the release of actual earnings).

3 Independent variables are defined as follows: *PRND* is R&D capital divided by market value of equity. R&D capital is calculated as detailed in the comments of Table 4. *SIZE* is the logarithm of market value of equity. *CVER* is the earnings coefficient of variation (standard error of five years' earnings divided by the absolute value of mean earnings). ln(*AGE*) is the natural logarithm of the number of valid monthly return observations on *CRSP*.

Table 6 reports the estimates of the regressions in equations (5a) and (5b). The top regression (overall sample period) clearly indicates that R&D intensity is significantly associated with both forecast accuracy (left panel) and forecast bias (right panel): The higher the R&D intensity, the more *inaccurate* are analysts' forecasts (positive coefficient on *PRND* in the left panel), and the more optimistic (biased) are analysts' forecasts (negative coefficient on *PRND* in the right panel). For the absolute forecast errors (accuracy), the R&D impact was prevalent in the 1990s, as the R&D coefficients in the 1982–90 sub-period are statistically insignificant. For the forecast error (bias), the impact of R&D did not change substantially over the sample period. The control variables in Table 6 have coefficients with the expected signs: positive for earnings variability and negative for firm size and age. However, while firm size and earnings variability have a significant effect on the results, the effect of the age variable is marginal.

Overall, the finding that R&D intensity affects both the accuracy and bias of analysts' forecasts of earnings (Table 6) clearly indicates that analysts do not fully comprehend and incorporate the value of R&D in the information they convey to investors via earnings forecasts. This leads us to the final issue examined in this study.

4.2. Identifying the weakest links: an industry analysis

To gain further insight, we estimate equations (5a) and (5b), relating earnings forecast attributes to R&D intensity, firm size and earnings variability, for each of the fourteen industries with two-digit SIC codes in the sample for which we had at least 700 firm-year observations. Regression estimates are presented in Table 7 along with the median analysts' forecast errors, median absolute forecast errors and the median R&D intensity (*PRND*) for each industry.

Interestingly, the largest estimated R&D coefficients (*PRND*, estimating the impact of R&D intensity on forecast attributes) in both the accuracy and bias regressions are in industries with relatively low R&D intensity (see mean *PRND*): oil and gas, primary metals, and electric and gas services. It appears that analysts in these low-R&D industries ignore altogether the R&D investment and its outcomes, probably because they believe it is inconsequential. This ignorance, in turn, contributes to relatively large earnings forecast errors (e.g. 0.037 median *ABS*(*FE*) for oil and gas, and 0.040 for primary metals, the highest inaccuracies in Table 7).

Turning to sectors with high R&D intensity, we note in Table 7 that the regression coefficients of *PRND* (impact of R&D on forecast attributes) are highly significant in industrial machinery and computer equipment, in electrical equipment, and in the transportation equipment sectors. It is evident that having intensive R&D investment is essential in these industries, yet analysts fail to fully incorporate the potential and value of R&D in their forecasts. This results in relatively biased and inaccurate earnings forecasts. We conjecture that improved corporate disclosure about the nature and attributes of R&D (e.g. basic versus

Table 7 R&D intensity and the accuracy and bias of analysts' earnings forecasts by industry (2-digit SIC codes)

Industry title	*Sub-sample descriptive statistics*				*Dep. var. – absolute forecast errors (accuracy)*					*Dep. var. – forecast errors (bias)*				
	2-digit SIC	*ABS(FE) (median)*	*FE (median)*	*PRND (mean)*	*Int. t-stat.*	*PRND t-stat.*	*SIZE t-stat.*	*CVER t-stat.*	*Adj-R^2 (N)*	*Int. t-stat.*	*PRND t-stat.*	*SIZE t-stat.*	*CVER t-stat.*	*Adj-R^2 (N)*
Oil and gas extraction	13	0.037	−0.018	0.008	0.21	0.42	−0.03	0.02	0.06	−0.17	−0.82	0.02	−0.00	0.04
					8.57	1.72	−6.55	4.30	(839)	−6.20	−2.96	5.58	−0.17	(839)
Food and kindred products	20	0.015	−0.004	0.023	0.08	−0.02	−0.01	0.02	0.12	−0.04	−0.00	0.01	−0.02	0.07
					8.86	−0.47	−6.49	6.88	(958)	−3.74	−0.06	3.66	−6.16	(958)
Printing, publishing, etc.	27	0.012	−0.002	0.007	0.11	0.11	−0.01	0.02	0.07	−0.07	−0.01	0.01	−0.02	0.07
					7.87	0.93	−6.76	6.64	(833)	−4.91	−0.09	5.11	−4.42	(833)
Chemicals and allied products	28	0.022	−0.008	0.142	0.14	0.01	−0.02	0.02	0.06	−0.08	−0.06	0.01	−0.01	0.03
					13.29	0.15	−10.07	6.83	(2,598)	−7.55	−3.15	5.62	−4.59	(2,598)
Primary metal industries	33	0.040	−0.018	0.028	0.10	0.22	−0.01	0.03	0.17	−0.09	−0.35	0.01	−0.02	0.09
					6.52	3.32	−4.59	10.84	(819)	−4.90	−4.29	4.71	−6.22	(819)
Fabricated metal	34	0.026	−0.011	0.037	0.09	0.06	−0.01	0.03	0.16	−0.05	−0.12	0.01	−0.02	0.11
					6.47	0.99	−4.71	9.03	(703)	−3.05	−1.81	3.18	−7.26	(703)
Industrial, commercial machinery, computer equipment	35	0.030	−0.015	0.138	0.12	0.13	−0.02	0.02	0.15	−0.09	−0.12	0.02	−0.01	0.10
					14.93	8.06	−12.60	12.02	(2,691)	−10.47	−6.98	10.89	−9.03	(2,691)
Electrical, other electrical equipment	36	0.028	−0.012	0.128	0.10	0.06	−0.01	0.02	0.07	−0.08	−0.12	0.01	−0.01	0.05
					9.22	2.50	−6.94	9.80	(2,679)	−7.31	−4.87	8.27	−5.93	(2,679)
Transportation equipment	37	0.024	−0.009	0.101	0.06	0.09	−0.01	0.03	0.18	−0.09	−0.14	0.02	−0.02	0.16
					4.64	2.73	−3.20	11.96	(890)	−6.09	−3.73	6.61	−8.97	(890)

Table 7 (continued)

Industry title	*Sub-sample descriptive statistics*				*Dep. var. – absolute forecast errors (accuracy)*					*Dep. var. – forecast errors (bias)*				
	2-digit SIC	*ABS(FE) (median)*	*FE (median)*	*PRND (mean)*	*Int. t-stat.*	*PRND t-stat.*	*SIZE t-stat.*	*CVER t-stat.*	*Adj-R^2 (N)*	*Int. t-stat.*	*PRND t-stat.*	*SIZE t-stat.*	*CVER t-stat.*	*Adj-R^2 (N)*
Measuring instruments, photo equipment, watches	38	0.026	−0.013	0.138	0.11 13.70	0.02 0.98	−0.01 −9.19	0.01 8.87	0.10 (2,179)	−0.08 −9.01	−0.01 −0.42	0.01 7.60	−0.01 −6.77	0.06 (2,179)
Communications	48	0.019	−0.006	0.014	0.09 6.35	0.05 0.85	−0.01 −4.06	0.01 3.79	0.05 (714)	−0.05 −2.84	−0.17 −2.51	0.01 2.55	−0.00 −1.52	0.02 (714)
Electric, gas, sanitary services	49	0.012	−0.002	0.001	0.05 9.45	0.18 1.29	−0.01 −6.57	0.02 21.56	0.19 (2,253)	−0.02 −3.05	−0.86 −0.67	0.01 3.10	−0.02 −18.88	0.15 (2,253)
Durable goods, wholesale	50	0.028	−0.011	0.006	0.13 6.94	−0.15 −0.95	−0.02 −5.28	0.03 8.25	0.13 (862)	−0.09 −4.52	−0.06 −0.33	0.02 4.18	−0.02 −5.57	0.07 (862)
Business services	73	0.027	−0.012	0.090	0.14 14.82	0.01 0.39	−0.02 −11.62	0.02 9.13	0.10 (2,322)	−0.10 −9.75	−0.03 −1.69	0.01 8.87	−0.01 −6.88	0.06 (2,322)

Notes:

1 Table 7 presents regressions by two-digit SIC codes for two models: The panel on the right contains regression estimates for equation (5a), and the panel on the left contains regression estimates for equation (5b). See Table 6 comments for equation details. Only industries with at least 700 observations are presented.

2 The dependent variables are forecast errors (right panel) and absolute forecast errors (left panel). Forecast errors (*FE*) are calculated as actual earnings per share minus earnings per share forecasted eight months prior to fiscal year-end (approximately 12 months prior to the release of actual earnings).

3 Independent variables are defined in the comments of Table 6.

applied research), as well as information about the consequences of R&D (e.g. the share of revenues generated from recently introduced products) may improve the quality of analysts' earnings forecasts, and, in turn, the efficiency of capital markets.

5. CONCLUSION

Corporate financial reports are frequently and justifiably criticized for failing to provide users with sufficient information about intangible assets. However, since investors are exposed to substantial information beyond financial reports, a thorough analysis of intangibles-related information deficiencies and the consequent policy recommendations cannot be restricted to corporate financial statements. The question we accordingly raise is this: Does the information available to investors beyond financial reports compensate for the reports' deficiencies in general, and in intangibles-intensive companies in particular?

We estimate the beyond-financial-report information by the incremental (over financial reports) contribution to investors of analysts' earnings forecasts – presumably reflecting all the information possessed by analysts from financial reports and other sources. We address the issue of intangibles-related information deficiencies and the related contribution of analysts by comparing the extent of analysts' incremental information contribution in R&D-intensive companies relative to those with low levels of R&D or no R&D at all.

Our findings are somewhat mixed – they indicate that analysts' incremental contribution to investors' decisions is larger in R&D-intensive companies than in companies with low levels of (or no) R&D, indicating that the intangibles-related financial report deficiencies are compensated to some extent by other information sources, through analysts' activities. However, this compensation is modest and far from complete, as indicated by the documented association between R&D intensity and the quality (bias and accuracy) of analysts' forecasts. We identify the most serious deficiencies of analysts' information in (a) sectors with low-R&D intensity, and (b) among the sectors with high-R&D intensity, in the industrial machinery and computer equipment, electrical equipment and transportation sectors. Taken together, our evidence suggests the need for a continued concern and action of accounting policy-makers with intangibles-related information deficiencies. Sadly, as of this writing, such action has been negligible.

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NOTES

1 This is often referred to as 'price chasing' by analysts.
2 The validity of these signals was confirmed by various researchers, such as Abarbanell and Bushee (1997) and Francis and Schipper (1999).
3 Capital market researchers use various model specifications, some different from the one we present in equation (1). To examine the robustness of our findings to model specification, we re-estimated our regressions with the Easton–Harris (Easton and Harris, 1991) specification, where returns are regressed on the levels and changes of earnings (along with the levels and changes of the present value earnings forecasts). Estimates from these Easton–Harris regressions are very close (in terms of R^2 values – the statistic of interest to us) to the estimates generated by the model in equation (1) and reported in Tables 2 and 3.
4 The *Wall Street Journal*'s 'Heard on the Street' column (12 April 2000) argued that analysts adjust their forecasts and recommendations to justify price increases, rather than conduct an independent analysis. An article in the *New York Times* (8 August 2000), 'A Bull Retreats in Downgrade of Web Shares', reports on Morgan Stanley's analyst Mary Meeker, and Merrill Lynch's Henry Blodget, raising loss-per-share estimates for Internet stocks and downgrading recommendations in response to a sharp market decline. There was no market reaction to these downgrades, which is consistent with the argument that analysts reacted to the market, rather than the reverse.
5 Conrad *et al.* (2002) found that analysts are equally likely to upgrade or downgrade a company's stock following a large stock price increase. However, analysts are more likely to downgrade a company's stock following a large stock price decline. They also found that upgrades are more likely if there is an investment banking relation with the company for which the recommendation is issued.
6 The historical (from the 1920s to present) risk premium in the United States is approximately 7%. However, many experts believe that the risk premium has declined significantly in the decades since 1980, to levels in the range 3–5%. Claus and Thomas (2001) provide support to this level of risk premium.
7 We interpret the significant coefficient on the present value of analysts' forecasts as indicating the information contribution of analysts to investors. However, we cannot rule out the possibility that investors are 'fixated' on analysts' earnings forecasts, and their reaction to the forecasts leads to mispricing.
8 In the original Lev and Thiagarajan (1993) study, the AR coefficient was negative and significant only during periods of high inflation. However, we have no explanation for the positive coefficient in Table 2.
9 While the theme of this study is intangibles, we focus in our empirical analysis on R&D, since R&D is the only intangible that is systematically reported by US companies.

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