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ANALYST FORECAST ACCURACY AND FIRM GROWTH

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ABSTRACT

This study examines the affect of business segment industry specialization as a supplement to portfolio complexity on forecast error and Tobin's Q. After controlling for diversification and growth potential, forecast error is negatively related to business segment industry specialization. Diversification (high growth firms) increases (decreases) forecast error. High growth, focused firms are associated with noncomplex portfolios and business segment industry specialization. Within a simultaneous equation model, forecast error does not predict the firm's Tobin Q ratio; however, Tobin's Q does predict whether analysts forecast accurately.

Keywords: Analyst forecasts, Growth firms, Tobin's Q, Forecast error

I. INTRODUCTION

Several studies argue that investors rely on analysts' recommendations and that their recommendations affect stock price movements.[1] Basu and Markov (2004) and Gu and Chen (2004) reported that analysts process information efficiently as evidenced by a low forecasting error of earnings estimates. Other studies question the value of analyst recommendations. For instance, Rajan and Servaes (1997) found that analysts are generally overly optimistic[2] about the growth prospects of recent IPOs as IPOs exhibited the worst stock price performance when analysts ascribed a high growth potential to them. In fact, they found an increase in IPO activity when analysts were optimistic of future performance versus when analysts were either neutral or negative concerning future performance. These findings were consistent with studies identifying inefficiencies in the analyst information market. Hence, the quality of information generated by financial analysts is widely debated in the literature.

Research reported in the accounting literature indicates that an analyst specializing in a few targeted industries more accurately forecasts earnings than an analyst following either many industries or following diversified firms. Gilson, Healy, Noe, and Palepu (2001) indicated that few prior studies accounted for the differences in an analyst's ability to forecast the earnings of focused versus diversified firms. They suggested that analysts following single industry firms have more accurate earnings forecasts than other analysts when the targeted firm emerged from a conglomerate breakup. Specifically, the study reported that an analyst specializing in fewer industries generated lower forecast error and provided higher quality forecasts of spin offs, equity carve outs, and targeted stock offerings performance than competing analysts. However, selection bias may exist to the extent that the post-conglomerate break-up leads to an increase to analyst coverage.

Gilson et al. (2001) contend that (1) investors are more interested in focused firms that provide greater investment opportunities than in diversified corporations, and (2) that analysts who cover diversified firms have expertise in only a portion of the conglomerates' operations and, therefore, provide less accurate estimates.[3] Their paper, however, did not directly test an analysts' ability to forecast diversified corporations' earnings relative to focused firms.

To date there is little evidence on the quality of analysts' earnings forecast given competing financial and structural characteristics. Gu and Wang (2005) reported that the information complexity attributable to intangible assets lead to a reduction in analysts' earnings forecasts. Duru and Reeb (2002) similarly reported that the information complexity attributable to international diversification also lead to a reduction in analysts' earnings forecasts and also resulted in a more optimistic earnings forecast.

Our study examines whether the high information complexity and low profitable growth opportunities associated with diversification increases the difficulty of the analysts' job. Consistent with Gu and Wang (2005), this analysis focuses on forecast error, since forecast error is an important determinant of the usefulness of analysts' research and recommendations. Specifically, we contribute to the literature of forecast accuracy by controlling for two firm characteristics not included in prior research: diversification and profitable growth opportunities. Our findings indicate a significant positive association between analyst forecast error and both the extent of industry diversification and profitable growth opportunities.

These findings suggest that the information complexity of diversified and low growth firms increases the difficulty of accurately forecasting earnings. Our findings are consistent with Lim's (2001) evidence that analysts' earnings forecast errors are greater for firms with less predictable earnings. Analysts are evaluated on the reliability of earnings estimates and, therefore, gravitate towards firms that are less complex and that provide lower forecast error. As such, selection bias with respect to firm characteristics questions the reliability of earnings estimates as a measure of analyst performance.

After controlling for diversification and growth potential, forecast error is negatively related to the analysts' degree of business segment industry specialization. For each analyst, business segment industry specialization is measured by the number of firm business segments in the industry predominate to the analyst's work portfolio divided by the total number of segments for all firms that the analyst follows. Results suggest that business segment industry specialization allows an analyst the opportunity to develop an in-depth understanding of the firm, which could result in greater forecast accuracy.

Doukas, Kim, and Pantzalis (2005) and Schipper (1991) argued that researchers, investors, and other analysts are interested in obtaining accurate earnings forecasts as a proxy for the capital markets' expectation of future earnings growth, Piotroski and Roulstone (2004), Ramnath (2002), Michaely and Womack (1999), Stickel (1992, 1995), Chung and Jo (1996), Rock, Sedo, and Willenborg (2000), Mikhail, Walther, and Willis (1997), and Bhushan (1989). Doukas et al. extended the "Neglected Firm's Hypothesis" of Arbel and Streble (1983) and found that strong analyst coverage, measured by the number of individuals making projections was associated with stock overvaluation and, as a result, low future returns. Alternatively, they found that weak analyst coverage was related to stock undervaluation and high future returns. In our analysis, the above results would translate into a negative relationship between the number of analysts following the firm and Tobin's Q since profitable future growth leads to higher future return. In contrast, we find a positive relationship and no evidence of nonlinearity in sensitivity tests.

Although our results do not suggest that analyst coverage can be excessive, we find support consistent with Doukas et al.'s (2005) assertion that analysts direct their attention to and provide recommendations for high profitable growth firms, which are more likely to generate lucrative investment banking fees. Moreover, we find that analysts who follow few industries in their portfolio and analysts who specialize in business segment industries tend to provide forecasts geared towards firms with a high Tobin's Q. Consequently, an endogenous relationship between forecast error and Tobin's Q may exist.

To control for endogeneity, we examined the extent to which analysts' forecast error influences investors' decisions. A positive relationship between Tobin's Q and relative forecast error exhibited via a three stage least squares simultaneous regression model would be consistent with analyst optimism and lead towards investor overconfidence. Our results suggest that forecast error does not predict year-end Tobin's Q, indicating that analysts forecast error does not influence capital markets' estimation of a firm's future profitable growth opportunities. Moreover, we provide evidence that the beginning of the year Tobin's Q is negatively related to relative forecast error suggesting that low growth firms' earnings are difficult to estimate.

The remainder of the paper provides a review of the literature, develops the hypotheses employed, describes the sample selection and research design, presents the results of the analysis, concludes, and suggests direction for future research.

II. LITERATURE REVIEW

With respect to industry experience Abarbanell and Lehavy (2003), Brown, Foster, and Noreen (1985), Hope (2003), and Markov and Tamayo (2006) identified systematic and time persistent differences in earnings forecast accuracy. They concluded that the most accurate analysts accumulate industry expertise. In contrast, Mikhail, Walther, and Willis (1997, 2003) and Clement (1999) found that forecast accuracy is not related to industry expertise. They reported that more experienced analysts have smaller forecast errors than novice analysts as measured by the number of quarter forecasts issued for a particular firm. They concluded that forecasts become more accurate as the number of quarters an analyst follows a firm increased.

Experience was not used in our study for several reasons. Jacob, Lys, and Neale (1999) and Hong, Kubik, and Solomon (2000) argued that "tenure" was not an appropriate explanatory variable because time based tenure does not differentiate between analysts who recently left the profession on their own, those who were fired, and those individuals who were recently hired. Jacob et al. indicated that analyst tenure is unimportant for it is not related to forecast error. Hong, Lim, and Stein (2000) reported that analyst's average tenure to be but four and a half years.

We focused on industry specialization as an important variable. Gilson et al. (2001) found that specialists had lower forecast error than generalists; provided more forecast than generalists, and tended to follow focused firms more than conglomerates. They used a dichotomous variable and classify industry specialist at 3, 4, and 6 firms. They measured specialization based on total number of firms followed. However, what if all of an analyst's effort is not directed to areas of specialization, would a relative measure of specialization not be more appropriate? For example, if an analyst follows 20 firms but only 6 are in the same industry, would the total number of firms followed appropriate? In this case an analyst spends only 6/20th or 30% of his time on investigating firms in a specified industry. Is the analyst an industry specialist given the analyst has but 6 similar firms their work portfolio? In contrast, what if an analyst who follows multi-segment firms has 2 companies in his/her portfolio, but follows 6 distinct industries. The generalist in this case spends 2/6 or 33% of the time on a specific industry.

Jacob et al. (1999) found analyst industry specialization was not significant when measured as the percentage of companies followed per industry. They argue that proxies for industry specialization were not robust so to capture analyst expertise. Their findings caution using the percentage of companies followed per industry as a key determinant of analyst forecast accuracy. Clement, Rees, and Swanson (2003) agreed that the general experience variable is subject to survivorship bias.

We investigated applying a multi-dimension measure of specialization based on individual analysts' resource allocation decisions. Such a relative industry specialization measure was designed to avoid the issues addressed in above studies.

III. RESEARCH HYPOTHESES

Analyst value is measured by the amount and accuracy of information that they disseminated to the capital markets. We refer to information dissemination or intermediation as cognizance. Jacob et al. (1999) suggested that cognizance, identified by new sources of information, improves as the number of analysts that follow a particular company increases. The improvement exists as a result of an increase of information exchanged between analysts and a subsequent decrease to the cost of information acquisition. Thus, forecast error should decrease with the number of analysts following a firm. In support of their findings, Lys and Soo (1995) indicated that earnings forecast accuracy increased with analyst following.

We hypothesize the following (in alternate form):

Hypothesis 1: *Forecast error is negatively related to the number of analysts following the firm.*

Gilson et al. (2001) argued that information cognizance, as measured by the number of analysts issuing earning forecasts for a particular firm, is an important component to forecasting and, thus, capital market valuation. Market valuation and profitable growth potential (Tobin's Q) may be effected by the number of analysts because investors capitalize their forecasts as soon as they become public. Chen and Steiner (2000), Moyer, Chatfield, and Sisneros (1989), and Chung and Jo (1996) found that Tobin's Q was an increasing function of the number of analysts following the firm. Therefore, we predict the following hypothesis (in alternate form):

Hypothesis 2: *Tobin's Q is positively related to the number of analysts following the firm.*

An analyst's portfolio's complexity refers to its industry composition. Clement (1999) proposed that specialization enabled an analyst to develop a depth of understanding which provides considerable synergies for forecasting company earnings within a particular industry. This specialization could lead to economies of scale. The supposition is that complexity increases as the number of industries within the analyst's work portfolio rises because the analyst cannot devote a lot of attention to an individual firm or industry.

Clement (1999) found that portfolio complexity, as measured by the number of industries an analyst follows, is negatively associated with forecast accuracy, as measured by the relative absolute value of the error. Jacob et al. (1999) used a similar proxy for complexity; the mean number of industries followed by analysts in a calendar year, and found that increased complexity yielded less accurate earnings forecasts.

We posit that analysts face diminishing returns to effort, thus, the magnitude of forecast error will increase as the number of industries in an analyst's work portfolio increase. We used Clement (1999), and Jacob et al. (1999) proxy for complexity (percentage of companies followed with the same two digit SIC code) by computing the percentage of time an analysts allocated resources to a particular industry as 100/mean number of business segment industries. The alternate hypothesis is as follows:[4]

Hypothesis 3: *Forecast error is positively related to the complexity of the analyst's portfolio.*

The null hypothesis is also plausible. Mikhail et al. (1997) find no association between forecast accuracy and proxies for industry classification. The absence of a correlation may be due to their unique specification for industry expertise. The first proxy, industry concentration, equals the number of firms for which the analyst issues quarterly forecasts for the a two-digit SIC code divided by the number of firms with the same SIC code within the Zachs database. The first proxy measures the percentage of firms that analyst covers within an industry. The second measure, industry experience equals the number of prior quarters the analyst issued a forecast for a firm in the same two-digit SIC code as the company being followed.

We also examine whether future profitable growth, as measured by Tobin's Q, is positively correlated with analyst industry specialization. According to Piotroski and Roulstone (2004), an analyst's comparative advantage lies in interpreting specific industry or market sector trends and improving intra-industry information transfers. Therefore, the alternate hypothesis is as follows:

Hypothesis 4: *Tobin's Q is negatively related to portfolio complexity.*

Jacob et al. (1999), Clement (1999), and Mikhail et al. (1997) stated that the extent of an analyst's firm specific skill and knowledge affect forecast accuracy and, therefore, firm value. Firm specific experience is measured as the number of years for which an analyst makes at least one forecast during the first eleven months of the year. These studies found a decline in analysts' absolute forecast error as an analyst's company-specific experience increased. Consequently, an analyst's firm specific expertise should be both negatively related to forecast error and positively related to profitable growth opportunities.

Although previously validated constructs and measurement items were used earlier, we chose to create two new proxies for analysts' firm specific specialization. The two measures are proxies for the time an analyst allocated resources to the industry segments of a firm's business units. The first proxy, coverage, is equal to the dollar amount of sales of the business segments followed by the analyst within the same industries divided by the firm's total sales. Sales coverage is expected to be negatively correlated with forecast error and positively related to Tobin's Q. The second measure, firm expertise, equals the number of firm business segments followed by analyst divided by the number of business segments for all firms followed. The alternative hypotheses are as follows:

Hypothesis 5: *Forecast error is negatively related to analyst firm specialization as measured by sales coverage and business segment industry coverage.*

Hypothesis 6: *Tobin's Q is positively related to analyst firm specialization.*

Gu and Wang (2005) argued that analysts facing economic resources constraints have less ability to forecast the earnings of high information complexity firms. As such, analyst earnings forecasts are less accurate for information complex firms such as those with diversified business segments or those with few profitable growth opportunities. It is expected that greater forecast errors occur when firms are diversified or have low growth options. The alternate hypotheses are as follows:

Hypothesis 7: *Forecast error is positively related diversification and negatively related to profitable growth opportunities.*

Hypothesis 8: *Tobin's Q is negatively related to diversification.*

IV. RESEARCH DESIGN

To assess whether either analyst or firm characteristics are related to forecast accuracy over we reviewed firms over a six year period, 2000-2005. Firms included for analysis were identified from several sources: (1) the COMPUSTAT line-of-business and annual databases, and (2) I/B/E/S detailed annual and quarterly database. The COMPUSTAT line-of-business database reports sales, net income, total assets, and SIC codes for a firm as a whole as well as for each segment (four-digit SIC code), to a maxim mum of ten industry segments, annually. We used the active and research files of COMPUSTAT so that our sample included firms subsequently delisted due to mergers, bankruptcies, and other concomitant events. The initial sample from the COMPUSTAT consisted of 39,751 firms.

The sample was further constrained to firms with forecast estimates on the Institutional Broker's Estimate System (I/B/E/S). Actual earnings per share values were selected from the I/B/E/S database, for I/B/E/S adjusts reported earnings for accounting irregularities so that both forecasts and reported earnings are stated on the same basis. Similar to Brown (2001), we selected the most recent forecast made by an analyst prior to the earnings announcement date. Consistent with Clement (1999), we focused on an individual analyst instead of a team of analysts since the analyst identification code does not provide broker or individual analyst names.

Firms were further excluded from the COMPUSTAT sample for the following reasons: (1) a firm had extraordinary items in earnings per share or had missing quarterly earnings on COMPUSTAT; (2) a firm had small, negative, zero earnings per share values (e.g., earnings per share plus or minus 10 cents); (3) a firm had a forecast horizon less than 30 days; (4) forecasts had the analyst code = 0 (an analyst code of 0 does not correspond to a unique individual); (5) a firm had extreme forecast revisions (the 2nd and 98th percentiles as per Park and Stice [2000]); (6) fewer than 20 analysts followed the firm was for any given year; (7) analysts had only one earnings forecast for the year; or (8) firms had less than three analysts issuing an earnings forecast. One forecast, the most recent, was retained for each analyst for each quarter and the forecast had to have been made within three months (the time horizon) of the earnings announcement. The final sample consisted of 88,403 forecast observations made by 3,901 analysts for 3,347 different firms.

Our research examined whether relative forecast accuracy is correlated with the dissemination of information by analysts specializing in industries related to a target firm's business segments. Lys and Soo, Bolliger (2004), and Brown (2001) concluded that the accuracy associated to the most recent earnings forecast differentiate analysts' abilities. Lys and Soo (1995) found that an analyst's most recent forecast as the most accurate. Bollinger found that analysts deemed to be generalized industry specialists were more accurate than other analysts over given their most recent forecast. Coefficients from an ordinary least square regression model that relate analyst and firm characteristics to earnings forecast accuracy is estimated as follows:[5]

$$\begin{aligned} FE = \alpha_0 + \beta_1 ANALYST + \beta_2 COMP + \beta_3 SALES_{cov} \\ + \beta_4 IND_{cov} + \beta_5 Q + \beta_6 HI + \beta_7 TA + \beta_8 QTR_4 \end{aligned} \tag{1}$$

where:

FE measures an individual analyst's forecast error relative to the mean of all other analysts' forecast errors.
ANALYST is the logarithm of the number of analysts that follow an individual firm.
COMP equals 100 divided by the mean number of 2-digit SIC code segments that a specific firm's analysts follow.
$SALES_{cov}$ equals the dollar amount of sales for the firm's 2-digit segments that have analyst coverage divided by total sales for all of the firm's business segments.
IND_{cov} equals the number of the firms' 2-digit business segments that are followed by analysts divided by the firm's total number of 2-digit business segments.
Q measures the firm's growth potential and market value relative to book value of assets.
HI is the sales Herfindahl Index that measures the firm's business line (strategic) focus.
TA is the logarithm of total assets.
QTR_4 is a dichotomous variable equal to 1 if the forecast is in the fourth quarter.

We used the metric developed by Clement (1999) and Jacob et al. (1999) to measure relative recent forecast error. This metric was calculated using the analyst's most recent forecast within each quarter. The independent variables are measured at the beginning of the fiscal year. The relative accuracy measure, the dependent variable, in this study is the proportional mean absolute recent forecast error (FE). It is calculated as follows: FE_{ijt} = DFE_{ijt} / MFE_{ijt} where: DFE_{ijt} = differenced absolute forecast error calculated as AFE_{ijt} – $MAFE_{ijt}$; AFE_{ijt} = absolute forecast error of analyst i following firm j at time t; MFE_{jt} = mean absolute forecast error of analysts following firm j at time t. FE_{ijt} is a relative performance measure using a 30 day minimum forecast horizon. A value less than 1 represents better than average performance, while a value greater than 1 represents worse than average performance. FE_{ijt} controls both firm and year effects via adjusting forecast error by its firm year mean.

According to Brown (2001), researchers have identified several analyst characteristics related to the accuracy of earnings forecasts. Characteristics include company-specific knowledge, industry knowledge and the number of analysts following a firm. Based on Lys and Soo (1995), FE_{ijt} is expected to be negatively related to the number of analysts following a firm (ANALYST) indicating that forecast accuracy increases with cognizance. Mikhail et al. (1997) posit that the number of analysts following a firm is a proxy for the amount of publicly available information. Forecast accuracy decreases as complexity rises. Clement (1999) used the number of industries followed by analysts, whereas Jacob et al. (1999) calculated the percentage of analysts within a brokerage house following a particular firm's industry. Mikhail et al. identified the number of firms for which analysts issue forecasts within the same 2-digit SIC code as the designated firm divided by the total number of firms with the same 2-digit SIC code in the Zach's Investment Research database as the relevant characteristic to test. Gilson et al. (2001) measured industry specialization via a dichotomous variable equal to 1 if the analyst was a specialist who follows at least six firms in the same industry and zero otherwise.

The above studies only allowed each firm to have one 2-digit SIC code. Consequently, their measures did not consider diversification within an individual firm. To our knowledge Gilson et al. (2001) as the only other paper that indirectly focused on diversification. In an analysis of conglomerate break ups, they found that analysts with five or more firms within the same SIC classification as the spin off yielded a more accurate forecast for the spin-offs' subsequent earnings. In contrast, our study used unique proxies to measure different dimensions of analyst firm and industry-specific specialization. We focused upon industry classification of business segments versus the industry classification of the parent firm. Thus, we identified the extent to which an analyst's firm specific specialization concentrated on the business segments' industries for a particular company.

The precise definition of the variables follows: ANALYST = logarithm of the number of analysts who follow a particular firm; COMP = 100 / (mean number of 2-digit SIC codes), 100 represents total amount of resources; $SALES_{cov}$ = (Sales of Segments followed by analyst) / (Total Firm Sales); IND_{cov} = (number of firm business segments followed by analysts) / (number business segments for all firms followed by the analyst); TA = logarithm of beginning of the year total assets; QTR_4 is a dichotomous variable equal to 1 if the earnings forecast are made in the fourth quarter, else 0.

Other influences not documented in the forecasting literature are controlled for in our analysis. Firms with less diversified or focused strategies consistently outperformed diversified conglomerates, Blanchard, Lopez-de-Silanes, and Shleifer (1994), Berger and Ofek (1995), Denis, Denis, and Sarin (1997), and Servaes (1996). Following these studies, we used the Herfindahl Index (HI) as a continuous measure of industry concentration among a firm's business segments. The HI equals the sum of the squared values of sales per segment (2 digit SIC code) as a fraction of total firm sales. A one segment firm has an index that equals 1. Alternatively, if a firm has five equal sales segments its index equals .20. The higher the index the more focused the firm's strategic outlook.

Chung and Jo (1996) found that analysts tend to follow high Tobin's Q (Q) firms for firms with high Q ratios outperform firms with low Q ratios. Lang and Stulz (1994) presented Q as the capital market's ex ante performance measure of profitable growth opportunities and of an executives' ability to manage the firm that does not require the use of a risk adjustment. We construct Q using the Lang and Stulz's algorithm: Q = logarithm of beginning of the year ratio of the market value of the firm to the replacement value of assets.

The relationship between recent forecast error and either firm diversification strategy proxied by HI or of profitable growth opportunities as reflected in Q was not predicted in the literature. We anticipate a negative relationship if a focused strategy and high growth of firms' earnings are predicted.

Jensen and Meckling (1976) argued that one role of analysts is to monitor management and provide relevant information to stakeholders. Ceteris paribus, when the potential for and economic consequences of information complexity are great, analyst research activity is deemed to be the most necessary. Consequently, analysts make the capital markets more informationally efficient when monitoring poorly managed firms with low profitable growth opportunities. Thus, after controlling for diversification, the demand for monitoring activity from the most skilled analyst should be negatively related to Q.

$$\begin{aligned} Q = \alpha_0 + \beta_1 ANALYST + \beta_2 COMP + \beta_3 SALES_{cov} \\ + \beta_4 IND_{cov} + \beta_5 ROS + \beta_6 HI + \beta_8 TA \end{aligned} \tag{2}$$

where:

ROS = beginning of the year return on sales.

Our analysis controls for the firm structure because Lang and Stulz (1994) found that Q and diversification are negatively correlated. Further, they found that firms choosing to diversify had lower performance as measured by profitability and growth. They posited that firms have low Q ratios because they perform poorly and were seeking profitable growth opportunities. Control variables (R&D Expenditure Ratio and Advertising Expenditure Ratio) that have not been shown to be significantly related to Q in prior studies are not included in our analysis, Chung and Jo (1996) and Lang and Stulz.

Several studies report that stock prices reflect analysts' earnings estimates, Cragg and Malkiel (1982), Peterson and Peterson (1982), Rozeff (1983), Stanley, Lewehlen, and Schlarbau (1981), and Moyer et al. (1989). Thus, if analyst activities are beneficial to the capital market, smaller forecast error should be correlated with higher "capitalized value," which is consistent with a larger Q. Alternatively, if selection bias exists, then analysts who are considered "firm business segment" or "industry" specialists would gravitate towards high Q firms.

Three-stage least squares simultaneous regression, controls for the endogenous nature of forecast error and an analyst's self selection bias. One way to gain a better understanding of Q is to examine whether analyst forecast error exacerbates or reduces the transparency problem of diversified firms which may result in an uncertainty discount, e.g., lower Q. A negative coefficient on FE in Equation (4) would be consistent with analyst errors adversely affecting capital market's estimate of firms' profitable growth opportunities. A zero coefficient would indicate that the capital markets' estimates of earnings were not affected by analyst error. The estimated models are:

$$\begin{aligned} FE = \alpha_0 + \beta_1 Q + \beta_2 QD_{75\%} + \beta_3 QD_{25\%} + \beta_4 HI + \beta_5 ANALYST \\ + \beta_6 COMP + \beta_7 SALES_{cov} + \beta_8 IND_{cov} + \beta_9 QTR_4 \end{aligned} \quad (3)$$

$$Q = \alpha_0 + \beta_1 FE + \beta_2 TA + \beta_3 ROS + \beta_4 HI + \beta_5 ANALYST \quad (4)$$

where:

$QD_{75\%}$ is a dichotomous variable equal to 1 if the firm has a Q value in the 75th percentile, else 0;

$QD_{25\%}$ is a dichotomous variable equal to 1 if the firm has a Q value in the 25th percentile, else 0.

V. EMPIRICAL RESULTS

Table 1 presents Pearson correlation coefficients between recent forecast error (FE), profitable growth opportunities (Q), the four analyst characteristics (Analyst [ANALYST], Complexity [COMP], Firm Sales Coverage [$SALES_{cov}$], and Firm Industry Coverage [IND_{cov}]), and firm characteristics (Diversification Strategy [HI], Profitability [ROS], and Size [TA]). All of the coefficients are statistically significant at the 0.05 level, except for the coefficients associated with Firm Sales Coverage.

Table 1. Pearson Correlations

	FE	ANALYST	COMP	$SALES_{cov}$	IND_{cov}	Q	ROS	HI	TA
FE	1.000	-0.023	-0.006	0.000	-0.017	-0.380	0.000	-0.090	-0.010
ANALYST		1.000	0.071	-0.004	-0.090	0.169	0.299	0.172	0.700
COMP			1.000	0.000	0.476	0.208	0.094	0.510	-0.562
$SALES_{cov}$				1.000	0.699	0.003	0.000	0.001	-0.088
IND_{cov}					1.000	0.102	0.024	0.301	-0.002
Q						1.000	0.186	0.428	-0.109
ROS							1.000	0.160	0.153
HI								1.000	-0.188
TA									1.000

FE measures an individual analyst's forecast error relative to the mean of all other analysts' forecast errors. ANALYST is the number of analysts that follow an individual firm. COMP equals 100 divided by the mean number of 2-digit SIC code segments that a specific firm's analysts follow. A higher number is indicative with less portfolio complexity as indicative by fewer industries followed. $SALES_{cov}$ equals the dollar amount of sales for the firm's 2-digit segments that have analyst coverage divided by total sales for all of the firm's business segments. IND_{cov} equals the number of the firms' 2-digit business segments that are followed by analysts divided by the firm's total number of 2-digit business segments. Q is the market to replacement value of assets. ROS is return on sales (net income/net sales). HI (Diversification Strategy) is the sales Herfindahl Index that measures the firm's business line (strategic) focus. A Herfindahl Index equal to one indicates that the firm is only involved in one line of business and, therefore, has a focused strategy. The firm's strategic outlook is more diversified as the Herfindahl Index falls toward zero. TA is total assets.

Consistent with the existing literature, portfolio complexity and analyst following are related to forecast error. Forecast error is negatively correlated with both analyst and complexity. Likewise, an innovation of our paper, the importance of a specific firm's business segment industries relative to the industries from all of the firms' business segments in the analysts' portfolio (IND_{cov}) is negative related to forecast error. Thus, analyst characteristics are correlated with their ability to forecast firms' earnings.

We also find that forecast error is negatively correlated with profitable growth opportunities, which implies that analyst forecast earnings more accurately for highly profitable, well managed growth firms low growth firms. We are not yet in a position to whether analyst forecast accuracy induces management to choose positive net present value investments or simply whether high growth firms attract a different class of analysts than low growth firms. Consistent with Lang and Stulz (1994), Q is positively related to a focused strategy that concentrates on a few lines of business (HI). Also, consistent with Chung and Jo (1996), the correlations suggest that high growth firms (Q) were followed by more analysts (ANALYST) and exhibited a greater degree of profitability (ROS), but were negatively related to asset size (TA). The correlation between ANALYST and Q is significantly positive. The novel findings are that Q is also positively correlated with the complexity of the firms (COMP) and the number of business industry segments (IND_{cov}) in which the firm is engaged. Analysts that specialize in certain industries tend to follow high growth firms more so than low growth firms. The causality of the positive correlation will be examined later within a simultaneous equation model, Chen and Steiner (2000), Greene and Smart (1999) and Geweke, Meese, and Dent (1983).

The mean summary statistics categorized by firms' number of business segments are presented in Table 2. The descriptive statistics support Gilson et. al.'s (2001) assertion that more analysts monitor and predict earnings of single segment firms with focuses strategies (HI) than for larger more diversified firms. The average single segment firm has twenty analysts compared to a large diversified firm with ten segments that are followed by eight analysts.

Table 2. Descriptive Statistic (Mean) of Sample Data Categorized by the Number of Firms' Business Segments

Segments	1	2	3	4	5	6	7	8	9	10
Analyst Characteristics:										
ANALYST	20	20	20	18	11	10	10	8	7	8
COMP	71	62	48	40	40	37	30	25	19	18
$SALES_{cov}$	1.00	1.00	.99	.83	.83	.82	.80	.69	.40	.37
IND_{cov}	1.00	.92	.89	.87	.68	.67	.52	.47	.47	.43
Firm Characteristics:										
HI	1.0	.93	.94	.76	.71	.64	.59	.38	.17	.21
TA (billions)	.54	1.58	2.31	4.94	5.26	6.80	8.37	26.45	27.99	29.00
TS (billions)	.85	2.27	3.16	7.48	13.85	16.89	18.50	32.94	38.19	56.46

ANALYST is the number of analysts that follow an individual firm. COMP equals 100 divided by the mean number of 2-digit SIC code segments that a specific firm's analysts follow. A higher number is indicative with less portfolio complexity as indicative by fewer industries followed. $SALES_{cov}$ equals the dollar amount of sales for the firm's 2-digit segments that have analyst coverage divided by total sales for all of the firm's business segments. IND_{cov} equals the number of the firms' 2-digit business segments that are followed by analysts divided by the firm's total number of 2-digit business segments. Q is the market to replacement value of assets. The HI that measures the firm's business line (strategic) focus (Diversification Strategy). A HI equal to one indicates that the firm is only involved in one line of business and, therefore, has a focused strategy. The firm's strategic outlook is more diversified as the HI falls toward zero. TA is total assets. TS is total sales.

We show that analysts with less complex portfolios following fewer than two industries (100/71 = 1.4) tend to estimate earning for focused single segment firms. In contrast, analysts that monitor large diversified firms follow approximately six different industries. The number of firms followed by analysts concentrating on single segment firms reached a high of 27 in 1990. The number of firms followed by I/B/E/S analysts over the period from 2000 to 2005 is presented in Table 3.

Table 3. Number of Firms in Analysts' Portfolio over the Period from 2000 to 2005

Year	High	Low	Mean	Median	STD
2000	26	2	14	12	7
2001	27	2	14	12	7
2002	26	2	14	13	6
2003	26	2	14	12	6
2005	26	1	13	11	7

We examined whether analyst characteristics were associated with either relative forecast error or profitable growth opportunities proxied by Q. Table 4 reports the results of examining analyst forecast error associated with the number of analysts following the firm (ANALYST), the complexity of the analysts' work portfolio (COMP), and the degree of business segment industry specialization ($SALES_{cov}$ and IND_{cov}).

Table 4.

The relationship between industry-specific and firm-specific specialization, diversification strategy, or future profitable growth opportunities and forecast accuracy in an ordinary least squares cross sectional research design.

Equation (1): $FE = \alpha_0 + \beta_1 ANALYST + \beta_2 COMP + \beta_3 SALES_{cov} + \beta_4 IND_{cov} + \beta_5 Q + \beta_6 HI + \beta_7 TA + \beta_8 QTR_4$

Variable	Predicted Sign	Coefficient	*p*-Value
Intercept	+	0.14***	.0001
Analyst Characteristics:	-	-0.18***	.0001
ANALYST	-	-0.31	.1402
COMP	-	-0.01	.5977
$SALES_{cov}$	-	-0.22***	.0019
IND_{cov}			
Firm Characteristics:			
Q	-	-0.06**	.0508
HI	-	-0.02***	.0056
TA	-	-0.53	.1800
Other Control:			
QTR_4	+	0.29***	.0020

Entire Sample: Adjusted R^2 = 17.1%; F = 229.2; *p*-Value = .0001; ***, ** Significance levels represent two-tailed statistical tests for .001, .01 and .05 respectively. This table provides the summary results from estimating Equation (1) in a cross sectional regression model. For each variable included in Equation (1), the predicted sign, the coefficient, and the *p*-value. FE measures an individual analyst's forecast error relative to the mean of all other analysts' forecast errors. A negative beta coefficient on the independent variables indicates greater relative accuracy, whereas a positive coefficient is consistent with relative inaccuracy. All of the independent variables are measured at the beginning of the year. ANALYST is the logarithm of the number of analysts that follow an individual firm. COMP equals 100 divided by the mean number of 2-digit SIC code segments that a specific firm's analysts follow. A higher number is indicative with less portfolio complexity as indicative by fewer industries followed. $SALES_{cov}$ equals the dollar amount of sales for the firm's 2-digit segments that have analyst coverage divided by total sales for all of the firm's business segments. IND_{cov} equals the number of the firms' 2-digit business segments that are followed by analysts divided by the firm's total number of 2-digit business segments. Q measures the firm's growth potential and market value relative to book value of assets. HI is the sales Herfindahl Index that measures the firm's business line (strategic) focus. A Herfindahl Index equal to one indicates that the firm is only involved in one line of business and, therefore, has a focused strategy. The firm's strategic outlook is more diversified as the Herfindahl Index falls toward zero. TA is the logarithm of total assets. QTR_4 is a dichotomous variable equal to 1 if the forecast is in the fourth quarter.

The analysis in Tables 4 through 6 examined whether the number of analyst following the firm improves the quality of information, e.g., cognizance, as predicted in Hypotheses 1 and 2. As predicted in Hypothesis 1, the coefficient of -0.18 (p = .00) on ANALYST indicates that analysts forecasts are more accurate (FE) when a larger number of individuals are monitoring the firm's earnings. The negative relationship between FE and ANALYST supports findings by Jacob et al. (1999) and Lys and Soo (1995).

Consistent with Chen and Steiner (2000), Moyer et al. (1989), and Chung and Jo (1996), Table 5 shows a significant positive relationship between the number of analysts (ANALYST) and Q as evidenced by the 0.10 (p =.04) coefficient on ANALYST, supporting Hypothesis 2. Moyer, Chatfield, and Sisneros (1989) provide a plausible explanation for the positive relationship. The demand for analyst monitoring should be greater for high growth firms because the asset bases of these firms changes quickly. They suggest that more analysts are needed in order to keep investors apprised of earnings prospects and risks when firms have high growth rates. The authors acknowledge, however, that analyst coverage may be needed at low growth firms due to greater uncertainty regarding the company's future.

Table 6 presents the results from a three-stage least square simultaneous model that jointly estimates the relative forecast error and Tobin's Q within a system. The empirical specification allows us to interpret the causal relationship between the two dependent variables. In Equation (3), we find that relative forecast error continues to be negatively related to the number of analysts following the firm (ANALYST), but the coefficient of -0.02 (p = .06) is only marginally significant. In Equation (4), Tobin's Q (Q) is significantly related to the number of analysts (ANALYST) as evidenced by the coefficient of 0.45 (p = .03).

Table 5.

The relationship between industry-specific and firm-specific specialization and firm growth potential (market value) in an ordinary least squares cross sectional research design.

Equation (2): $Q = \alpha_0 + \beta_1 ANALYST + \beta_2 COMP + \beta_3 SALES_{cov} + \beta_4 IND_{cov} + \beta_5 ROS + \beta_6 HI + \beta_8 TA$

Variable	Predicted Sign	Coefficient	*p*-Value
Intercept	+	0.96***	.0110
Analyst Characteristics:		-0.10**	.0397
ANALYST	+	-0.20	.0706
COMP	?	-0.00	.9155
$SALES_{cov}$	?	-0.54**	.0120
IND_{cov}	?		
Firm Characteristics:			
ROS	+	0.86**	.0411
HI	+	1.80***	.0001
TA	-	-0.22**	.0217

Entire Sample: Adjusted R^2 = 29.8%; F = 225.3; *p*-Value = .0001; ***, **, * Significance levels represent two-tailed statistical tests for .001, .01 and .05 respectively. This table provides the summary results from estimating Equation (1) in a cross sectional regression model. For each variable included in Equation (1), the predicted sign, the coefficient, and the *p*-value. Q is the logarithm of the market to replacement value of assets. All of the independent variables are measured at the beginning of the year. ANALYST is the logarithm of the number of analysts that follow an individual firm. COMP equals 100 divided by the mean number of 2-digit SIC code segments that a specific firm's analysts follow. A higher number is indicative with less portfolio complexity as indicative by fewer industries followed. $SALES_{cov}$ equals the dollar amount of sales for the firm's 2-digit segments that have analyst coverage divided by total sales for all of the firm's business segments. IND_{cov} equals the number of the firms' 2-digit business segments that are followed by analysts divided by the firm's total number of 2-digit business segments. ROS is return on sales (net income/net sales). HI is the sales Herfindahl Index that measures the firm's business line (strategic) focus. A Herfindahl Index equal to one indicates that the firm is only involved in one line of business and, therefore, has a focused strategy. The firm's strategic outlook is more diversified as the Herfindahl Index falls toward zero. TA is the logarithm of total assets.

Tables 4 through 6 estimate whether analyst characteristics are related to relative forecast accuracy. Three independent variables are used to proxy for the analysts' degree of overall industry specialization (COMP) and firm business segment industry specialization ($SALES_{cov}$ and IND_{cov}). Complexity, overall industry specialization, is the degree of coverage allocated to individual industries within their work portfolio. This measure was an adaptation of Clement (1999) and Jacob et al. (1999) measures. In the ordinary least squares analysis the relationship between forecast error (FE) and firm complexity (COMP) is not significant. The coefficient of -0.31 has a *p*-value of 0.14. This finding is inconsistent with Hypothesis 3 and in contrast to both Clement and Jacob et al. that complexity is associated with less accurate forecasting. The insignificance of COMP in our analysis is driven by the inclusion of IND_{cov}, which measures business segment industry specialization. From Table 4's ordinary least squares regression model, the coefficient for IND_{cov} is -0.22 (p = .00) as predicted in Hypothesis 5.

Table 6. Contemporaneous Relationship between Analyst Forecast Error and Tobin's Q

Variable	Mean	Deviation	Median	25%	75%
FE	0.03	0.15	-0.01	-0.02	0.07
Q	1.04	0.42	0.95	0.23	1.88

Equation (3): $FE = \alpha_0 + \beta_1 Q + \beta_2 QD_{75\%} + \beta_3 QD_{25\%} + \beta_4 HI + \beta_5 ANALYST + \beta_6 COMP + \beta_7 SALES_{cov} + \beta_8 IND_{cov} + \beta_9 QTR_4$

Variable	Coefficient	*p*-Value
Intercept	+0.12***	0.00
Q	-0.37**	0.05
$QD_{75\%}$	-0.00	0.09
$QD_{25\%}$	+0.02**	0.05
HI	-0.08	0.70
ANALYST	-0.02*	0.06
COMP	-0.06**	0.05
$SALES_{cov}$	+0.00	0.40
IND_{cov}	-0.30**	0.04
QTR_4	+0.19**	0.05

Equation (4): $Q = \alpha_0 + \beta_1 FE + \beta_2 TA + \beta_3 ROS + \beta_4 HI + \beta_5 ANALYST$

Variable	Coefficient	*p*-Value
Intercept	+0.01***	0.05
FE	-0.09	0.62
TA	-0.40**	0.03
ROS	+0.83	0.97
HI	+1.10**	0.01
ANALYST	+0.45**	0.03

Three stage least squares (3SLS) regression to estimate the above structural model. The System Weighted R2 is 0.31. ***, **, * Significance levels represent two-tailed statistical tests for .001, .05 and .1 respectively. This table provides the summary results from estimating Equation (1) in a cross sectional regression model. For each variable included in Equation (1), the predicted sign, the coefficient, and the *p*-value. FE measures an individual analyst's forecast error relative to the mean of all other analysts' forecast errors. Q is the logarithm of market to replacement value of assets. All of the independent variables are measured at the beginning of the year. ANALYST is the logarithm of the number of analysts that follow an individual firm. COMP equals 100 divided by the mean number of 2-digit SIC code segments that a specific firm's analysts follow. A higher number is indicative with less portfolio complexity as indicative by fewer industries followed. $SALES_{cov}$ equals the dollar amount of sales for the firm's 2-digit segments that have analyst coverage divided by total sales for all of the firm's business segments.

IND_{cov} equals the number of the firms' 2-digit business segments that are followed by analysts divided by the firm's total number of 2-digit business segments. ROS is return on sales (net income/net sales). HI (Diversification Strategy) is the Herfindahl Index that measures the firm's business line (strategic) focus. A Herfindahl Index equal to one indicates that the firm is only involved in one line of business and, therefore, has a focused strategy. The firm's strategic outlook is more diversified as the Herfindahl Index falls toward zero. TA is the logarithm of total assets.

Likewise, in Table 5, COMP is only marginally related to Q as evidenced by the coefficient of 0.20 ($p = .07$) and IND_{cov} is positively related to Q (coefficient .54, $p = .01$). The marginal significance in COMP is inconsistent with Hypothesis 4, whereas the significant coefficient for IND_{cov} supports Hypothesis 6. Once again, a firm's business segment industry specialization appears to be a more important than industry specialization to an ordinary least squares regression model. Neither industry specialization variables are included in other studies estimating Q.

In the simultaneous equation model in Table 6 the results indicate that controlling for endogeneity (self selection bias by analysts with regard to firm characteristics) changes the results. From Equation (3), both the COMP (coefficient = -.06, p-value = .05) and IND_{cov} (coefficient = -.30, p-value = .04) are significantly related to relative forecast error. Hence, the greater the overall and business segment industry specialization of the analyst the greater the ability to accurately forecast firm earnings compared to analysts described as generalists. The simultaneous model provides results consistent with Hypotheses 4 and 6 and supports Clement (1999) and Jacob et al. (1999) prior findings.

Hypothesis 7 predicts that it is difficult for analysts to forecast earnings for firms whose assets have high information complexity. We use the firm's diversification strategy and its future profitable growth opportunities as proxies for information complexity. To test whether diversification and growth potential affect analysts' ability to forecast earnings, we included them as independent variables in Tables 4 through 6.

As predicted in Hypothesis 7, the ordinary least squares regression model from Table 4 reports a negative relationship between FE and the firm's HI. The coefficient of -.02 is significant at .0056. The negative relationship indicates that analysts' forecasts are more accurate for focused, single segment firms than for large diversified corporations. The above result indirectly supports Gilson et al. (2001) finding that analysts with general industry specialization are more accurate than generalists in a more general setting and not limited to conglomerate breakups. Thus, corporate focus can facilitate improved capital market intermediation by financial analysts with industry expertise for focused, single segment firms.

Table 6, however, shows that the negative relationship between the firm's diversification strategy and forecast error to be marginally significant as evidenced by the coefficient of -.08 (p = .07) when selection bias is controlled for empirically. This finding is inconsistent with Hypothesis 7. This suggests that an analyst's overall and business segment industry specialization are more important determinants of forecast accuracy than a firm's diversification strategy. Using two-digit SIC codes, Duru and Reeb (2002) also found industry diversification to be insignificantly related to forecast error.

In Table 5, the relationship between the firm's diversification strategy and Tobin's Q was significantly positive with a coefficient of 1.80 (p = .0001). Consistent with Hypothesis 8, single segment firms have higher profitable growth expectations as defined by the capital markets than do large corporations with multiple segments. The positive relationship supports Lang and Stulz's (1994) conclusion. After controlling for endogeneity, diversification strategy continues to be positively related to Tobin's Q. The coefficient of 1.10 was significant at the .01 level.

To our knowledge, no other study analyzes the relationship between Tobin's Q and forecast error. Chung and Jo's (1996) examination of the relationship between firm quality, e.g., Tobin's Q, and the dispersion of analysts' forecasts within a simultaneous equation model was the only closely related study. They found evidence that security analysts had a strong incentive to follow the stocks of high quality companies and that their estimates were reflected in capital market valuation (the dispersion of analysts' forecast estimates for the month of July was negatively related to Tobin's Q). Their results were consistent with the notion that the capital markets discounts a firms' profitable growth estimates via an analyst dispersion uncertainty premium. Thus, analyst uncertainty affects capital valuation of firms' market values.

Since we are interested in the relationships associated to analyst forecast accuracy, we include forecast error in our model instead of the dispersion (small forecast error is consistent with greater accuracy whereas small dispersion is associated with less analyst agreement perhaps due to less complexity). Lang and Lundholm (1996) suggested that forecast dispersion proxies for both uncertainty and a lack of consensus among analysts about the firm's future. They found forecast error to be positively related to dispersion in a linear model. Barron and Stuerke (1998) also found a positive relationship between the two variables. Yet, Brown (1998) stated that the use of analyst dispersion to proxy for ex ante uncertainty is controversial and that the relationship should be analyzed within a nonlinear model. Barry and Jennings (1992) found that divergence does not generally serve as an adequate proxy for uncertainty. In our analysis forecast error, ceteris paribus, is expected to be negatively related to Tobin's Q.

In Table 4, the relationship between capital market's expectation of firms' profitable growth potential (Q) and forecast error is significantly and negatively related. The coefficient of Q was -.06 has a *p*-value of .05. This finding supports Hypothesis 7, profitable growth opportunities coincide with analyst forecast accuracy.

Equations (3) and (4) in Table 6 analyze the relationship between analyst forecast error and Tobin's Q more thoroughly than in Table 4. Using dichotomous variables that identify the firms in the seventy fifth and twenty fifth percentiles with respect to Tobin's Q, we reexamine the above relationship within a simultaneous equation model. Equation (3) estimates a model that predicts relative forecast error using Tobin's Q and the two dichotomous variables. Tobin's Q continues to be negatively related to forecast error (coefficient = -.37, p = .05). The coefficient for the seventy fifth percentile variable were statistically and economically insignificant. The twenty fifth percentile, however, had a coefficient of .02 significant at the .05 level. Hence, firms with the lowest growth expectations had more inaccurate earnings forecasts than firms with a higher Tobin's Q. Tobin's Q could be a partial explanation for variation in analysts forecast.

Equation (4) simultaneously estimates a model that predicts Tobin's Q using forecast error as a determinant. We note that the coefficient of -.09 for forecast error was not significant (p = .62) and indicates that analysts' forecast error does not influence capital market's valuation and growth estimates. The finding that Tobin's Q explains forecast error when forecast error has no impact on capital market estimates suggests that it is easier for analysts to obtain reliable information from high growth (high quality) firms regarding their future earnings than for low growth companies.

The extant literature shows that size and a fourth quarter dichotomous variable are statistically related to forecast error. In Table 4, after controlling for analyst and firm characteristics, the coefficient of -.53 (p = .18) indicates that size is not significantly related to forecast error. Consistent with Mikhail et al. (1997), a binary variable, QTR_4 (equal to 1 if the earnings estimate and earning per share are in the fourth quarter) is positively related to forecast error. The coefficient of .29 in Table 4 is significant at p = .002. Likewise, the coefficient of .19 in Table 6 is significant at the .05 level. The positive coefficient is consistent with forecasting being more difficult in the fourth quarter than for the rest of the year.

Studies also find that size and profitability are related to Tobin's Q. Consistent with Chen and Steiner (2000), Chung and Jo (1996), and Lang and Stulz (1994), size (TA) is negatively related to Tobin's Q. In Table 5, the coefficient of -.22 at p = .02. In Equation (4), size continues to negatively related to Tobin's Q with a larger negative coefficient of -.40 (p = .03). Profitability as measured by return on sales is positively related to Tobin's Q. The coefficient of .86 is significant at the .01 level. Similarly, Chen and Steiner find Tobin's Q is positively related to return on assets. Chung and Jo report a positive relationship between Tobin's Q and return on capital.

The results in Tables 4 through 6 are robust to different specifications that are not reported in the text. Dichotomous variables for business segments as alternative to the Herfindahl Index are insignificant and most likely too course of a measure to capture the effects of diversification. The low R^2 explanatory power of the model also indicates that the HI is a better proxy for diversification strategy (focus) than fixed effect measures. Also, the results are robust with respect to time. Year fixed effect variables are statistically insignificant.

VI. SUMMARY AND CONCLUSIONS

We evaluated the effects of analyst specialization, business segment diversification, and expected profitable growth opportunities on analyst forecast accuracy. Based upon reported research findings we concluded that: forecast accuracy is driven by the type of firm that the analyst follows; firm performance or expected profitable growth opportunities are not driven by forecast accuracy; analysts identified as "firm" or "industry" specialists follow high Tobin's Q firms; research efforts need to control for the endogenous nature of analyst forecast error and analyst's self selection bias via an appropriate statistical methodology; that Tobin's Q is positively related to the number of analysts following the firm.

Our study supports prior research in that we find forecast accuracy to be greater for analysts specializing in a firms' business segment industries. These results were consistent with different types of analysts with varying characteristics playing more or less of a pivotal role. Few studies, however, analyze whether financial markets are influenced by analysts' forecasts. Existing research on forecast error focuses on the wide variation in analyst characteristics instead of firm characteristics. To our knowledge, no study relates either the accuracy of forecast estimates or analysts individual characteristics to financial performance (Tobin's Q) or structure of the firm (diversification) when determining the importance of analyst monitoring.

Brennan (1995) noted that security analysis is a costly activity with the benefits to capital markets remaining largely unexplored. Our study is the first to examine whether the degree of firm/industry specialization by analysts is related to profitable growth opportunities. Berger and Ofek (1995) found that an overinvestment in segments from diversified firms in industries with limited investment opportunities as measured by a low Tobin's Q ratio. Therefore, they conclude that diversified firms with low Tobin's Q are poorly managed relative to focused firms with high Tobin's Q.

Based on the above discussion we analyzed whether coverage by the most accurate analysts induce executives to manage their corporations more effectively by investing their resources in high growth, profitable industries (as measured by the firm's Tobin's Q). We found no evidence of analysts affecting management investment decisions. In a three-stage least squares simultaneous regression model, forecast error did not predict the value of end of year Tobin's Q. Hence, it appears that equity capital markets do not rely on the accuracy of analyst forecasts when estimating firms' profitable growth opportunities. Industry specialists, however, tend to follow firms with a high Tobin's Q, whereas generalists follow firms with a low Tobin's Q resulting in a higher forecast error.

We also ask whether both a firm's profitable growth opportunities and its extent of diversification are related to analysts' forecast accuracy. In other words, do analysts predict more accurately when firms' earnings are predictable? We consistently find that analysts with the highest accuracy follow well-managed focused firms with a high Tobin's Q. In contrast, the least accurate analysts have poorly managed, low Tobin's Q, or diversified firms in their portfolio.

Zach Wagner, senior pharmaceutical analyst at Edward Jones, provides a rational for our results. He states that well managed firms with few business segment industries are more transparent in the sense that they are willing to provide a guidance to analysts and, most likely, the capital markets prior to the forecast. On the other hand, executives at large diversified corporations and those at firms with low profitable growth opportunities are reluctant to be as forthcoming about the future earnings projection. Consequently, Mr. Wagner states that analysts following low growth or diversified firms are known to be less accurate when estimating earnings than when they monitor single segment and high growth firms. Instead of utilizing forecast error as criteria for judging performance, he states that his firm rewards analysts on their ability to project firms' cash flows and stock prices instead of earnings.

Academics studies provide support for Mr. Wagner's viewpoint. Literature reports that the quality of analyst earnings forecasts is positively affected by the quality of information disclosed by the firm's management. Byard and Shaw (2003) found that analyst forecasts are more precise when firms provide high quality financial disclosure as indicated by the AIMR ranking.

Our conclusion that high Tobin's Q firms are easier to forecast than other firms is supported by the extant literature. The literature reports that focused firms have high Tobin Q ratios and that high Tobin's Q firms have both higher profitability and a more stable cash flow than diversified corporations. Chen and Steiner (2000), Moyer et al. (1989), and Chung and Jo (1996) found that the dispersion of analysts' forecasts was low and that profitability, as measured by return to capital, was positive for high Tobin's Q firms.

Future research should revisit the significance of analysts' forecasting to the capital markets by examining the importance of information complexity as measured by research and development. Gu and Wang (2005) found analysts forecast to be less accurately when firm were less transparent.

NOTES

[1] Greene and Smart (1999) find that traders rely on recommendations of analysts who are featured on the Wall Street Journal's "Investment Dartboard." Junttila, Kallunki, Karja, and Martikainen (2005) report that technology firms' nonfinancial information as measured by analysts' perceptions of value as measured by their opinions in the Most Admired Companies survey in Fortune magazine is valuable. Also see Piotroski and Roulstone (2004), Park and Stice (2000), De Bondt and Thaler (1985), Abarbanell (1991), Lys and Sohn (1990), Givoly and Lakonishok (1979).

[2] Guedj and Bouchaud (2005) also find that analysts are on average overly optimistic and show a pronounced herding behavior for US, EU, UK and JP stocks during the period 1987-2004. The herding effect is more pronounced in US than EU stocks.

[3] On average, the level of analyst coverage for break up firms increases by 45 percent in the three fiscal years following a break up. The increase in coverage by industry specialists occurs for newly created focused subsidiary firms, but not for parent firms.

[4] Gilson et al. (2001) measure industry specialization with a dichotomous variable equal to one if the analyst covered at least five other firms in the same two-digit SIC industry. Jacob et al. (1999) measure industry specialization as the percentage of companies

followed by an analyst with the same two-digit SIC code. None of the studies' measures, however, take into account the possibility that large corporations invest in multiple industries because they only allow each firm to have one SIC code.

5 Articles in the judgment and decision making research found that coarse measures of experience (i.e., number of years worked) do not reflect the task-specific knowledge (Anderson & Goldsmith, 1994). Several studies in the accounting literature are consistent with their findings with respect to forecast accuracy (see Clement et al., 1993; Hong et al., 1998; Jacob et al., 1999; Jacob & Lys, 2000). Clement (1999) reports mixed results for different years.

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