ANALYSTS RELIANCE ON THE CAPITAL MARKET'S ESTIMATE FOR FIRM GROWTH POTENTIAL: AN EMPIRICAL ANALYSIS OF FORECAST ERROR AND BIAS

By

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ABSTRACT

The popular press often states that analyst decisions over an extended time period have significant influence over security prices. It is often assumed that analysts add value by conducting in-depth research on public traded firms that enable investors to gauge the attractiveness of each stock. We analyse whether either analyst forecast error or the magnitude of error bias affect the market's estimated of a firm's future growth potential as measured by Tobin's Q and vice-versa. The findings show that analyst have no influence over capital market perception of firm value. Instead, analyst forecast error and bias herds around movement in Tobin's Q. (JEL G10, G29)

Keywords: Analyst forecast error and bias, Tobin's Q, Information intermediation.

INTRODUCTION

Financial analysts serve as a conduit between investors within the general public and many corporations (Jackson and Madura (2007); Kwag and Small (2007)). Security analysts are purported to improve market efficiency by providing investors with material information necessary to make informed decisions (Moyer, Chatfield and Sisneros (1989)). For example, Chung and Jo (1996) show that the monitoring of corporate decisions by financial analysts positively impacts market efficiency by reducing agency cost, which makes information more credible. It is assumed that security analysts provide market participants non-public information on a timely basis. Yet, the underlying assumption regarding the relevance of analysts' decisions is debated extensively.

Jackson and Madura (2007) find that recent accounting regulation has effectively reduced analysts' information advantage and, thus, their impact on firm valuation, which should be exhibited as a decoupling of the relationship between investors' estimation of firm value (growth opportunities) and the analysts' decisions with respect to earning. Kwag and Small (2007) also find evidence of reduced intermediation effectiveness. They show that analysts forecast firms' earnings less accurately subsequent to recent regulation causing them to overstate earnings.

We extend these studies by examining whether analyst information intermediation ineffectiveness as measured by forecast error or bias impact investors' perception of firms' growth potential. Consistent with Chung and Jo (1996), the relationship between the markets' estimates of firm value as measured by Tobin's Q and the analysts' prior forecast error or bias is estimated within a simultaneous equation model. Following Jackson and Madura (2007) and Kwag and Small (2007), the relationship between Tobin's Q and analyst information ineffectiveness is analyzed across different regulatory regimes. By not solely using the number of analysts following a firm, we extend these studies by addressing the question of whether intentional or unintentional forecasting inaccuracies affects the capital market, due to investors' tendency to incorporate prior forecast error into their valuation estimates.

Within the context of our study evidence that analysts' error or bias undermine the integrity of the capital market is consistent with a negative relationship between the overestimation of earnings, positive forecast error or bias, and the markets expectation with respect to firm value, Tobin's Q. A positive (non-positive) relationship prior to (subsequent to) the Regulation Fair Disclosure Act (also referred to as Regulation FD) supports the contention that analyst estimates were not a critical information source for investors after 2001 in the sense that analyst forecast error or bias had less of an impact on firm value subsequent to the implementation of this law.

Although some academic studies show that investors never relied on analysts because there forecasts simply restated public information (Givoly and Lakonishok (1980) and Stickel (1992)), others show a statistically significant relationship between value and analysts' decisions (Gleason and Lee (2003) and Elgers, Lo and Pfeiffer (2001)). Similar to Jackson and Madura (2007) and Kwag and Small (2007), the motivation for this study is to provide insights into the validity of security analysts' role and provide guidance to investors.

The results of our analysis show that investors were never swayed by analysts forecast error or bias: analyst inaccuracies were uninformative to market participates across disclosure time periods. Neither historical analyst forecast error or bias were predictors of future Tobin's Q in the next period. Tobin's Q, however, was a significant determinant of both in a subsequent period. Since the capital market influences analysts' expectations, a unique herding behavior exists--a tendency to follow the lead of the equity capital markets. We, therefore, extend the existing literature that focuses on herding as a phenomenon of analysts following other professionals (Ehrbeck and Waldmann (1996), Hong et al. (2000), and Scharfstein and Stein (1990)). Reputational herding theory has resulted in a litany of research that posits that analysts bias their forecast towards a previous consensus estimate from other professionals that follow the firm (see, for example, Graham, 1999). These studies, however, do not evaluate whether security analysts base their forecasts on capital market perceptions, a different type of herding behavior.

Our study also extends another line of research concluding that analysts' error and bias are positively correlated with capital market valuation of stock price. For example, Easton and Sommers (2007) find that overly optimistic analyst earnings forecasts exist when the market yields upwardly biased estimates of implied equity premium of three percent. Using another approach, we deviate by empirically testing for the causality of the relationship. We find that neither earnings forecast error nor bias influences the market's growth expectations, and the causality is reversed.

The contributions of this study, therefore, are twofold. First, by implementing a simultaneous equation model, this study is able to examine the causation between market expectations and financial analyst forecast decisions. Analysts are overly optimistic about next-year earnings when the market previously deemed a firm had large profitable growth opportunities and vice versa. Second, although previous research has found that forecast accuracy decreases after the ratification of Regulation Fair Disclosure, our findings show that financial analyst decisions have no influence over capital market perception of firm value. This result is particularly important given that the primary role of financial analyst is to serve as an information intermediary for the investing market.

1. Related Research

Our study contributes to the financial economics literature by examining the links between investor valuation and analyst forecast decisions, which to date, have not been extensively investigated. These findings deviate from earlier research that document a significant and positive relationship between analyst monitoring and firm valuation by directly testing for accuracy as measured by forecast error and bias. Moreover, we use Tobin's Q as a proxy for firm value in lieu of stock returns.

Brennan et al. (1991) find that stock returns adjust to new information regarding the number of analyst following the firm, which proxies for monitoring by informed investors. They assert that stocks extensively followed by analysts have higher stock returns than ones followed by fewer analysts. From this correlation, they imply that analysts provide a valuable intermediation service to investors. Yet, these authors do not directly test the value of analyst intermediation because of the indirect analyst following proxy and their ordinary least squares empirical specification which does not account for causality. In our opinion, the value of analysts' decisions is directly related to the accuracy and bias of their forecasts coupled with potential empirical evidence that investors actually incorporate these decisions into their valuation estimates. An alternate hypothesis for their results is that analysts herd around stocks that have high stock returns. If so, their conclusion regarding analyst worth may be inconclusive.

Libby and Tan (1999) answer a different question and show that analysts' revise their earnings projections to incorporate profit warning and non-public information. Libby and Tan (1999) extend the work of Kasznik and Lev (1995) that reports that forecast revision error and bias for earnings announcements are more negative than for warnings announcements. Libby and Tan (1999) investigate analysts' reactions to qualitative warnings of adverse earnings and attempt to reconcile analysts' more negative forecast revisions. Our study attributes analysts' inaccuracies to a broader valuation environment than earnings or warning announcements.

Several studies verify that analysts exhibit varying levels of ability to evaluate public companies (Chung and Jo (1996), Clement (1999), and Mikhail et al. (1997)). These studies suggest that in the absence of ability, security analyst might tend to alter their evaluation to incorporate the opinion of a more informed source. Several researchers extend the seminal theoretical work of Scharfstein and Stein (1990) conjecturing that the earnings forecast will be biased towards a previous value (Trueman (1994)), a consensus (Lamont (1995), or the opinion of an established professional (Graham (1999)). These studies suggest that if multiple analysts engage in herding behavior for whatever reason their valuations become similar undermining the integrity of the analyst opinion and the confidence of the investors they serve.

Similarly, several other studies find that analysts do not fully incorporate into their earnings forecasts relevant accounting information [Sober (1992), Abarbanell and Bushee (1997)] supporting the notion that analysts are simply herding around the opinion of another source of information than that of the public company. We postulate that that source of information is the market's estimate of a firm's growth opportunities. Klein (1990) finds that analysts remain overly optimistic about the future earnings of firms with large stock price declines, but the earnings for firms with extreme price increases are not overly predicted by analysts. Alternatively, Dechow and Sloan (1997) and Fuller, Huberts, and Levinson (1993) conclude that systematic bias in analyst forecasts explains the low stock returns of growth firms.

Chung and Jo (1996) examine the impact of security analyst's monitoring and marketing functions on the market value of firms. Utilizing three stage least squares regression estimation, Chung and Jo seek to understand the relationship between the number of financial analysts following a firm, Tobin's Q and the dispersion of analysts' forecast. Chung and Jo (1996) find that, Tobin's Q is significantly and positively associated with the number of analysts following the firm. Chung and Jo (1996) interpret Tobin's Q as a measure of quality suggesting that better firms attract more analysts. They do not examine whether growth opportunities as measured by Tobin's Q influences analysts' forecast error and bias.

Other existing studies report security analyst following has is positively related to firm value as measured by Tobin's Q [Chen, Chan, and Steiner (2002)]. Doukas, Kim, and Pantzalis (2005) also provide evidence that the market's earnings expectations are affected by analyst coverage. Strong analyst coverage as measured by the number of individuals making earnings projections is associated with high earnings expectations by investors, but low future returns. In contrast, weak analyst coverage is related to low expectations, but high future return.

The findings could be interpreted in several ways. Either capital market participants increase their expectation of growth when many analysts provide information about, or awareness of, a specific firm or the number of analysts following the firm rises after investors increases their estimate of firm value. Since these studies measure number of analysts following the firm instead of outcomes from their decision process, it is undetermined whether security analysts' error, bias, specialization, or experience impacts Tobin's Q [also see Skinner and Sloan (2002)].

Another strand of research examines the relevance of analyst following to the capital market after recent regulation that demanded greater transparency for accounting financial information [Heflin et al. (2003)]. A few studies indirectly show that analysts' comparative advantage with respect to acquiring private firm-specific information has eroded subsequent to the Regulation Fair Disclosure Act (RFD). Jackson and Madura (2007) find that analysts following is not related to the abnormal share price response to profit warnings (CAR 0, +1), but it is related to leakage prior to the announcement (CAR -11, -1). This finding corroborates their underlying assumption that analyst following no longer impacts the market's reaction to a profit warning announcement because analysts cannot give some investors early notification of the warning after Regulation FD.

Kwag and Small (2007) also study the impacts of Regulation FD. By analyzing the direction and magnitude of financial analysts' earnings forecast around the passage of Regulation FD, Kwag and Small contend that the accuracy of financial analysts' earnings estimates has decreased since the ratification of Regulation FD. The authors utilize ordinary least square regression analysis to conduct their examination.

Clement, Rees and Swanson (2003), Gilson, Healy, Noe and Palepu (2001), Clement (1999) and Jacob, Lys, and Neale (1999) provide a motive for hypothesizing that the capital markets may view specialists and experienced professionals differently from other analysts since they are more accurate predictors of earnings, spend more time on a particular task, and have extensive information sources. Clement (1999) reports that forecast error for an analyst who follows eight industries (the 90th percentile) are 2.9 percent larger than an analyst who concentrates on a single industry.

Clement (1999) states that specialization and experience enable analysts to develop an in-depth understanding or employ a more complex framing algorithm that can provide considerable synergies in forecasting companies within a particular industry. Zuckerman (1999) also suggests that analysts specialize to economize on the costs of information gathering and analysis and, 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.

Alternatively, it is possible that the capital market ignores all analysts' forecasting decisions completely. Instead, investors may focus solely on the information environment as characterized by age of the forecast, dispersion of forecast estimates, increased uncertainty due to fourth quarter reporting, and the firm's strategic focus (business segment diversification) rather than analyst decisions or characteristics.

2. Hypothesis Development

2.1 Analyst Misestimation or inaccuracy

Our study analyzes whether analyst inaccuracy as defined by recent forecast error or bias either affects or is affected by the capital market's estimate of firm's future growth opportunities. The first joint hypotheses to be examined within a simultaneous regression model are as follows:

$H1_A$: Investors incorporate analysts' recent earnings forecasts error or bias into their assessment of a firm's ability to sustain future growth opportunities as defined by Tobin's Q.

$H1_B$: Analysts incorporation of investors' estimate of growth opportunities into future earnings estimates (measured as forecast error or bias) is positively related to ex post Tobin's Q.

2.2 Analyst Specialization, Experience and Portfolio Complexity

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. Clement and Tse (2005) find that analysts with high self efficacy or boldness are associated with prior accuracy, experience, and a fewer number of industries the analyst follows. The empirical corollary is provided in the following hypotheses:

$H2_A$: Specialists and experienced individuals' forecasts of earnings are more accurate (lower error) than those of generalists and less experienced professionals, and

$H2_B$: Growth opportunities are perceived to be higher when specialists have exhibited a positive bias or large error in the past.

H3: Analyst accuracy increases as the individual's portfolio complexity decreases or the number of years experience in the industry increases.

2.3 Regulation Fair Disclosure Act

Kwag and Small (2007) find that analysts overstate earnings more in the post Regulation Fair Disclosure Act (RFD) period. We further examine the conclusiveness of their findings after accounting for casualty. Thus, we utilize a simultaneous regression model to test Kwag and Small (2007) following hypothesis ($H2_A$):

H4: Analyst forecast error or bias have increased in the post-RFD period relative to the pre-RFD period.

3. Methodology

3.1 Sample Selection

In order to assess whether analyst decisions or characteristics are related to forecast error or bias over the period of January 1990 to December 2005, we construct a sample utilizing several sources: 1) I/B/E/S summary/detailed annual and quarterly database, 2) the COMPUSTAT line-of-business and annual databases, and 3) the CRSP database. I/B/E/S International Inc., a unit of Thomson Financial, provides security analyst forecast data. The COMPUSTAT line-of-business database reports sales, net income, total assets, and Global Industry Classification Standards (GICS)[1] codes for a firm as a whole and for each segment. We use the active and research files of COMPUSTAT so that the sample includes firms that were subsequently delisted due to mergers, bankruptcies, and so on. CRSP is an acronym for the Center for Research and Security Prices, provides monthly and daily stock market prices.

The forecasts used in this study are obtained from the U.S. Editions of the Detailed Earnings Estimate History database produced by the Institutional Broker's Estimate System (I/B/E/S). I/B/E/S is a database that provides forecasts on individual firm's earnings for individual analysts over a period of time. Actual earnings per share are also included in the database. I/B/E/S makes adjustments to reported earnings for accounting irregularities and dilution factors so that all forecasts and reported earnings are stated on the same basis. Similar to Brown (2001), we obtain the last forecast made by each analyst during the period as long as it was made before the earnings announcement date. Consistent with Clement (1999), we focus on individual analysts instead of teams.

We then exclude firms from the sample for the following reasons: 1) firms that had extraordinary items in earnings per share or had missing quarterly earnings on COMPUSTAT; 2) firms that have small, negative, or zero earnings per share values (e.g., earnings per share plus or minus 10 cents); 3) forecasts when the analyst code=0 since this code does not correspond to a unique analyst; 4) following Park and Steice (2000), the extreme forecast revisions at the 2^{nd} and 98^{th} percentiles are eliminated; 5) analysts that had only one earnings forecast for the year; and 6) firms that do not have a following of at least two analysts. The final sample has 283,009 quarterly earnings per share forecast observations made by 4,456 analysts for 7,641 different firms.

3.2 Research Design: Three Stage Simultaneous Regression Models

The three stage least square regression model, a combination of multivariate regression (seemingly unrelated, SUR) and two stage least squares, is chosen to analyze the relationship between analyst forecast error or bias and the market's estimate of potential growth. Three stage least squares model controls for the bias induced by unobservable variables by estimating the covariance matrix between the error terms [see Geweke, Meese and Dent (1983), Greene (1993), and Chung and Jo (1996)]. The system of equations treat forecast error (bias in a separate analysis) and the logarithm of actual Tobin's Q as jointly determined endogenous variables as follows:

[1] GICS codes are intended to supersede Standard Industry Classification (SIC) codes (www.census.gov/epcd/naics.htm). A company can have more than one GICS classification. The first represents the main area of business. Additional codes reflect other unique industry segments. GICS is defined and maintained by Standard & Poors and Morgan Stanley Capital International. The codes are accessible through Compustat. Bhojraj, Lee and Oler (2003) argue that the GICS industry classification is preferable.

Equation 1

Forecast $Error_{t+1} = b_0 + b_1 ln(Tobin\ Q)_t + b_2 specialization_t + b_3 high\ growth_t * specialization_t + b_4 low\ growth*specialization_t + b_5 Portfolio\ Complexity_t + b_6 ln(Analysts)_t + b_7 ln(Analyst\ Experience)_t + b_8 Age\ of\ Forecast_t + b_9 QTR4DUM + b_{10} ln(Size)_t - b_{11} Focused\ Strategy_t + b_{12} RegulationFD$

Equation 2

$ln(Tobin's\ Q)_{t+1} = b_0 + b_1 Forecast\ Error_t + b_2 specialization_t + b_3 specialization*Forecast\ Error_t + b_4 ln(Analysts)_t + b_5 ln(dispersion\ of\ analyst\ forecasts)_t + b_6 ln(Size)_t + b_7 Focused\ Strategy_t + b_8 RegulationFD$

Equation 1 is a specification that tests whether recent consensus forecast error is influenced by the capital market's past estimate of a firm's growth potential as measured by Tobin's Q. Equation 2 is a specification that relates past analysts' decisions (i.e., forecast error or bias) to the capital market's estimate of profitable growth opportunities. We also analyze whether specialists and experienced professionals forecast earnings more accurately than generalists and less experienced professionals for firms in general and for companies classified as high and low growth companies. The anticipated relationship between the dependent and independent variables is expressed in equation 1 and 2 by the sign of the coefficients.

4. Variables

4.1 Forecast Error Construct

Analyst value to the capital markets is often measured by the accuracy of the most recent earnings forecast (Brown, 2001). The general consensus is that large (small) forecast error reflects a limited (expert) ability to forecast future earnings per share. We use the metric developed by Clement (1999) and Jacob, Lys and Neale (1999) to measure relative recent consensus forecast error within each quarter. The dependent variable in the first equation of the three stage least squares model is the analysts' relative accuracy measured as the proportional mean absolute recent forecast error ($PMAFE_t$) during the quarters prior to the calculation of year-end Tobin's Q. It is calculated as follows:

$PMAFE_{ijt} = DAFE_{ijt}/MAFE_{ijt}$

where:

$DAFE_{ijt}$ = differenced absolute forecast error calculated as $AFE_{ijt} - MAFE_{ijt}$.

AFE_{ijt} = absolute forecast error of an analyst following firm j at time t.

$MAFE_{ijt}$ = mean absolute forecast error of all analysts following firm j at time t.

$PMAFE_{ijt}$ is a relative performance measure that uses a 30 day minimum forecast horizon, which is then averaged over all the analysts that follow that specific firm $PMAFE_t$. Values less than 1 represent better than average performance, while a value greater than 1 represents worse than average performance. The $PMAFE_{ijt}$ variable controls for both firm and year effects by adjusting forecast errors by their related firm year mean.

In the second equation of the three stage least squares model, the empirical specification uses a continuous $PMAFE_t$ variable calculated during the quarter prior to estimating the firms' Tobin Q_{t+1} and two dichotomous variables that identify when specialists are providing coverage for either high or low growth stocks.

4.2 Forecast Bias Construct

Consistent with Das, Levine, and Sivaramakrishan (1998), the forecast bias is the signed forecast error defined as the actual earnings per share for a firm minus the mean corresponding analysts' most recent forecast for a firm divided by the quarter end stock price. Forecast bias is calculated prior to the calculation of Tobin's Q.

5. Analyst Specialization and Experience

In our analysis, specialization refers to the extent that analysts are knowledgeable about the industries related to a specific firm's business segments. We use a multi-dimensional measure of specialization that is based on the number of business segments reported by the firm and the number of segments in the analysts' portfolio. The specialization variable equals the firm's number of business segments (six digit GICS codes) that an analyst monitors divided by the number of business segments for all firms in that analyst's portfolio, averaged over all the analysts that follow that specific firm, measured at the end of the year prior to the calculation of forecast error and Tobin's Q [see Dunn and Nathan (2005)]. Analysts' general experience is measured as the number of prior quarters for which an analyst follows a specific firm makes at least one forecast for the first eleven months of the year for any firm in the IBES database at the end of the year, averaged over all the analysts that follow that specific firm.

6. Estimated Growth Potential

Tobin's Q is defined as the ratio between the stock market valuation of existing real capital assets and their current replacement cost. According to Hayashi (1982), Tobin's Q is interpreted as an estimate of the capital markets ex ante valuation of the future stream of marginal profits attributable to an additional unit of capital, divided by that unit's price. As such, Tobin's Q is a measure of whether the firm can be considered as a high or low growth stock [see Chung and Pruitt (1994)].

Abel and Blanchard (1986) surmise that very high or very low Tobin's Q reflects deviations from fundamentals because it is a function of market psychological sentiment. Moreover, the estimate is desirable because, according to Lang and Stulz (1994), it does not need an adjustment for risk. We therefore construct Tobin's Q using the algorithm by Lang and Stulz (1994). Then, consistent with Eleswarapu and Reinganum (2004), the top 25 percentile with the highest Q ratio is classified as high growth firms. The firms in the bottom 25 percentile quartile with the lowest Q ratios are considered to be low growth firms.

In the first equation, Tobin's Q is a continuous variable that is measured at the end of the period prior to the calculation for forecast error. Similarly, the two dichotomous variables equal to 1 if the firm is in the top or bottom quartiles are measured at the end of the year prior to the calculation for forecast error. In the second equation the continuous Tobin's Q_{t+1} dependent variable is measured at the end of the year after the calculation of forecast error.

7. Regulation Fair Disclosure Act

A dichotomous variable Regulation FD equals one if the time period is after October 2000, and zero otherwise. The Regulation Fair Disclosure Act was proposed by the Securities and Exchange Commission (SEC) in December 1999 and ratified in October 2000. Regulation FD mandates that all publicly traded companies disclose material information to all investors at the same time [Heflin, Subramanyam, and Zhang (2003)]. The impact of Regulation FD on forecast error and Tobin's Q is inconclusive.

8. Other Constructs

The study also controls for other variables that have been included in prior studies: firm characteristics (focus and size), factors that relate to analyst information intermediation efficiency (number of analysts, complexity of analyst's portfolio, fourth quarter bias, and forecast dispersion, and age of forecast). Firm size, equal to the natural log of the market value of equity at the beginning of the year, is expected to be negatively related to both forecast error and Tobin's Q [Chung and Jo (1996) and Clement (1999)].

Several studies find that diversification makes the analysts' task more difficult due to the cost of investigation, which results in less accurate earnings forecast [Gilson, Healy, Noe and Palepu's (2001)]. Likewise, many studies report that diversified firms have lower growth potential as measured by Tobin's Q [Lang and Stulz (1994), Berger and Ofek (1995)]. Thus, we expect that a focused strategy as measured by the Herfindahl index is negatively related to forecast error and positively related to Tobin's Q. Following these studies, we use the Herfindahl index as a continuous measure of industry concentration among a firm's business segments. The Herfindahl index equals the sum of the squared values of sales per segment (GICS) 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.

Jacob, Lys, and Neale (1999) argue that analyst information dissemination improves as the number of analysts that follow a particular firm increases because the cost of information acquisition decreases. In support of their findings, Lys and Soo (1995) find that earnings forecast accuracy increases with analyst following. Moyer, Chatfield, and Sisneros (1989) and Chung and Jo (1996) find that the market's estimate of growth opportunities as measured by Tobin's Q is an increasing function of the number of analysts following the firm.

Clement (1999) and Jacob, Lys and Neale (1999) find that recent forecast error, the relative absolute value of the error, is positively related to the complexity of the analysts' portfolio, measured as the number of industries that an analyst follows. Portfolio complexity is calculated as the mean number of GICS codes in an analyst's portfolio, averaged for all security experts that follow a particular firm at the beginning of the year.[2]

Fourth quarter effect (QTR4DUM) is a dichotomous variable equal to one if the earnings forecast is made in the fourth quarter. Lim (2001) finds that forecast error is higher in the fourth quarter than the rest of the year. Age of forecast is measured by the number of days between the forecast date and the earnings announcement date. Mikhail, Walther and Willis (1997) report that forecast error increases with forecast age.

Barron and Stuerke (1998) and Johnson (2004) state that dispersion, the sample variance for analysts' earnings forecast for each firm at the beginning of the year, controls for the difficulty of forecasting earnings. Since the information environment is most likely different for glamour and value firms, the extent of divergence among analysts is expected to be higher for glamour firms than for value firms. Hence, we predict that dispersion is positively related to Tobin's Q. Due to the fact that both forecast error and dispersion are measures of ex ante uncertainty in the literature, we do not include dispersion as an independent variable in Equation 1.

[2]Portfolio Complexity equals the mean number of GICS codes in an analyst's portfolio, averaged for all security experts that follow a particular firm at the beginning of the year. The measure is a proxy for the percentage of time those analysts allocate their resources to a particular industry. Our study alters Clement's (1999) definition by considering every business segment (all GICS codes) instead of just the dominant SIC industry code for the firm. Portfolio Complexity is not included in the second equation because it is expected to indirectly impact Tobin's Q through forecast error.

Descriptive statistics for 3 months forecast, analyst and firm measures for high (High Q) and low (Low Q) growth firms

Variable	Mean	Median	Mean High Q	Mean Low Q
Forecasted EPS				
Forecast Error	.0042	.0023	.0068	.0011
Forecast Bias	.00039	.00027	.00014	-.0002
Dispersion of Forecast	.138	.054	.27	.004
Forecast Age	46	52	33	55
Analyst Demographics				
Number of Analysts	14	10	20	6
Analyst Experience (yrs)	4.30	5	2.77	6.12
Portfolio Complexity	5	6	3	11
Specialization	.44	.52	.61	.29
Firm Characteristics				
Tobin's Q	1.61	1.28	7.73	.22
Focus Strategy	.18	.19	.44	.09
Size (billions)	4.20	9.91	1.85	13.67

Table 1. Reports the descriptive statistics for the variables. The definitions for the variables in the Table are as follow:

High Growth = dummy variable equal to 1 if the firm's Tobin's Q is in the 75th percentile of the sample.
Low Growth = dummy variable equal to 1 if the firm's Tobin's Q is in the 25th percentile of the sample.
Forecast Error = the differenced absolute forecast error divided by the mean absolute forecast error of all analysts following a specific firm, averaged over all the analysts that follow that specific firm.
Forecast Bias = the signed forecast error defined as the actual earnings per share for a firm minus the mean corresponding analysts' most recent forecast for a firm divided by the quarter end stock price.
Dispersion of Forecast = the signed forecast error defined as the actual earnings per share for a firm minus the mean corresponding analysts' most recent forecast for a firm divided by the quarter end stock price.
Forecast Age = the number of days between the forecast date and the earnings announcement date, averaged over all the analysts that follow that specific firm.
Number of Analysts = log of the number of analysts that follow an individual firm.
Analyst Experience = log of the number of prior quarters for which an analyst that follows a firm makes at least one forecast for any firm in the IBES database for the first eleven months of the year, averaged over all the analysts that follow that specific firm.
Portfolio Complexity = the mean number of GICS codes in an analyst's portfolio, averaged for all security experts that follow a particular firm at the beginning of the year.
Specialization = the firm's number of business segments (six digit GICS codes) that an analyst follows divided by the number of business segments for all firms in that analyst's portfolio, averaged over all the analysts that follow that specific firm.
Tobin's Q = the ratio between the stock market's valuation of existing real assets and the current replacement costs.
Focused Strategy = the sum of the squared values of sales per segment (GICS code) as a fraction of total firm sales calculated at the end of the year prior to the calculation of forecast error and Tobin's Q: 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.
Size= log of the market value of equity.

9. Results

9.1 Descriptive Statistics

Table 1 provides descriptive statistics for several of the variables used in the 3SLS regression for the sample as a whole and the sub sets of high Q and low Q firms. The first two columns provide the mean and median consensus quarterly earnings per share forecast error for the entire sample and for those firms with the highest and lowest growth prospects as perceived by the capital markets. Consistent with previous studies, we find evidence that analysts tend to be optimistic. The statistics reveal that analysts, in general, overestimate firms' earnings per share as indicated by the mean and median relative forecast errors of 0.42% and 0.23%, respectively. The descriptive statistics in column three and four show that analysts are overly optimistic for high growth firms, but much less optimistic for low growth firms. Hence, forecasts for high growth firms are more overstated than the forecasts for low growth firms. The forecast error for the sub-sample of high and low growth firms are 0.68% and the 0.11%, respectively.

Differences in the mean forecast bias and dispersion for high and low growth firms also exist. As indicated by the mean and median bias values of .039% and 0.027% for the entire sample, respectively, analysts are optimistically biased about firms' projected earnings. The statistics reveal analysts' tendency to be less optimistically biased about high Q firm's future earnings. The mean consensus forecast bias for the sample of high growth firms of 0.014% is smaller than the mean bias of 0.039% for the entire sample.

The tendency for analysts to have less bias and larger forecast error may be based upon the fact that there is greater uncertainty among the analysts who provide projections for high profile growth firms which have Tobin's Q ratios averaging 7.73. The dispersion of analyst forecasts is much higher for high Q firms (27%) than for the entire sample mean (13.8%) and median (5.4%). The heterogeneity among earnings forecasts could be due to the large number of analysts (20) that follow these small firms with focused strategies (0.44) and the fact that these analysts have relatively less general experience as indicated by the average years of 2.77. This fact that these analysts specialize in certain industries (0.61) and have less complex portfolios (3 industries on average) is surprising given that their forecast error is large.

In contrast, analysts that follow low Q value firms are pessimistically biased about future earnings estimates as indicated by the mean negative 0.02% statistic, which is lower than the mean value of 0.039%. It appears that analysts in this sub sample generally agree as reflected by the mean dispersion statistic of 0.4%, which is appreciably lower than the mean and median dispersion figures of 13.8% and 5.4%, respectively. The low dispersion among analysts for low growth firms could be due to the small number of analysts per firm (6) and the analysts' experience (6.12 years). Also, these stocks are large, diversified firms that are perceived to have anemic growth opportunities as reflected by the Tobin's Q ratio of 0.22. In addition, the analysts that follow low growth firms have complex portfolios with an average of eleven industries.

9.2 Analyst Influence

To determine the relationship between analyst earnings decisions and the capital market's estimate of firm growth potential, we estimate two regression models. Table 2 reports the results from a 3SLS regression model that simultaneously predicts firm consensus forecast error and Tobin's Q. The independent variables jointly account for 42.9 percent of the variation in ex ante analyst consensus forecast error and Tobin's Q. The first and second columns report the estimates from the models that predict forecast error and Tobin's Q respectively. The coefficient b_1 in the first column is interpreted as the mean change in forecast error as the firm's Tobin's Q increases, while controlling for the other independent variables. The 0.081 coefficient is statistically significant at the 0.01 level, indicating that the level of analyst forecast error increases as the capital market's estimation of Tobin's Q rises. Thus, if a firm's Tobin's Q increases by a point, the model in column one predicts that the analysts' forecast error raises substantially from 0.007 to 0.088. This finding is economically relevant establishing that analyst has inherent forecast error (0.007) and that error is magnified to 0.088 (0.007 + 0.081) when evaluating firm with high Tobin's Q.

This finding is consistent with analysts herding around the capital market's estimate of firm growth potential[3]. Our conclusion about herding is made after taking into

[3]Kwag and Small report a statistically insignificant relationship between foreca st error or absolute forecast error and the firm's market-to-book value of equity within the same year. Our analysis deviates from their paper by examining for ecast error for the quarter with Tobin's q from the prior year.

Associations between factors that simultaneously predict consensus analyst forecast error and the natural logarithm of Tobin's Q within a three stage least square regression during January 1990 to December 2005.

	Forecast $Error_t$	$LnTobin'sQ_t$
Intercept	0.007**	1.277**
	(2.63)	(2.99)
Ln(Tobin'sQ_{t-1})	0.081**	-
	(4.17)	
Forecast $Error_{t-1}$	-	0.600
		(0.15)
$Specialization_{t-1}$	-0.086**	0.477**
	(-3.66)	(5.59)
Specialization * Forecast Error		0.152
		(1.20)
High Growth*$Specialization_{t-1}$	-0.009	-
	(-1.00)	
Low Growth*$Specialization_{t-1}$	0.022	-
	(0.18)	
Portfolio $Compexity_{t-1}$	0.502	-
	(1.19)	
Ln(Number of $Analysts_{t-1}$	-0.001	0.029**
	(-0.92)	(7.33)
Ln(Analyst $Experience_{t-1}$	-0.028**	-
	(-4.26)	
Forecast Age_t	0.009**	-
	(6.00)	
Ln(Dispersion of $Forecast_{t-1}$)	-	-0.115**
		(-3.62)
$QTR4DUM_t$	0.032*	-
	(2.09)	
Ln($Size_{t-1}$)	0.000**	-0.107**
	(5.00)	(-5.54)
Focused $Strategy_{t-1}$	-0.040**	0.237**
	(-3.31)	(5.02)
RegFD	-0.000	0.000
	(0.90)	(0.11)
System-Weighted R2	.429	
System-Weighted MSE	2.284	

*, ** Significant at .05 and .01 (two-tailed), respectively.

Table 2. Provides the results from a simultaneous regression model that predicts the analyst's mean forecast error and the firm's Tobin's Q (*, ** Significant at .05 and .01 two-tailed), respectively, The definitions for the variables are as follows:

Variable Definitions:

Forecast Error = the differenced absolute forecast error divided by the mean absolute forecast error of all analysts following a specific firm, averaged over all the analysts that follow that specific firm.

Tobin's Q = the log of the ratio between the stock market's valuation of existing real assets and the current replacement costs.

Specialization = the firm's number of business segments (six digit GICS codes) that an analyst follows divided by the number of business segments for all firms in that analyst's portfolio, averaged over all the analysts that follow that specific firm.

High Growth = dummy variable equal to 1 if the firm's Tobin's Q is in the 75^{th} percentile of the sample.

Low Growth = dummy variable equal to 1 if the firm's Tobin's Q is in the 25^{th} percentile of the sample.

Portfolio Complexity = the mean number of GICS codes in an analyst's portfolio, averaged for all security experts that follow a particular firm at the beginning of the year.

Number of Analyst = log of the number of analysts that follow an individual firm.

Analyst Experience = log of the number of prior quarters for which an analyst that follows a firm makes at least one forecast for any firm in the IBES database for the first eleven months of the year, averaged over all the analysts that follow that specific firm.

Forecast Age = the number of days between the forecast date and the earnings announcement date, averaged over all the analysts that follow that specific firm.

Dispersion of Forecast = the signed forecast error defined as the actual earnings per share for a firm minus the mean corresponding analysts' most recent forecast for a firm divided by the quarter end stock price.

QTR4DUM= dummy variable equal to 1 if the forecast is made in the fourth quarter of the year.

Size = log of the market value of equity.

Focused Strategy = the sum of the squared values of sales per segment (GICS code) as a fraction of total firm sales calculated at the end of the year prior to the calculation of forecast error and Tobin's Q: 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.

RegFD= dummy variable equal to 1 if the forecast is made or Tobin's Q is calculated prior to 2000.

account Lim's (2001) finding that forecast error is higher in the fourth quarter than the rest of the year. As a result, the empirical specification controls for this with a fourth quarter effect (QTR4DUM) dichotomous variable equal to one if the earnings forecast is made in the fourth quarter and zero otherwise. As expected, consensus forecast error is positively related to the fourth quarter dichotomous variable which indicates that the market's expectation of growth decreases with uncertainty. The rationale is that firms have lower (higher) market estimates because they have higher (lower) uncertainty as evidenced by analyst dispersion, which causes the required rate of return to be larger (smaller) [see Barron and Stuerke (1998)]. The 0.032 coefficient on QTR4DUM is statistically significant at the five percent level.

The second specification in column two captures the change in Tobin's Q that results from an increase in analyst forecast error. This specification analyzes whether investors are influenced by mistakes in analysts' publicly available earnings estimates when estimating the growth potential of publicly traded firms. The 0.600 coefficient on ex post forecast error is statistically insignificant. This finding is consistent with investors ignoring the accuracy of analysts' forecast decisions.

Table 3 repeats the analysis in Table 2, but the specifications substitute forecast bias for forecast error. Forecast bias is an analysts' intentional or unintentional tendency to systematically provide high or low earnings forecasts for specific firms, whereas forecast error estimates mistakes that could be random [Guedj and

Associations between factors that simultaneously predict consensus analyst bias and the natural logarithm of Tobin's Q within a three stage least square regression during January 1990 to December 2005.

	Forecast Error$_t$	LnTobin'sQ$_t$
Intercept	-0.011**	1.162**
	(12.29)	(3.19)
Ln(Tobin'sQ$_t$)	0.042**	-
	(0.08)	
Forecast Bias$_t$	-	0.191
		(0.60)
Specialization$_t$	-0.097**	0.764**
	(-5.44)	(4.01)
ForecastBias$_t$ * Specialization$_t$		-0.111
		(-0.60)
Portfolio Compexity$_t$	-0.047	-
	(1.33)	
Ln(Number of Analysts$_t$	-0.076*	0.990**
	(-2.00)	(4.01)
Ln(Analyst Experience$_t$	-0.005	-
	(1.92)	
Forecast Age$_t$	0.006**	-
	(11.04)	
Ln(Dispersion of Forecast$_t$)	-	-0.417**
		(-8.10)
QTR4DUM$_t$	0.015*	-
	(2.32)	
Ln(Size$_t$)	-0.024**	-0.233**
	(-4.05)	(2.60)
Focused Strategy$_t$	-0.071**	1.722**
	(-2.99)	(3.86)
RegFD	-0.013	0.000
	(1.56)	(0.01)
System-Weighted R2	0.399	
System-Weighted MSE	1.925	

*, ** Significant at .05 and .01 (two-tailed), respectively.

Table 3. Provides the results from a simultaneous regression model that predicts the analyst's mean forecast bias and the firm's Tobin's Q (*, ** Significant at .05 and .01 two-tailed), respectively. The definitions for the variables are as follows:

Forecast Bias= the signed forecast error defined as the actual earnings per share for a firm minus the mean corresponding analysts' most recent forecast for a firm divided by the quarter end stock price.
Tobin's Q = the log of the ratio between the stock market's valuation of existing real assets and the current replacement costs.
Specialization = the firm's number of business segments (six digit GICS codes) that an analyst follows divided by the number of business segments for all firms in that analyst's portfolio, averaged over all the analysts that follow that specific firm.
Portfolio Complexity = the mean number of GICS codes in an analyst's portfolio, averaged for all security experts that follow a particular firm at the beginning of the year.
Number of Analysts = log of the number of analysts that follow an individual firm.
Analyst Experience = log of the number of prior quarters for which an analyst that follows a firm makes at least one forecast for any firm in the IBES database for the first eleven months of the year, averaged over all the analysts that follow that specific firm.
Forecast Age = the number of days between the forecast date and the earnings announcement date, averaged over all the analysts that follow that specific firm.
Dispersion of Forecast = the signed forecast error defined as the actual earnings per share for a firm minus the mean corresponding analysts' most recent forecast for a firm divided by the quarter end stock price.
QTR4DUM= dummy variable equal to 1 if the forecast is made in the fourth quarter of the year.
Size = log of the market value of equity.
Focused Strategy = 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.
RegFD= dummy variable equal to 1 if the forecast is made or Tobin's Q is calculated prior to 2000.

Bouchard (2005)]. In the literature positive (negative) bias values denote over (under) forecasting and zero values are consistent with no bias. The authors state that analysts often have positive bias because they are reluctant to report information because the benefits of being optimistic outweigh the costs associated with less credibility. Hence, we investigate whether analysts' bias affects the capital market's valuation of firm's earnings potential.

Similar to our interpretation of Table 2's results, we find that analyst bias is positively impacted by the capital market's estimate of a firm's growth potential, but Tobin's Q is not statistically related to ex post forecast bias in column one. The coefficient of 0.042 on the Tobin's Q variable is statistically significant at the one percent level. Thus, even though the unconditional bias of -0.011 on the intercept term for the analysts in the sample is pessimistic. The bias increases by 0.042 as Tobin's Q increases by one unit such that the bias becomes optimistic as indicated by a value of 0.031 (-0.011+ 0.042). In contrast, the capital market appears to not incorporate analyst forecast bias into their estimate of a firm's future growth opportunity. In column two, the coefficient of 0.191 on the forecast bias variable is statistically insignificant.

9.3 Analyst Credibility

Our analysis to this point reveals that analysts' decisions about forecasted earning are not an important component of the capital market's valuation process for the sample as a whole. Givoly (2003), Gilson, Healy, Noe and Palepu (2001) and Park and Stice (2000), however, assert that that the degree of specialization and an individual's experience should affect how investors' assess the credibility of their forecast decisions. In fact, Chen, Chan and Steiner (2002) conclude that all security analysts are not created equal and that their forecast abilities are related to factors such as specialization and industry experience.

In Tables 2 and 3, the model specifications analyze whether analysts that are experienced or specialists forecast earnings more accurately than other professional and whether these individuals' forecast error or bias are subsequently incorporated into the capital market's estimate of a firm's growth potential. The results in Table 2 reveal that individuals who specialize in following firms in a particular industry or professionals that have more experience as indicated by the number of quarters that they provided forecasts for I/B/E/S are more accurate. The specialization coefficient is interpreted as the mean change in forecast error as the number of industries that the analyst has in his portfolio declines. The empirical results show that all analysts are not the same. Specialists tend to be more accurate and precise relative to professionals who could be considered as generalists. The coefficient of -0.086 on the specialization variable is statistically significant at a one percent level. Similarly, Table 2 reports that experienced analysts utilize their expertise and knowledge to reduce the error in their earnings forecast relative to less experienced individuals. In the first column, the coefficient of -0.028 on the analyst experience variable is statistically significant at the 0.01 level.

In addition, Table 3 establishes that specialists' forecasts have lower bias relative to other professionals, thus a one percentage rise in specialization results in a 9.7% decrease in forecast bias. In the first column of Table 3, the coefficient of 0.097 on the specialist variable is statistically significant. Thus, as the intersection between the firm's industry segments and the number of unique segments for all of the companies in an analyst's portfolio increases, the tendency to become optimistic about a particular firm's earnings falls. Experience, however, is not significantly related to forecast bias. The coefficient of -0.005 on experience is not statistically significant in Table 3.

These findings are consistent with Clement (1999) in that specialist and experienced analyst are able to reduce forecast error. However, these findings do not extend to firms with high nor low Tobin's Q. Specialists, therefore, do not adjust their forecasting models for high and low growth stocks. In column one in Table 2, specialists do not have better or worse forecasting ability for the highest or lowest growth firms relative to the rest of the sample. The coefficients on the high growth-specialization and low growth-specialization interaction variables are -0.009 and 0.022, respectively. Both coefficients are not statistically significant.

Despite the strong evidence in support of specialist and analyst experience with respect to accurately forecast firm earnings, investors do not incorporate specialists' forecast error into their assessment of firm growth as estimated by Tobin's Q. The coefficient on the interaction term specialization*forecast error is 0.152, but not statistically different from zero, even though specialists and experienced individuals produce the most accurate forecasts as reflected by the statistically significant coefficients of -0.20 and -0.86 in column one. The results are consistent with capital market participants not relying on analysts' earnings information.

Specialists, however, appear to provide non-earnings information to the market when they provide coverage for firms. In the Tables 2 and 3, the statistically significant coefficients of 0.477 and 0.764 on specialization indicate that the market increases its estimate of firm growth opportunities as evidenced by Tobin's Q, respectively. This result within a simultaneous equation model is consistent with specialists inducing the capital market to increase firm value by making investors cognizant of firm's additional growth opportunities.

9.4 Regulation Fair Disclosure

Regulation Fair Disclosure Act was proposed by the SEC in December 1999 and ratified in October 2000. Regulation FD mandates that all publicly traded companies disclose material information to all investors at the same time [Heflin, Subramanyam, and Zhang (2003)]. In our analysis, a dichotomous variable Regulation FD equals one if the time period is after 2000, and zero otherwise. The insignificant coefficients on Regulation FD in Tables 2 and 3 are both statistically and economically insignificant. As such, neither analyst forecast error nor the capital market's estimate of a firm's future growth opportunity is affected by the more stringent disclosure regulation.

As a sensitivity test, consistent with Kwag and Small (2007), we evaluate whether consensus forecast error decreased subsequent to the implementation of Regulation FD. The univariate analysis (not reported) reveals that accuracy decreased as evidenced by a larger absolute forecast error in the post-Regulation FD years. Therefore, the tendency for analysts to herd around capital market estimates of growth potential is not driven by their access to information relative to other investors as determined by this recent regulation.

Ke and Yu 2006 conclude that analysts used earnings forecast bias to curry favor with management in the years prior to Regulation FD, which should have not been possible afterward due to more detailed disclosure and access to management information from conference calls. As such, we rerun the results and replace consensus forecast error with consensus forecast bias in Table 3. Tobin's Q predicts forecast bias (coefficient of 0.042), but bias does not predict Tobin's Q for all analysts (coefficient of 0.191) or for those who are specialists (coefficient of -0.111). Within the model, Regulation FD did not affect either consensus forecast bias (coefficient of -0.013) or Tobin's Q (coefficient of 0.000).

9.5 Other factors

Analysts are constantly exposed to diverse and often conflicting information. This study controls for these factors: the complexity of portfolio, age of forecast, the size of the firm, intensity of analyst coverage (number of individuals), firm's portfolio focus, and dispersion of all analysts' forecasts. These factors have been hypothesized to influence analyst forecast error and bias as well as the capital markets perception of firm growth.

Both Tables 2 and 3 report no significant impact on forecast error and bias resulting from portfolio complexity. Thus the average number of GICS codes in an analyst's portfolio has no significant bearing on forecast error or bias. Conversely, consistent with Mikhail, Walther and Willis (1997) we report that forecast error increases with forecast age. Thus as an analyst's forecast becomes outdated and new firm specific information becomes relevant the forecast error and bias increase. The forecast age variable coefficients on forecast error and bias are 0.009 and 0.006, respectively, in Tables 2 and 3. Both coefficients are statistically significant at a one percent level.

Previous literature finds a direct correlation between the analyst coverage and a firm's Tobin's Q. Consistent with Chen, Chan, Steiner (2002) and Doukas, Kim, and Pantzalis (2005), we find a positive relationship between the number of analyst following a firm and capital market expectations measured by Tobin's Q. The coefficients in Table 2 and 3 for the natural logarithm of the number of analyst are 0.029 and 0.99, respectively. Both number of analyst variables are statistically significant at the one percent level. The results, however, are inconsistent with earnings forecast error decreasing with analyst following. In Table 2, the coefficient of -0.001 on number of analysts is statistically insignificant. In contrast, the number of analysts following the firm reduced forecast bias. The remaining variables, focused strategy and size, have results that are consistent with prior research.

Conclusion

In this study we examine the impact of analysts' decisions on the markets' perception of growth opportunities as well as the market's impact on security analysts' forecast accuracy. Our main finding is that analyst forecast accuracy does not exert a significant impact on the market's perception of growth potential. Neither relative forecast error nor bias is a statistically significant predictor of Tobin's Q. We do, however, find that Tobin's Q value is a positive and statistically significant predictor of forecast error. Essentially, analysts' forecasts become less accurate as firms' perceived growth opportunities increase. The result that Tobin's Q effect forecast bias and error suggest that there is a degree of inefficiency in the analyst intermediation market.

References

[1]. Abel, A. and O. Blanchard. (1986). The present value of profits and cyclical movements in investment. *Econometrics* 54: pp.249-272.

[2]. Abarbanell, J. and B. Bushee. (1997). Fundamental analysis, future earnings, and stock prices. *Journal of*

Accounting Research 35: pp.1-24.

[3]. **Barron, O. and P. Stuerke. (1998).** Dispersion in analysts' earnings forecasts as a measure of uncertainty. *Journal of Accounting, Auditing, and Finance* 13: pp.245-270.

[4]. **Berger, P., and E. Ofek, (1995),** 'Diversification's effect on firm value', *Journal of Financial Economics* 37, pp. pp.39-65.

[5]. **Brennan, M. and P. Hughes, (1991),** 'Stock prices and the supply of information', *Journal of Finance* 66, pp. pp.1665-1690.

[6]. **Brown, L. (2001).** How important is past analyst forecast accuracy? *Financial Analyst Journal* 57: pp.44-49.

[7]. **Chen, C., K. Chan, and T. Steiner. (2002).** Are all security analysts equal? *Journal of Financial Research*.25: pp.415-430.

[8]. **Chung, K. and H., Jo. (1996).** The impact of security analysts' monitoring and marketing functions on the market value of the firms. *Journal of Financial and Quantitative Analysis*. 31: pp.493-512.

[9]. **Chung, K., and S. Pruitt. (1994).** A simple approximation of Tobin's q. *Financial Management*. 23: pp.70-74.

[10]. **Clement, M. (1999).** Analyst forecast accuracy: Do ability, resources, and portfolio complexity matter? *Journal of Accounting and Economics* 27: pp.285-304.

[11]. **Clement, M. and S. Tse. (2005).** Financial analyst characteristics and herding behavior in forecasting. *Journal of Finance* 60: pp.307-341.

[12]. **Clement, M., L. Rees and E. Swanson. (2003).** The influence of culture and corporate governance on the characteristics that distinguish superior analysts. *Journal of Accounting, Auditing and Finance* 18: pp.593-618.

[13]. **Das, S., C. Levine, and K. Sivaramakrishan. (1998).** Earnings predictability and bias in analysts' earnings forecast. *Accounting Review* 73: pp.277-294.

[14]. **Dechow, P. and R. Sloan. (1997).** Returns to contrarian investment strategies: test of naïve expectations hypothesis. *Journal of Financial Economics* 43: pp.3-27.

[15]. **Doukas, J., C. Kim, and C. Pantzalis. (2005).** Two faces of analyst coverage. *Financial Management* 34: pp.99-125.

[16]. **Dunn, K., and S. Nathan. (2005).** Analyst industry diversification and earnings forecast accuracy. *Journal of Investing* 14: pp.7-15.

[17]. **Easton, P., and G. Sommers. (2007).** Effect of analysts' optimism on estimates of the expected rate of return implied by earnings forecasts. *Journal of Accounting Research* 45: pp.983-1015.

[18]. **Ehrbeck, T. and R. Waldmann. (1996).** Why are professional forecasters biased? Agency versus behavioral explanations. *Quarterly Journal of Economics* 111: pp.21-40.

[19]. **Eleswarapu, V., and M. Reinganum. (2004).** The predictability of aggregate stock market returns: evidence based on glamour stock. *Journal of Business* 77: pp.275-294.

[20]. **Elgers, P., M. Lo, and R. Pfeiffer. (2001).** Delayed security price adjustments to financial analysts' forecast of annual earning. *Accounting Review* 76: pp.613-632.

[21]. **Fuller, R., L. Huberts and M. Levinson. (1993).** Returns to E/P strategies, higgledy-piggledy growth, analysts' forecast errors, and omitted risk factors. *Journal of Portfolio Management* 19: pp.13-24.

[22]. **Geweke, J., R. Meese, and W. Dent. (1983).** Comparing alternative tests of causality in temporal systems. *Journal of Econometrics* 21: pp.161-194.

[23]. **Gleason, C. and C. Lee. (2003).** Analysts' forecasts revisions and market price discovery. *Accounting Review* 78: pp.193-225.

[24]. **Gilson, S., P. Healy, C., Noe, and K. Palepu. (2001).** Analyst specialization and conglomerate breakups. *Journal of Accounting Research* 39: pp.565-582.

[25]. **Givoly, D., (2003),** 'Discussion-The influence of culture and corporate governance on the characteristics that distinguish superior analysts', *Journal of Accounting, Auditing, and Finance* 18, pp. 619-623.

[26]. **Givoly, D. and J. Lakonishok. (1980).** Financial analysts' forecasts of earnings: the value to investors.

Journal of Banking and Finance 4: pp.221-223.

[27]. **Graham, J. (1999).** Herding among investment newsletters: theory and evidence. *Journal of Finance* 54: pp.237-268.

[28]. **Greene, W. H.(1993).** *Econometric Analysis*, New York, NY, Macmillan Publishing Co.

[29]. **Guedj, O. and J.P. Bouchaud, (2005),** 'Experts' earning forecasts: Bias, herding and gossamer information, *International Journal of Theoretical and Applied Finance* 8, pp. 933-

[30]. **Hayashi, F. (1982).** Tobin's marginal q and average q: A neoclassical interpretation. *Econometrica* 50: pp.213-224.

[31]. **Heflin, F., K. Subramanyam, and Y. Zhang. (2003).** Regulation FD and the financial information environment: early evidence. *Accounting Review* 78: pp.1-38.

[32]. **Hong, H., J. Kubik, J., and A. Solomon, (2000),** 'Security analysts' career concerns and herding of earnings forecasts', *Rand Journal of Economics* 31, pp. 121-144.

[33]. **Jackson, D. and J. Madura. (2007).** Impact of regulation fair disclosure on the information flow associated with profit warnings. *Journal of Economics and Finance* 31: pp.59-74.

[34]. **Jacob, J., T. Lys, and M. Neale. (1999).** Expertise in forecasting performance of security analysts. *Journal of Accounting and Economics* 28: pp.51-82.

[35]. **Johnson, T. (2004).** Forecast dispersion and the cross-section of expected returns. *Journal of Finance* 59: pp.1957-1978.

[36]. **Kasznik, R. and B. Lev. (1995).** To warn or not to warn: management disclosures in the face of an earnings surprise. *Accounting Review* 70: pp.113-134.

[37]. **Ke, B. and Y. Yu. (2006).** The effect of issuing biased earnings forecasts on analysts' access to management and survival. *Journal of Accounting Research* 44: pp.965-999.

[38]. **Klein, A. (1990).** A direct test of the cognitive bias theory of share price reversals. *Journal of Accounting and Economics* 13: pp.155-166.

[39]. **Kwag, S. and K. Small. (2007).** The impact of regulation fair disclosure on earnings management and analyst forecast bias. *Journal of Economics and Finance* 31: pp.87-97.

[40]. **Lamont, O. (1995).** Macroeconomic forecasts and microeconomic forecasters, *NBER Working Paper* pp.52-84.

[41]. **Lang, L. and R. Stulz. (1994).** Tobin's q, corporate diversification, and firm performance, *Journal of Political Economy* 102, pp.1248-1280.

[42]. **Libby, R. and H. Tan. (1999).** Analysts' reactions to warning of negative earnings surprises. *Journal of Accounting Research* 37: pp.415-435.

[43]. **Lim, T. (2001).** Rationality and analysts' forecasts' forecasts bias. *Journal of Finance* 56: pp.369-385.

[44]. **Lys, T., and L. Soo. (1995).** Analysts' forecast precision as a response to competition. *Journal of Accounting, Auditing, and Finance* 10: pp.751-765.

[45]. **Mikhail, M., B., Walther, and R. Willis. (1997).** Do security analysts improve their performance with experience? *Journal of Accounting Research* 35: pp.131-166.

[46]. **Moyer, C., R. Chatfield, and P. Sisneros. (1989).** Security analyst monitoring activity: agency costs and information demands. *Journal of Financial Quantitative Analysis* 24: pp.503-512.

[47]. **Park, C. and E. Steice. (2000).** Analyst forecasting ability and the stock price reaction to forecast revisions. *Review of Accounting Studies* 5: pp.259-272.

[48]. **Piotroski, J., and D. Roulstone. (2004).** The influence of analysts, institutional investors, and insiders on the incorporation of market, industry, and firm-specific information into stock prices. *Accounting Review* 79: pp.1119-1151.

[49]. **Scharfstein, D. and J. Stein. (1990).** Herd behavior and investment. *American Economics Review* 80: pp.465-479.

[50]. **Servaes, H. (1996).** The value of diversification during the conglomerate merger wave. *Journal of Finance* 51: pp.1201-1226.

[51]. **Skinner, D. and R. Sloan. (2002).** Earnings surprises, growth expectations, and stock returns or don't let an earnings torpedo sink your portfolio. *Review of Accounting Studies* 7: pp.289-312.

[52]. **Stickel, S., (1992),** 'Reputation and performance among security analysts', *Journal of Finance* 47, pp.1811-1836.

[53]. **Thomas, L. and C. Krebs. (1997).** A review of statistical power analysis software. *Bulletin of the Ecological Society of America* 78: pp.126-139.

[54]. **Trueman, B. (1994).** Analyst forecasts and herding behavior. *Review of Financial Studies* 7: pp.97-124.

[55]. **Zuckerman, E. (1999).** The categorical imperative: securities analysts and the illegitimacy discount. *American Journal of Sociology* 104: pp.1398-1438.

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