



MIT Sloan School of Management

**Working Paper 4243-02
March 2002**

DETERMINANTS OF THE INFORMATIVENESS OF ANALYST RESEARCH

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Determinants of the Informativeness of Analyst Research

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First draft: January 2002

Revised: March 2002

Abstract

Analyst research helps prices reflect information about a security's fundamentals. However, analysts' private incentives potentially contribute to misleading research and it is possible that the market fixates on such misleading and/or optimistic reports. We examine cross-sectional determinants of the informativeness of analyst reports, i.e., their effect on security prices, controlling for endogeneity among the factors affecting informativeness. Analysts are more informative when the potential brokerage profits are higher (e.g., high trading volume and high volatility) and when they reveal 'bad news.' Analyst informativeness is reduced in circumstances of increased information processing costs. We fail to find evidence that informativeness of analyst reports is due to market's fixation or over- or under-reaction to analyst reports.

We are grateful to Wayne Guay for helpful comments.

Determinants of the Informativeness of Analyst Research

“No matter what the market does, analysts just seem to keep saying ‘buy,’ ” said Senator Joseph Lieberman (D., Conn.). One reason for this, he suggested, is that banks and investment firms for which the analysts work earned millions of dollars arranging mergers or stock offerings for the companies being analyzed. “These influences compromise analysts’ objectivity and mean that the average investor should take their bottom line recommendation with at least a grain of salt, if not a whole bucket,” Mr. Lieberman said. (*The Wall Street Journal*, February 28, 2002, p. A3).

1. Introduction

We examine cross-sectional determinants of the informativeness of analyst reports, i.e., the average stock price reaction to the release of an analyst forecast revision. In an efficient market, why do some firms’ prices react more to analyst reports than others? What firm characteristics are associated with cross-sectional variation in the informativeness of analyst reports? Does price response to analyst reports increase in analyst following? Unlike previous research on the relation between analyst following and firm characteristics, we focus directly on the informativeness of analyst reports and thus on the nature of analysts’ output and its effect on security prices. While analysts are typically viewed as enhancing the informativeness of prices in a capital market, we also entertain the hypothesis that investors fixate or over- or under-react to analyst reports that might be biased or misleading. Several behavioral finance theories and voluminous accumulated evidence suggest capital market inefficiency with respect to analyst reports (see Kothari, 2001, Lee, 2001, and Hirshleifer, 2001, for reviews). If markets were naïvely fixated on analyst reports and/or over- or under-reacted to analyst reports, then analyst following would be an imperfect and/or biased indication of the degree of informational efficiency of the firm’s stock prices. Instead, it would make the firm’s stock returns predictable. We test for this implication.

Analysts are dominant information intermediaries in capital markets. The importance of their role in capital markets has spurred research on the relation between analyst following and

firm characteristics (e.g., Bhushan, 1989a, O'Brien and Bhushan, 1990, and Lang and Lundholm, 1996). Research finds that analyst following, i.e., analyst research, and the quality of firms' financial disclosures are complements (e.g., Lang and Lundholm, 1996). Analyst research increases in corporate disclosure quality either because demand for analyst services increases in the level of corporate disclosure that users interpret differentially (Merton, 1987, Harris and Raviv, 1993, Kandel and Pearson, 1995, and Bamber, Barron, and Stober, 1999), or because analysts' costs decrease in disclosure quality (e.g., Bhushan, 1989a, and Healy and Palepu, 2001). Evidence also shows that analyst research influences the informational efficiency of capital markets. Specifically, the speed with which prices reflect public information increases with analyst following (e.g., Hong, Lim and Stein, 2000, and Elgers, Lo, and Pfeiffer, 2001). Finally, prior research (e.g., Givoly and Lakonishok, 1979, Lys and Sohn, 1990, Francis and Soffer, 1997) shows analyst reports, on average, convey information to the capital market.¹

However, analyst research may not entirely represent the flow of value relevant information to the market.² First, with the objective of generating investment banking and brokerage business for their firms, analysts provide information and other services to market participants. As one of the services, analysts might simply repackage and re-transmit corporate disclosures, i.e., provide fundamental analysis to individual investors and money managers, which serves as input into investment decisions. Thus, some analysts might follow companies or produce additional research reports even when they are unable to provide information beyond

¹ As noted earlier, behavioral finance theories and evidence suggest a portion of the stock price movement following analyst reports might be a result of the market's naïve fixation on analyst reports or its over- or under-reaction to analyst reports.

² Other researchers also doubt whether quantity of disclosure adequately proxies for the amount of information to the market. For example, Barth (2002) wonders "... whether more disclosure results in more information to the market" in the context of the informativeness of voluntary management forecasts. The concern is that quantity might affect quality and/or result in substitution.

that impounded in prices at the time of their reports. Lang and Lundholm (1996) label this as analysts' information intermediary role. While such reports might be useful to institutions and/or individuals in their investment decisions, and thus help analysts generate commissions by routing institutional and individual investors' trades through the brokerage houses employing the analysts (see Irvine, 2000, and Lin and McNichols, 1998), they will not make prices more informative.

Second, other analysts and the timeliness of corporate disclosures are likely to serve as partial substitutes for the informativeness of an individual analyst's research. Transparent and timely disclosures, voluntary or mandatory, might preempt the informativeness of analyst reports (e.g., Bhushan, 1989b, and Francis, Schipper, and Vincent, 2001). This might seem inconsistent with the evidence that measures of corporate disclosure quality and the amount of analyst research are complements (see Lang and Lundholm, 1996). However, whereas analyst *activity* might be related to the (perceived) quality and quantity of corporate disclosures, it does not necessarily translate into greater *informativeness* of analyst research.

Finally, many allege analysts misinform the market, presumably for private gains. For example, Arthur Levitt, the former SEC Chairman, claims, "... analysts' employers expect them to act more like promoters and marketers than unbiased and dispassionate analysts." (The Washington Post on June 13, 2001.) As another example, CNBC in an attempt to calm an ethics controversy requires that "analysts disclose their trading in any stock they discuss. They also prohibit analysts from buying a stock, touting it on the network as a good investment, then selling it as soon as the price goes up – a practice known on the Wall Street as pump and dump." (Times Union, Albany, NY, December 24, 1998).

Reinforcing the anecdotal evidence, academic research suggests that analysts' incentive to generate investment banking and brokerage business for their firms compromises their objectivity and results in optimistically biased forecasts, stock recommendations, and analysis (e.g., Lin and McNichols, 1998, Michaely and Womack, 1999, and Dechow, Hutton, and Sloan, 2000). Analyst incentives to misinform, combined with mounting evidence of market inefficiency with respect to analyst reports (i.e., market's fixation or under- or over-reaction to analyst reports) implies analyst research cannot be unambiguously interpreted as serving to enhance informational efficiency of the capital markets. Consistent with the latter notion, Barth and Hutton (2001, p. 33) conclude, "... investors do not heed the information in analyst forecast revisions"

In sum, offsetting forces influence the informativeness of analyst research, suggesting the necessity to examine the extent to which analyst research conveys information to capital markets. Therefore, we estimate the determinants of the price reaction to analyst reports. For reasons discussed below, our research design addresses the endogenous nature of analyst activity and the informativeness of their reports. We also examine whether price movements associated with analyst reports subsequently reverse. Price reversals are expected if the market overreacts to analyst reports and/or if the market fixates on analysts' optimistic and/or misleading forecasts.

Summary of results. We analyze analyst forecasts, stock returns, and firm characteristics for almost 11,000 firm-year observations from 1995 to 1999. We measure informativeness as the average abnormal absolute stock price reaction to analyst forecast revisions. Analyst research, on average, is significantly informative and it exhibits substantial cross-sectional variation in our sample firms. Two-stage-least-squares regression results show that, as predicted, analyst informativeness increases in return volatility and trading volume. Since average

informativeness is positive, aggregate informativeness grows with the number of analysts following a firm. However, the marginal effect of analyst following on the informativeness of an analyst's research report is not statistically distinguishable from zero. One might suspect that competition among analysts might result in a negative marginal effect of analyst following on informativeness. Our results suggest that analysts' supply increases with opportunities to provide informative research, but not beyond the point when the marginal effect becomes negative.

We also find that analyst informativeness and the timeliness of financial information, measured as the contemporaneous association between security prices and financial information, are complements. Finally, results show that analyst research is far more informative when analysts issue a negative forecast revision than positive.

Our return reversal tests fail to indicate that the market is fixated on misleading analyst research or that it over-reacts to analyst reports. Bid-ask spread and other trading frictions generate some return predictability that is germane to the entire population and is observed in any period, not just around analyst forecast revision dates. However, we do not observe any difference between return predictability for firms with high analyst informativeness and that for firms with low analyst informativeness. Thus, evidence is not consistent with over-reaction to analyst research or the market's fixation on analyst reports. Since we perform only short horizon return reversal tests, we cannot speak to the possibility of long-term predictability of returns.

Contributions to the literature. In the current climate of strong conflicting opinions about the quality of analyst research and the market's ability to discern the 'hype' in analyst reports, research that discriminates between the conflicting opinions assumes importance. We are unaware of any prior study that systematically estimates the price impact of individual

analyst research and its cross-sectional determinants. We depart from the tradition of examining the relation between analyst following and firm characteristics to the determinants of analysts' output, i.e., price informativeness of their research. The empirical analysis in the paper recognizes the endogenous nature of analyst research activity and various firm characteristics. Finally, we examine whether the market's reaction to analyst research is consistent with investor rationality.

Outline. Section 2 surveys previous research on the determinants of analyst informativeness in the context of our study. Section 3 describes the data, regression model, and main results from estimating the relation between analyst informativeness and its determinants. Section 4 examines whether analyst informativeness is consistent with investor rationality or suggestive of the market participants' fixation on optimistic and/or misleading analyst forecasts or over- or under-reaction to analyst research. We offer concluding remarks in section 5.

2. Determinants of analyst informativeness

In this section we discuss the determinants of analyst informativeness and describe the simultaneous equations model we use to empirically estimate its determinants. We rely on prior theoretical and empirical research (referenced in the introduction) for cross-sectional determinants of the informativeness of analyst reports. We approach the informativeness of analyst reports as an attribute that is shaped by the forces of demand for and supply of analyst informativeness in a market setting. Naturally, we expect informativeness to increase in firm and institutional characteristics that proxy for the demand for analysts' services and the informativeness to wane in the analysts' cost of supplying new information about a firm. However, analyst informativeness and many of the demand and supply variables affect each other, thus leading to endogeneity. In this setting, ordinary least squares estimation of the

determinants of analyst informativeness would likely yield biased and inconsistent coefficient estimates. We therefore estimate the model of the determinants of analyst informativeness using a simultaneous equations framework, i.e., two-stage least squares, 2SLS, (e.g., O'Brien and Bhushan, 1990, and Alford and Berger, 1999).

Determinants of analyst informativeness. We model analyst informativeness as a function of a set of demand and supply variables and number of analysts. Formally,

$$AI_T = \alpha + \beta X_T + \gamma Y_T + \delta \text{Num_analysts} + \varepsilon$$

where

AI_T = analyst informativeness,

X_T = variables proxying for the *demand* for analyst informativeness,

Y_T = variables proxying for the *supply* of analyst informativeness,

β and γ are coefficient vectors associated with the demand and supply variables, δ is the coefficient on the number of analysts variable, ε is an error term, and

Num_analysts_T = number of analysts following a firm, which is included to differentiate analyst informativeness, AI, from number of analysts, a proxy often used in prior research for analyst informativeness (e.g., Brennan and Subramanyam, 1995). Number of analysts is neither a demand nor a supply variable, but it is a noisy proxy for analyst informativeness, the dependent variable. We offer a detailed discussion of this variable below.

Endogenous variables affecting analyst informativeness. The demand for and the supply of analyst informativeness are likely to be influenced by trading volume, return variability, number of shareholders, fraction of the firm owned by institutional investors, and a set of characteristics like firm size, number of business segments, and the number of firms in an industry. Of these, we believe trading volume and return variability are particularly endogenous, whereas the remaining variables are either weakly endogenous or exogenous. We briefly explain below the endogenous determinants of analyst informativeness.

Trading volume. Analyst informativeness and trading volume should be positively related for at least three reasons. First, brokerage commissions are proportional to trading volume in a security. Brokerage houses compete for trading volume and offer analyst research as a service to their clients in generating trading business. Informativeness of the analyst research is likely to positively influence a brokerage firm's success in generating trading volume.

Second, (uninformed) liquidity traders contribute to the overall trading volume in a security. Holding the supply of shares constant, the marginal impact of liquidity trading is to make the price process noisier, i.e., increase volatility (see Verrecchia, 1982 and Bhushan, 1989a). This noise creates a profit opportunity for informed traders, which increases (i) trading volume, and (ii) the demand for informative analyst research that traders might use to become informed and capitalize on the profit opportunity.

Finally, trading volume can arise because of heterogeneous beliefs prior to information arrival (e.g., Beaver, 1968, Karpoff, 1986, and Kim and Verrecchia, 1991a and 1991b) or differential interpretation of the information (e.g., Karpoff, 1986, Harris and Raviv, 1993, Kandel and Pearson, 1995, and Kim and Verrecchia, 1997). Regardless of whether investor disagreement in beliefs is prior to or after the arrival of information, the greater the disagreement, the greater the demand for analyst research that can resolve the disagreement and restore consensus. Thus, the demand for analyst informativeness is positively related to trading volume via the divergence of beliefs among investors.

While we outline the reasons for the demand for analyst informativeness to increase in trading volume, the converse is also true, thus making trading volume endogenous with respect to analyst informativeness. For example, informative research might motivate the brokerage firm to be aggressive in its trading in the security to profit from the informativeness of the

research. Research can also generate private information that increases heterogeneity in investor beliefs and thus trade.

Return variability. High return volatility results from high uncertainty about a security's cash flow and thus presents traders with an opportunity to gain from information acquisition, i.e., informative research, which would mitigate the uncertainty. Return volatility can also be indicative of information asymmetry between management and outside investors. Under these circumstances, voluntary disclosure by the management as well as analysts' private information gathering activities can ameliorate information asymmetry. Therefore, return variability spurs demand for informative analyst research. Return volatility also helps conceal informed trades (see O'Brien and Bhushan, 1990), which in turn creates a demand for informative analyst research.

Return variability and analyst informativeness are endogenous because analyst informativeness affects return variability. Informative analyst research dampens price volatility, which is a primary objective of corporations in promoting analyst following and thus analyst research.

Exogenous determinants of analyst informativeness. We next describe the exogenous determinants of analyst informativeness. While none of the following variables is strictly exogenous, *a priori* the degree to which these variables and informativeness are likely to be jointly determined appears negligible.

Number of shareholders. The number of shareholders affects the demand for analyst informativeness directly as well as through its effect on trading volume. The larger the number of shareholders the greater the opportunities for brokerage firms to sell their research to investors and generate commissions from the resulting trading volume. Of course, the brokerage firms

should find more success as their analysts' research becomes more informative. However, as demand drives more analysts to follow a company, they are less likely to be able to individually produce informative research.

We expect some degree of endogeneity between the number of shareholders and analyst informativeness. Informative research might attract investors to a security. However, the net effect of informativeness on shareholder interest in a security is ambiguous. Informed analysts might make uninformed investors reluctant to invest in the security for fear that they might be at a disadvantage with respect to analysts' preferred clients. In fact, as the informativeness of the typical analyst diminishes because of competition among analysts, investors might find the security attractive for investment because they perceive little information disadvantage. So, a negative relation between the number of shareholders and the informativeness of analyst reports is also plausible.

Institutional ownership percentage. Analyst research is an important input in investors' decision to invest in a stock (e.g., Merton, 1987, and Brennan and Hughes, 1991). For information purposes as well as for fiduciary responsibility reasons, institutional investors seek analyst reports (see O'Brien and Bhushan, 1990). Thus, institutional ownership in a stock would increase the demand for informative analyst research. If the demand arose primarily to satisfy money managers' fiduciary responsibility to make prudent investment decisions, then institutional ownership would create a demand for *analyst reports*, not necessarily informative research.

Institutional ownership is endogenous with respect to analyst informativeness. Analysts' informative research in a security will likely stimulate institutional investors' interest and provide them with opportunities to profit from their investment. However, institutional

ownership is more likely determined by the institution's investment objectives and optimal portfolio considerations, so we treat institutional ownership as an exogenous determinant of analyst informativeness.

Number of analysts. Analyst following is perhaps the most extensively researched variable in the literature. Strictly speaking, it is neither an endogenous nor an exogenous variable with respect to analyst informativeness. In fact, past research typically regards number of analysts as a proxy for informativeness. Consistent with this characterization, Brennan and Subramanyam (1995, p. 362) assume that "The number of investment analysts researching a firm is a simple proxy for the number of individuals producing information about the value of the firm..." They find increased analyst following reduces information asymmetry as proxied for by the adverse selection cost of trading in a stock.³

Since analyst reports on average convey information to the market that results in statistically detectable price movements (e.g., Lys and Sohn, 1990), aggregate analyst informativeness would increase in the number of analysts. However, the relation between the number of analysts and the informativeness of an individual analyst report could be positive or negative. On one hand, greater opportunities to be informative induce analysts to follow a firm, so one might expect a positive association, and by this logic, the number of analysts is endogenous with respect to informativeness. On the other hand, as discussed in the introduction, (i) analysts might simply repackage available information in their research reports and thus perform an information intermediary role (see Lang and Lundholm, 1996); or (ii) they might misinform the market, presumably for private gains; or (iii) analysts might be partial substitutes

³ Also see Hong, Lim, and Stein (2000) and Barth and Hutton (2001) who assume that the reduction in information asymmetry is proportional to analyst following.

for each other. For these reasons, informativeness of analyst reports might be negatively related to the number of analysts following a firm.

We include number of analysts as an explanatory variable for the informativeness of an analyst report to examine whether it is distinct from analyst following. Since previous research uses analyst following as a proxy for analysts' informativeness about a firm, our result that a number of additional determinants of the informativeness of an analyst report exist is helpful to future research seeking a more direct measure of informativeness than analyst following.

Firm size. Previous research suggests the demand for analyst research and information produced about a security increase in firm size (e.g., Bhushan, 1989b, Collins, Kothari, and Rayburn, 1987, and Lang and Lundholm, 1996). Bhushan (1989b) argues that investors in general and informed traders in particular are likely to value information about a large firm more because large stocks are more liquid. Thus, holding the price impact constant, informed traders could execute larger trades in large firms. While firm size spurs the demand for analyst research, it also influences the supply of analyst research through the effect of firm size on the cost of producing analyst research. Because many analysts are likely to follow a large firm, the cost of producing an informative report might be high. On the other hand, because of the large number of sources of price relevant information for a large firm, individual analysts might be able to produce informative research notwithstanding the large supply of analysts following a large firm. This conclusion, however, must be tempered by the fact that a large firm's cash flows are likely to be more diversified than that of a small firm, so the marginal impact of a piece of cash flow information about a large firm on its stock price might be limited. Overall, the net effect of firm size on the informativeness of analyst reports is ambiguous.

Number of firms in an industry. The number of firms in an industry is likely to reduce analyst informativeness because information about one firm is also informative about other firms in an industry. Evidence of an industry factor in returns and earnings dates back at least to King (1966) and Brown and Ball (1967). Research also documents evidence of intra-industry information transfers (e.g., Foster, 1981). Thus, informativeness of an analyst report preempts the informativeness of research reports on other firms in the industry and thus raises the cost of informative research. Therefore, we predict a negative impact of the number of firms in an industry on analyst informativeness.

Correlation between the firm and market return. The higher the correlation between a firm's stock return and the market, the larger the macroeconomic component of the firm's return and smaller the impact of firm-specific information on the firm's returns (Bhushan, 1989b). Thus, analysts' information acquisition costs would decrease in the correlation of a firm's returns with the market and analyst following would rise. The resulting increased competition among analysts and the fact that macroeconomic information accounts for a relatively larger fraction of a firm's return variability, combine to diminish the informativeness of analyst reports. The logic here is similar to the effect of the number of firms in an industry on analyst informativeness.

Number of lines of business. Bhushan (1989b) and others argue that analysts' information gathering costs increase in a firm's number of lines of business. Increased costs reduce analyst following. Therefore, we believe the effect on analyst informativeness is ambiguous. The high cost of information gathering and lower analyst following might decrease the amount of information in each analyst report and thus lower analyst informativeness. On the

other hand, fewer analyst reports reduce competition and lessen preemption of information, making each research report more informative.

Return-earnings correlation. The return-earnings correlation (i.e., the strength of contemporaneous association between stock returns and accounting earnings) affects analyst informativeness for at least three reasons. First, a high return-earnings correlation means a firm's earnings are relatively timely in reflecting the impact of economic events affecting a firm's stock price. Timeliness makes analysts' task of uncovering price-relevant information more difficult and therefore lowers analyst informativeness. However, the greater information gathering difficulty raises analyst's costs and thus reduces the supply of analysts, which can positively influence informativeness. Second, King, Pownall, and Waymire (1990) suggest that analyst following would increase in return-earnings correlation, because the cost of forecasting earnings is likely to decrease in the strength of the return-earnings correlation. The lower cost of information gathering increases analyst informativeness, but increased analyst following might dampen informativeness. Finally, Lang and Lundholm (1996) find that accounting disclosures and analyst following are complements. Since high return-earnings correlation implies more accounting disclosures in terms of quantity and timeliness, high analyst following is expected. Increased analyst following would lower analyst informativeness because of competition among analysts. Due to the offsetting effects described above, return-earnings correlation's net effect on analyst informativeness is indeterminate.

Asymmetric informativeness of good and bad news in research reports. Competing arguments predict an asymmetric market reaction to good and bad news in analysts' reports. First, Hong, Lim, and Stein (2000) argue that management has stronger incentives to highlight good news than bad news, and therefore absent analysts, bad news is expected to propagate

through prices more slowly. Thus, analysts play a more significant role in the dissemination of bad news because managers' efforts are deficient. This logic predicts greater analyst informativeness when analysts revise earnings forecasts downward, i.e., disseminate bad news. Second, contracting considerations and litigation create an asymmetric demand for accounting conservatism, i.e., prompter disclosure of bad news than good news (see Skinner, 1994, Basu, 1997, and Ball, Kothari, and Robin, 2000). Therefore, management is more likely to pre-empt bad news from analyst reports and bad news analyst reports' informativeness will be muted.

Growth opportunities. Firm's growth and/or investment opportunities are reflected in the market-to-book ratio. The direction of growth opportunities' effect on analyst informativeness is unclear. Growth firms have more unrecorded, intangible assets and their valuation depends heavily on the forecasts of future profitability and growth. These forecasts require expertise and the collection of data beyond the financial statements, implying higher information supply costs for analysts. However, investors lacking expertise and access to supra-financial statement data will demand increased analyst guidance for these firms. The equilibrium quantity of information supplied, i.e., analyst informativeness, is uncertain given these countervailing influences on demand and supply.

Ownership concentration and insiders' holdings. External investor demand for corporate financial information and analysis is low in firms with high levels of owner-manager holding or insider holdings. In such firms, insiders have access to the information, and with limited outside ownership, outsiders' demand for financial information and analysis is low. We do not examine the role of insider ownership on analyst informativeness for lack of machine-readable data availability. However, high insider ownership is not the norm for our sample of relatively publicly traded, large firms. Economic effects of insider ownership on properties of

the information environment of capital markets are important in cross-country analyses (see, for example, Ball et al., 2000, Bushman and Smith, 2001, and Healy and Palepu, 2001) because in many countries insiders hold large fractional ownership.

3. Data, regression model, and results

This section describes our data sources and sample, data, descriptive statistics, regression model, and the results. Section 3.1 presents data sources, sample and the regression model. We discuss the descriptive statistics and cross-correlations in the data in section 3.2. Section 3.3 contains our main results.

3.1 Data and the regression model

Data. The empirical analysis is based on data gathered from several sources: I/B/E/S, CRSP, Compustat, and CDA Spectrum. We begin with all individual analyst forecast revisions in the I/B/E/S detailed tape from 1995 to 1999. The sample period begins in 1995 because conversations with I/B/E/S representatives indicate that the “Estimate date” in the I/B/E/S detail file does not accurately represent the release dates of analyst forecasts prior to this time. For all firms on I/B/E/S, we compile individual analyst forecast revision dates for each company-year. Each calendar day with at least one analyst forecast revision reported on the I/B/E/S tape is treated as a forecast revision date.

Stock return data are from the CRSP tapes. We compute size-adjusted returns on each forecast revision date by subtracting the size-matched-decile return from the firm’s raw return. We obtain trading volume, return variability, firm size, i.e., market capitalization, and some other data (see below) from the CRSP tapes. Financial data and the number of shareholders data come from Compustat. We obtain data on institutional holdings at calendar year ends from CDA Spectrum. We lose approximately one-half of the firm-year observations available from the

I/B/E/S detail database, with corresponding CRSP data, due to missing Compustat segment data and missing CDA Spectrum data on institutional ownership. We delete firms with negative shareholders' equity to permit meaningful market-to-book ratios. The final sample comprises 10,823 firm-year observations for 3,171 firms.

We define analyst informativeness, AI, as the sum of the absolute size-adjusted-returns on all the forecast revision dates for a firm in a given calendar year divided by the sum of absolute size-adjusted-returns for all trading days for the firm for the calendar year, and finally, we divide this quotient by the number of forecast revision dates in a given calendar year. That is,

$$AI = \frac{[\sum_{\tau=1 \text{ to } NREVS} |R_{\tau,s} - RS_{\tau}|]}{\{[\sum_{\tau=1 \text{ to } 250} |R_{\tau,s} - RS_{\tau}|] \times NREVS\}}$$

where

$R_{\tau,s}$ is a firm's stock return on day τ and the firm belongs to the NYSE size decile portfolio s ,

$\tau = 1$ to $NREVS$ are analyst forecast revision dates for the firm in a given year with 250 trading days,

$NREVS$ is the number of unique analyst forecast revision dates, and

RS_{τ} is the return on the NYSE decile portfolio s on day τ .

If analysts were to supply no information then the absolute return on a forecast revision date should be equal on average to the absolute return on any other trading date. In a given calendar year with 250 trading days, each trading day would yield, on average, $1/250^{\text{th}}$ of the sum of the absolute returns and thus AI would equal 0.004.

Two-stage-least-squares regression model. Our main analysis of cross-sectional variation in analyst informativeness, AI, is based on a two-stage-least-squares estimation of a system of three equations, which is equivalent to the following OLS implementation (see Murphy and Zimmerman, 1993, for a similar application):

$$AI = \alpha + \beta_1 \text{Fitted}(\sigma^2(R)) + \beta_2 \text{Fitted}(\text{LnVOL}) + \beta_3 \text{INST} + \beta_4 \text{LnOwners} + \beta_5 \text{MB} + \beta_6 \text{LnMV} + \beta_7 \text{NSIC} + \beta_8 \text{MMRsQ} + \beta_9 \text{NSEGS} + \beta_{10} \text{AccRsQ} + \beta_{11} \text{LnAnalyst} + \beta_{12} \text{GNEWS} + \varepsilon_1 \quad (1)$$

$$\sigma^2(R) = \alpha + \beta_1 \text{INST} + \beta_2 \text{LnOwners} + \beta_3 \text{MB} + \beta_4 \text{LnMV} + \beta_5 \text{NSIC} + \beta_6 \text{MMRsQ} + \beta_7 \text{NSEGS} + \beta_8 \text{AccRsQ} + \beta_9 r_{-} \text{LnVOL} + \varepsilon_2 \quad (2)$$

$$\text{LnVOL} = \alpha + \beta_1 \text{INST} + \beta_2 \text{LnOwners} + \beta_3 \text{MB} + \beta_4 \text{LnMV} + \beta_5 \text{NSIC} + \beta_6 \text{MMRsQ} + \beta_7 \text{NSEGS} + \beta_8 \text{AccRsQ} + \beta_9 r_{-} \sigma^2(R) + \varepsilon_3 \quad (3)$$

where

$\sigma^2(R)$ is the daily return variance for firm *i* in year *t* computed from the CRSP daily return file,

LnVOL is the natural log of total trading volume for firm *i* in year *t* (Compustat #28),

INST is the percentage of shares held by institutions for firm *i* in year *t* computed as institutional shareholding at year-end as reported on CDA Spectrum divided by shares outstanding at the end of year *t* (Compustat 25),

LnOwners is the natural log of the number of thousands of shareholders of firm *i* in year *t* (Compstat #100),

MB is the market-to-book ratio for firm *i* in year *t* ($[\text{Compstat \#24} \times \text{Compustat \#25}] / \text{Compustat \#60}$),

LnMV is the natural log of the market value of firm *i* at the end of year *t* (CRSP),

NSIC is the number of firms in firm *i*'s industry in year *t* (CRSP) divided by the total number of firms on CRSP in year *t*,

MMRsQ is the R^2 from firm *i*'s market-model regression in year *t* (CRSP),

NSEGS is the number of industry segments on the Compstat business information file in year *t*,

AccRsQ is derived from the fitted residual from a pooled cross-sectional regression of prices on the book values of shareholders' equity and earnings using data from 1985 to 1995. Each firm's annual residual from the pooled regression is scaled by price and squared. We then calculate an average residual for each firm using time series observations for the firm. We subtract this average from the average for the entire population of firms to create AccRsQ, a relative measure of the firm's

accounting-based pricing errors. The larger the value of AccRsq , the better the ability of net income and book value of equity in explaining prices.⁴

- GNEWS** is an indicator variable equal to 1 if the number of positive revision dates exceeds the number of negative revision dates in firm-year t . A revision date is considered to be positive if more analysts revise up than down on that date,
- LnAnalyst** is the log of the number of analysts following the firm in year t ,
- r_** indicates that the variable is assigned a number 0, 1, or 2 on the basis of ranking each year all firm-year observations for the variable into three equal portfolios, and
- Fitted(.)** indicates predicted values produced by equations (2) and (3).

As discussed above, we treat volume and return variance as endogenous variables in this model. However, because all variables are fundamentally related to the firm's information environment, they are all related to each other and thus endogenous. Indeed, given this fundamental relation, arguing that a given variable can be used as an instrument to identify the system and therefore included in some equations and excluded in others is problematic. As discussed earlier, we partially circumvent the problem by treating all the variables except analyst informativeness, volatility, and trading volume as exogenous. However, all three models contain subsets of the variables, so the system is not identified in spite of the large number of exogenous variables. If instruments for the endogenous variables were available, then the model can be estimated and problems due to the endogenous determination of analyst informativeness, volatility, and trading volume, and due to under-identification of the system can be resolved. Toward this end, we follow Hentschel and Kothari (2001) in performing an instrumental variables regression that is equivalent to a two-stage least squares regression.

⁴ Our measure of AccRsq differs from the typical measure based on a firm-specific time-series regression of prices on financial variables. Our preference for a pseudo explanatory power measure of the price-earnings relation derived from a pooled regression is for practical reasons. Use of a pooled regression instead of firm-specific time-series regressions avoids burdensome data-availability requirements. If we were to estimate firm-specific time-

Ideal instruments correlate highly with the level of the endogenous variables but not with the relatively small variation around those levels, which is likely due to the endogenous nature of the relationship among the variables (Greene, 2000, pp. 370-375). In our context, for reasons discussed earlier, we expect return volatility to influence analyst informativeness and vice versa. However, most of the difference in volatility between high volatility stocks (e.g., young, growing and high technology stocks) and low volatility stocks (e.g., low growth, mature, regulated industry stocks) is unlikely to be attributable to variation in analyst informativeness. Instead, endogeneity likely pertains to the variation within the high volatility stocks that might be related to the variation in analyst informativeness. Similar arguments apply to trading volume. In the spirit of the above discussion, we construct an instrumental variable for analyst informativeness as follows. We rank annually the sample firms according to return volatility and assign firms to three portfolios, with the lowest (highest) volatility portfolio rank of 0 (2). These portfolio ranks are used as instruments to proxy for the level of volatility, but the instruments are not correlated with the endogenous variability around those levels. The same approach applies to trading volume. We use the portfolio rank values instead of actual volatility or trading volume in models (2) and (3) above. The fitted values from these two equations are then substituted in equation (1) to explain cross-sectional variation in analyst informativeness.

3.2 Descriptive statistics and cross-correlations

Table 1 reports descriptive statistics for the pooled sample of 10,823 firm-year observations from 1995 to 1999. Analyst informativeness averaged across all firms is 0.0045. As noted earlier, since we measure analyst informativeness as a ratio of price reaction to analyst reports normalized by the price movement during the entire year, under the null of zero

series regressions using historical data (i.e., time series ending before the start of the sample period), we must require data availability of at least 15-20 years, which would result in a loss of 70-80% of the sample.

informativeness of an analyst report, AI, would be 0.0040 (= 1/250 trading days in a year).⁵ Both mean and median AI estimates in table 1 indicate analyst informativeness, which is consistent with the findings in the research on the properties of analyst forecasts.

[Table 1]

We examine whether our estimate of analyst informativeness is biased upward because of the possibility that analyst report dates are clustered around earnings announcement dates. Since earnings announcement period has long been shown to be one of greater return volatility (e.g., Beaver, 1968), our measure of AI using absolute returns around analyst report dates is potentially contaminated by earnings announcement period volatility and thus mechanically indicates information in analyst reports. We therefore recalculate AI deleting all analyst report dates within a three-day window centered on quarterly and annual earnings announcement dates. Less than one percent of the forecast revision dates are lost, and the mean and median average analyst informativeness are unchanged.

Descriptive statistics for the remaining variables in table 1 indicate that firms in our sample are large with several analysts following them. The average market-to-book ratio is 3.84, which is due in part to the bull market of the 1990s. The number of firms in an industry, NSIC, is deflated by the number of firms on CRSP in each year and therefore the average is only 0.0071. It translates into an average of 84 firms in each four-digit SIC code industry. NSIC refers to the number of all the firms in a four-digit SIC code industry on CRSP, not just the number of firms for an industry included in our sample.

⁵ Since AI is calculated as a ratio of sums of absolute returns, we examine whether it is biased. We construct a bootstrap distribution for AI using randomly selected event dates for the sample firms. For each firm-year in our sample, the number of random event dates is set equal to the actual number analyst revision dates for that firm-year. This process produces a sample of 10,823 AI observations with random analyst forecast dates. The sample mean (median) is 0.0040 (0.0039). With 250 trading days in a year, this is exactly the average value expected when event-dates are no more informative than non-event dates.

More than half of the sample firms report financial information for only one segment. The 75th percentile for NSEGS is 2. The last row in table 1 reports statistics for the number of analyst forecast revision dates, NREVS, for our sample. Since the average number of analysts following a firm is about 6, average NREVS of about 31 implies each analyst issues about 5 earnings forecasts a year. There are about 300,000 unique firm-analyst forecast revision dates in our sample over from 1995 to 1999.

We report cross-correlations among the variables in table 2. Correlations are estimated using data pooled across the five-year sample period. AI exhibits significant positive product moment correlation with volatility and trading volume. However, the rank correlation is almost zero. Endogenous relations among these variables preclude us from drawing strong inferences from univariate correlations. Firm size, volatility, trading volume, and analyst following are the most highly cross-correlated variables. A negative relation between firm size and return volatility and a positive relation between firm size and trading volume and analyst following are well known from previous research. Our measure of the strength of the relation between financial statements and stock prices, AccRsq, is highly positively correlated with firm size, with a product-moment correlation of 0.58. This is consistent with the evidence in Hayn (1995) and Collins, Maydew, and Weiss (1997) that size has a strong negative effect on the price-earnings relation, perhaps because of the higher frequency of losses among small firms.

[Table 2]

3.3 Results

Table 3 reports results of estimating the two-stage-least-squares regression model (i.e., equations 1-3) about the determinants of analyst informativeness. We estimate the model each year and report time-series means of the 2SLS regression coefficients. The t-statistics are for the

sample mean coefficients, calculated using the standard deviation of the respective sample of estimated coefficients (see Fama and MacBeth, 1973). We report results with and without trimming extreme observations from the data, where extreme observations are those in the lowest and highest percentiles of the annual distribution for each variable. Since the two sets of results are quite similar, we discuss results using the outlier-trimmed sample.

Overall, the results are highly consistent with the predicted relations between analyst informativeness and its determinants. Both return volatility and trading volume positively influence the informativeness of analyst research, although the effect of trading volume is significant only at the 0.10 level. In results that we do not tabulate, OLS estimation of the model indicates that return volatility does not affect analyst informativeness. We believe the lack of a relation in OLS estimation is due to failure to address endogeneity. Number of shareholders reduces analyst informativeness, which suggests that the incremental demand for analyst services from shareholders increases analysts' supply to the point that the marginal effect of shareholders on informativeness is negative. Low informativeness is likely attractive to shareholders in that they might not (perceive themselves to) be informationally disadvantaged. The number of analysts, LnAnalysts, does not significantly impact informativeness. Perhaps more importantly, the relation is not significantly negative. That is, competition among analysts does not result in a negative marginal effect of an additional analyst. However, this result should not be interpreted to mean an absence of informativeness. Summary statistics show that analyst reports on average are informative, i.e., our AI measure is significantly greater than 0.0040. Thus, notwithstanding an insignificant coefficient on LnAnalysts, our results show that analysts' aggregate informativeness for a firm does increase in total number of analyst reports for the firm.

[Table 3]

Analyst informativeness significantly declines in both market model r-square (MMRs_{sq}) and number of segments (NSEGS). The result of reduced informativeness for firms with multiple segments is not helpful to investors seeking guidance from analyst reports in cases where information analysis is likely to be costly. However, since analysts specialize in individual industries, reports for multi-segment firms might be less accurate (see Gilson, Healy, Noe, and Palepu, 2001). An alternative interpretation of the negative impact of MMRs_{sq} and multi-segment firms on analyst informativeness, together with the highly significant negative coefficient on the number of shareholders, is that all of these variables reduce analyst informativeness through their high correlation with firm size (see table 2). This inference is weakened, however, because firm size (LnMV) itself is not significantly related to informativeness.

Results in table 3 show that the stronger the relation between accounting information and security prices, AccRs_q, the higher the analyst informativeness. This result extends the finding in the literature that timely (often interpreted as high quality) accounting disclosures, i.e., high AccRs_q, and analyst following are complements (e.g., Lang and Lundholm, 1996). We show that informativeness is also a complement. The result is consistent with high AccRs_q raising the demand for analyst informativeness, without a commensurately offsetting increase in analysts' cost of supplying informativeness.

Finally, the good news dummy, GNEWS, proxying for whether on average earnings forecast news for a firm is good or bad during a year, is highly significantly negative. This result implies bad news analyst forecasts have greater price impact than an upward forecast revision and is consistent with Hong et al. (2000) hypothesis that management touts good news and thus pre-empts it from analyst reports. In contrast, analysts appear to dig up bad news and

communicate to the market participants before the management or other sources pre-empting its contents. We check whether our result is due to analysts' alleged tendency to issue optimistic forecasts (see, for example, Stickel, 1990, Abarbanell, 1991, and Lim, 2001). This would make bad news forecasts rare and newsworthy to the market. However, GNEWS has an average value of 0.38, which means for only 38% of the firm-year observations analysts revised their earnings forecasts upward during the five-year sample period from 1995 to 1999. The low average for GNEWS during a bull-market period of the 1990s might seem surprising. However, even in bull markets, the median firm does not grow much, just as the median firm's stock return is typically negative.

Summary. Overall, the evidence suggests analyst reports are significantly price informative and their informativeness increases with return volatility and trading volume after controlling for their endogenous determination. Evidence also suggests that informativeness does not diminish with the addition of a marginal analyst, which is consistent with competition among analysts resulting in supply of analysts until the marginal effect on informativeness is zero. Finally, we find evidence that analyst reports are far more informative when they convey bad news than good news.

4. Return reversal tests

Evidence of analyst informativeness in the previous section can be an outcome of investors rationally processing information in analyst reports and pricing stocks on the basis of economic fundamentals of the companies. On the other hand, informativeness might be due in part to investors' naïve fixation on optimistic or misleading analyst reports, or investor under- or over-reaction to analyst reports. Rational reactions to analyst reports do not generate return predictability, whereas predictability of returns would be consistent with investor irrationality,

i.e., market inefficiency. We perform tests of short-horizon return predictability in an attempt to provide evidence that might be helpful in interpreting the analyst informativeness results in the previous section.

While the evidence below fails to indicate return predictability associated with analyst informativeness, and is thus consistent with prices rationally reflecting information in analyst reports, we acknowledge that we cannot rule out long horizon return predictability associated with analyst forecasts. In our context, long horizon return predictability tests to evaluate properties of analyst informativeness are tenuous. The large number of individual analyst reports for each firm generate highly overlapping, multiple long horizon subsequent returns. We are unable to craft tests that would successfully correlate analyst informativeness to long horizon price performance following analyst reports.

We examine whether the narrow-window price reaction to analyst reports is permanent, or suggestive of over- or under-reaction. Our goal is to test whether predictability varies with analyst informativeness. If a security is highly responsive to analyst reports, does it indicate over-reaction that is reversed subsequently? Alternatively, does it suggest the market's fixation on analysts' optimistic reports and thus does it reverse itself subsequently? To tease out the marginal predictability associated with informativeness, we control for any predictability in returns that might be germane to the population of the stocks and also control for other known determinants of return predictability. Research in the finance literature reports conflicting evidence regarding market overreaction (see Jegadeesh, 1990, Lehmann, 1990, Lo and MacKinlay, 1988 and 1990, and Ball, Kothari, and Wasley, 1995). A portion of the apparent overreaction is related to bid-ask bounce and other trading friction. Since these frictions are negatively correlated with size, return predictability tends to be pronounced for small stocks.

Skipping a day between the event-period and subsequent-period return mitigates the predictability impact of the bid-ask bounce.

We estimate the following model to test whether return predictability is associated with analyst informativeness:

$$SRET1 = \alpha + \beta_1 SRET + \beta_2 (\text{LnMV} \times SRET) + \beta_3 (Q1_AI \times SRET) + \beta_4 (Q5_AI \times SRET) + \varepsilon_1 \quad (4)$$

$$SRET1 = \alpha + \beta_1 SRET + \beta_2 (\text{LnMV} \times SRET) + \beta_3 (\text{AvgAI} \times SRET) + \varepsilon_2 \quad (5)$$

where

SRET1 compounded size adjusted return for event days +3 to +5 where event day 0 is the analyst forecast revision date,

SRET compounded size adjusted return for event days -1 to +1,

AI is as defined in section 3,

LnMV log of market value of equity at the beginning of year t,

Q1_AI is a dummy variable with value equal to 1 if a firm belongs to the lowest quintile of stocks ranked on the basis of each firm's average AI, calculated using the firm's AI values for all years prior to the year of the forecast revision date,

Q5_AI same as Q1_AI except that it is for the highest quintile,

AvgAI average AI calculated for each firm using its AI values for all years prior to the year of the forecast revision date.

The regression eq. (4) and (5) test whether the correlation between three-day returns around analyst forecast dates and the subsequent three-day returns varies with analyst informativeness. We repeat the above using a five-day return window (days -2 to +2 for SRET and +4 to +8 for SRET1) instead of three. In eq. (3), we test whether return predictability differs between the firms with lowest and highest quintiles of estimated analyst informativeness. In eq. (4), we use a continuous measure of analyst informativeness to test for variation in return predictability as a function of AI. Use of extreme quintile dummies is a means of dealing with

the errors-in-variables problem if AI were a noisy proxy for analyst informativeness. If analyst informativeness were due to investor overreaction, we expect the coefficient on Q5_AI interaction variable to be less than that on Q1_AI interaction variable in eq. (4), and the coefficient on AvgAI interacted with SRET to be negative. We predict the same sign on the coefficients if the market were to be fixated on optimistic or misleading analyst forecasts, although the reversal might not occur in a short period of three days following the forecast revision. Both eq. (4) and (5) use a firm-specific measure of AI that is calculated using historical data up to the year of forecast revisions analyzed in each quarterly cross-sectional regression. Since AI itself is a function of forecast revision period stock returns, a contemporaneous measure of AI has the potential to impart a spurious negative association between SRET1 and SRET. As a result of using a historical measure of AI, we estimate quarterly regressions only for four years from 1996 to 1999.

Both models (3) and (4) include the firm's forecast revision date return, SRET, by itself to control for the average degree of return predictability in the sample firms. We also interact SRET with market capitalization, LnMV, to control for return predictability due to various trading frictions under the assumption that market capitalization is a summary proxy for the trading frictions.

We estimate models (4) and (5) cross-sectionally each calendar quarter from the first quarter of 1996 to the fourth quarter of 1999 using data for all forecast revision dates in each quarter. Table 4 reports time-series means of the regression coefficients and adjusted R²s from the 16 quarterly cross-sectional regressions. Panel A reports results using three-day and panel B using five-day return windows. Results fail to indicate a reversal of the analyst informativeness effect. The estimated coefficients on Q1_AIxSRET and Q5_AIxSRET from eq. (4) are

statistically insignificant and, more importantly, are not consistent with the investor over-reaction hypothesis because the coefficient on Q5_AIxSRET is not more negative than that on Q1_AIxSRET. We draw similar inference from the estimated coefficient on analyst informativeness interacted with SRET in eq. (5).

[Table 4]

Results in table 4 show that the control variable, SRET, is significantly negative, consistent with evidence in the finance literature of short-horizon return predictability that might be due in part to bid-ask spreads and other trading frictions. Consistent with the effect of trading frictions on return predictability, the coefficient on firm size interacted with SRET is significantly positive in both eq. (4) and (5). This means, the negative predictability of returns in the entire sample, i.e., the coefficient on SRET, is muted in large firms as seen from the positive coefficient on LnMVxSRET.

While we interpret the negative β_1 coefficient on SRET as short-horizon return predictability in a typical stock, an alternative interpretation would be that it represents reversal of apparent analyst informativeness. To discriminate between these two explanations, we re-estimate eq. (4) and (5) except that we use randomly selected analyst forecast revision dates to calculate SRET and SRET1. The estimated degree of return reversal is slightly more pronounced than that reported in table 4, although the differences are not statistically significant. Specifically, using the three-day window in eq. (4), the β_1 using random dates is -0.094 (t-stat = -1.81) compared to -0.071 (t-stat = -1.88) in table 4, and the corresponding numbers using the five-day window are -0.120 (t-stat = -2.21) and -0.094 (t-stat = -2.21). Overall, we find not evidence to suggest that short-window return predictability is any different around analyst forecast revision dates than other dates.

5. Summary and conclusions

Unlike much of the past research on the determinants of analyst following as a proxy for the firm's information environment, we focus on the informativeness of analyst forecast revisions and its cross-sectional determinants. Our main findings based on a two-stage-least-squares regression estimation that accounts for the endogenous relationships among various factors are: (i) Analyst informativeness increases in uncertain environments (i.e., return volatility) and heterogeneity of investor beliefs as proxied for by trading volume; (ii) The marginal impact of an (additional) analyst report on informativeness is indistinguishable from zero; (iii) Analyst informativeness is negatively related to variables that proxy for analysts' information processing costs; and (iii) Consistent with investor rationality, the market's short-horizon reaction to analyst research does not reverse.

Our finding that the estimated informativeness of an analyst report does not decline with the number of analyst reports for a firm has two important implications. First, combined with our finding that analyst informativeness is related to information processing costs, the result suggests that the ability to supply information is an important impetus for an analyst when deciding to follow a company. Moreover, our inability to find return reversals and our finding that analyst are more informative when conveying bad news imply that the market filters out the 'hype' in analyst reports, which is aimed at generating brokerage commissions and investment banking fees. While we cannot rule out long-term mis-pricing associated with misleading analyst reports, we believe our results provide an important counterbalance against those who argue that analysts' incentives to generate revenues for their employers lead to mis-informative analyst research and pricing distortions. Second, the result supports the reliability of the analyst following as a proxy for information production about a firm. This proxy is widely used in the

literature (e.g., Bhushan, 1989b, O'Brien and Bhushan, 1990, Brennan and Subramanyam, 1995, and Lang and Lundholm, 1996).

Our results point to a direction for future research on analyst informativeness. If information provision is a significant motive for analysts, then an interesting question is whether analysts increase the scope of the information set upon which market's expectations and therefore prices are conditioned. We find that analysts are more informative when financial statements are more highly related to prices. However, the evidence does not inform the reader whether analysts lever-up the information contained in prior financials or whether they merely "pre-announce" the information contained in future financial statements. Thus, an interesting question is whether analysts merely preempt the information that would otherwise have been provided by other sources including, financial statements, voluntary disclosures by managers, and the financial press.

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Table 1
Descriptive Statistics

This table presents univariate statistics. The sample is derived from all analyst earnings forecast revisions on the I/B/E/S detail database between January 1, 1995 and December 31, 1999. Firm-years with I/B/E/S data are merged with CRSP, Compustat, and CDA Spectrum for data on stock returns, financial information, and institutional ownership. Firm-years with missing data are discarded. The statistics are based on a final sample of 10,823 firm-year observations.

| | Mean | Std. dev. | Q1 | Median | Q3 |
|---------------------|--------|-----------|--------|--------|--------|
| AI | 0.0045 | 0.0015 | 0.0038 | 0.0043 | 0.0051 |
| $\sigma^2(R)$ | 0.0016 | 0.0026 | 0.0005 | 0.0010 | 0.0020 |
| LnVOL | 3.32 | 1.64 | 2.16 | 3.26 | 4.41 |
| INST | 0.44 | 0.24 | 0.24 | 0.44 | 0.63 |
| LnOwners | 1.42 | 1.25 | 0.47 | 1.10 | 2.03 |
| MB | 3.84 | 7.73 | 1.12 | 1.94 | 3.87 |
| LnMV | 12.77 | 1.86 | 11.39 | 12.59 | 13.91 |
| NSIC | 0.0071 | 0.0021 | 0.0008 | 0.0021 | 0.0072 |
| MMRs _{sq} | 0.07 | 0.08 | 0.01 | 0.04 | 0.10 |
| NSEGS | 1.78 | 1.33 | 1.00 | 1.00 | 2.00 |
| AccRs _{sq} | 23.00 | 20.97 | 26.42 | 30.99 | 31.40 |
| LnAnalyst | 1.68 | 0.93 | 1.10 | 1.61 | 2.40 |
| GNEWS | 0.38 | 0.49 | 0.00 | 0.38 | 1.00 |
| NREVS | 31.2 | 29.0 | 10.0 | 22.0 | 42.0 |

Variable Definitions (for firm *i* for use in a regression in year *t*)

| | |
|---------------|---|
| AI | is the sum of absolute size-adjusted returns on analyst earnings forecast revision dates for a firm in year <i>t</i> divided by the sum of absolute size-adjusted returns for the firm in year <i>t</i> , all divided by the number of analyst revision dates for the firm in year <i>t</i> , |
| $\sigma^2(R)$ | is the daily return variance for year <i>t</i> computed from the CRSP daily return file, |
| LnVOL | is the natural log of total trading volume in year <i>t</i> -1 (Compustat #28), |
| INST | is the percentage of shares held by institutions for firm <i>i</i> in year <i>t</i> computed as institutional shareholding at year-end as reported on CDA Spectrum divided by shares outstanding at the end of year <i>t</i> (Compustat 25), |

| | |
|-----------|--|
| LnOwners | is the natural log of the number of shareholders of firm <i>i</i> in year <i>t</i> (Compustat #100), |
| MB | is the market-to-book ratio for firm <i>i</i> in year <i>t</i> ($[\text{Compustat \#24} \times \text{Compustat \#25}] / \text{Compustat \#60}$), |
| LnMV | is the natural log of the market value of firm <i>i</i> at the end of year <i>t</i> (CRSP), |
| NSIC | is the number of firms in firm <i>i</i> 's industry in year <i>t</i> (CRSP) divided by the total number of firms on CRSP in year <i>t</i> , |
| MMRsq | is the R^2 from firm <i>i</i> 's market-model regression in year <i>t</i> using CRSP daily returns, |
| NSEGS | is the number of industry segments on the Compustat business information file in year <i>t</i> , |
| AccRsq | is derived from the fitted residual from a pooled cross-sectional regression of prices on the book values of shareholders' equity and earnings using data from 1985 to 1995. Each firm's annual residual from the pooled regression is scaled by price and squared and then we calculate an average residual for each firm using time series observations for the firm. We subtract this average from the average for the entire population of firms to create AccRsq, a relative measure of the firm's accounting-based pricing errors. |
| LnAnalyst | is the log of the maximum number of analysts issuing one-year-ahead earnings forecasts in firm-year <i>t</i> , |
| GNEWS | is an indicator variable equal to 1 if the number of positive revision dates exceeds the number of negative revision dates in firm-year <i>t</i> . A revision date is considered to be positive if more analysts revise up than down on that date, and |
| NREVS | is the number of unique analyst earnings forecast revision dates from I/B/E/S for firm <i>i</i> in year <i>t</i> . |

Table 2
Cross-Correlations among Variables

This table contains values of the correlations between various variables. Spearman (Pearson) correlations are below (above) the diagonal. The sample is derived from all analyst earnings forecast revisions on the I/B/E/S detail database between January 1, 1995 and December 31, 1999. Firm-years with I/B/E/S data are merged with CRSP, Compustat, and CDA Spectrum for data on stock returns, financial information, and institutional ownership. Firm-years with missing data are discarded. The statistics are based on a final sample of 10,823 firm-year observations. Variable definitions appear in table 1. Correlations significant at the 0.05 level, two-tailed, appear in bold.

| | AI | $\sigma^2(R)$ | LnVOL | INST | Ln Owners | MB | LnMV | NSIC | MMRs _q | NSEGS | AccRs _q | LnAnalyst | GNEWS |
|--------------------|--------------|---------------|--------------|--------------|--------------|--------------|--------------|--------------|-------------------|--------------|--------------------|--------------|--------------|
| AI | 1.00 | 0.01 | 0.01 | 0.02 | -0.06 | 0.03 | -0.03 | 0.05 | -0.04 | -0.03 | 0.04 | -0.02 | -0.05 |
| $\sigma^2(R)$ | 0.09 | 1.00 | -0.03 | -0.27 | -0.17 | 0.08 | -0.31 | 0.23 | -0.16 | -0.12 | -0.28 | -0.23 | -0.08 |
| LnVOL | 0.07 | -0.07 | 1.00 | 0.42 | 0.50 | 0.24 | 0.74 | 0.14 | 0.55 | 0.18 | 0.18 | 0.70 | 0.16 |
| INST | 0.07 | -0.40 | 0.45 | 1.00 | 0.22 | -0.03 | 0.55 | -0.12 | 0.36 | 0.18 | 0.36 | 0.54 | 0.21 |
| Ln Owners | -0.04 | -0.40 | 0.43 | 0.26 | 1.00 | 0.04 | 0.62 | -0.11 | 0.42 | 0.31 | 0.15 | 0.51 | 0.08 |
| MB | 0.03 | 0.08 | 0.44 | 0.07 | 0.12 | 1.00 | 0.13 | 0.20 | 0.11 | -0.04 | 0.00 | 0.07 | 0.05 |
| LnMV | 0.03 | -0.56 | 0.71 | 0.60 | 0.53 | 0.32 | 1.00 | -0.10 | 0.65 | 0.35 | 0.39 | 0.78 | 0.23 |
| NSIC | 0.03 | 0.38 | 0.13 | -0.16 | -0.11 | 0.22 | -0.13 | 1.00 | -0.03 | -0.16 | -0.08 | -0.06 | -0.00 |
| MMRs _q | 0.02 | -0.27 | 0.57 | 0.43 | 0.34 | 0.26 | 0.65 | -0.02 | 1.00 | 0.21 | 0.20 | 0.51 | 0.17 |
| NSEGS | 0.03 | -0.29 | 0.14 | 0.18 | 0.27 | -0.04 | 0.31 | -0.19 | 0.18 | 1.00 | 0.12 | 0.24 | 0.00 |
| AccRs _q | 0.03 | -0.54 | 0.23 | 0.44 | 0.27 | 0.11 | 0.58 | -0.21 | 0.30 | 0.20 | 1.00 | 0.34 | 0.08 |
| LnAnalyst | 0.05 | -0.39 | 0.69 | 0.56 | 0.45 | 0.20 | 0.79 | -0.05 | 0.54 | 0.21 | 0.45 | 1.00 | 0.12 |
| GNEWS | -0.05 | -0.13 | 0.16 | 0.21 | 0.08 | 0.15 | 0.24 | -0.01 | 0.19 | 0.00 | 0.13 | 0.12 | 1.00 |

Table 3
Annual Two-Stage-Least-Squares Estimation

This table presents the time-series means of coefficients, t-statistics for the averages of the coefficients, and average adjusted R²s from annual cross-sectional two-stage-least-squares regression model below. The sample is derived from all analyst earnings forecast revisions on the I/B/E/S detail database between January 1, 1995 and December 31, 1999. Firm-years with I/B/E/S data are merged with CRSP, Compustat, and CDA Spectrum for data on stock returns, financial information, and institutional ownership. Firm-years with missing data are discarded. The final sample consists of 10,823 firm-year observations. Variable definitions appear in table 1.

$$\text{PSRATIO} = \alpha + \beta_1 \text{Fitted}(\sigma^2(R)) + \beta_2 \text{Fitted}(\text{LnVOL}) + \beta_3 \text{INST} + \beta_4 \text{LnOWNERS} + \beta_5 \text{MB} + \beta_6 \text{LnMV} + \beta_7 \text{NSIC} + \beta_8 \text{MMRs}q + \beta_9 \text{NSEGS} + \beta_{10} \text{AccRs}q + \beta_{11} \text{GNEWS} + \varepsilon_1 \quad \text{Model 1}$$

$$\sigma^2(R) = \alpha + \beta_1 \text{INST} + \beta_2 \text{LnOWNERS} + \beta_3 \text{MB} + \beta_4 \text{LnMV} + \beta_5 \text{NSIC} + \beta_6 \text{MMRs}q + \beta_7 \text{NSEGS} + \beta_8 \text{AccRs}q + \beta_9 r_ \text{LnVOL} + \varepsilon_2 \quad \text{Model 2}$$

$$\text{LnVOL} = \alpha + \beta_1 \text{INST} + \beta_2 \text{LnOWNERS} + \beta_3 \text{MB} + \beta_4 \text{LnMV} + \beta_5 \text{NSIC} + \beta_6 \text{MMRs}q + \beta_7 \text{NSEGS} + \beta_8 \text{AccRs}q + \beta_9 r_ \sigma^2(R) + \varepsilon_3 \quad \text{Model 3}$$

| Independent Variables | Predicted sign | Model 1 | | Model 1 – Outliers Trimmed | |
|--------------------------|----------------|-------------|--------|----------------------------|--------|
| | | Coefficient | t-stat | Coefficient | t-stat |
| Fitted ($\sigma^2(R)$) | + | 9.3491 | 2.09 | 13.0748 | 3.80 |
| Fitted (LnVOL) | + | 0.0078 | 2.47 | 0.0045 | 1.50 |
| INST | + | 0.0314 | 1.44 | 0.0340 | 1.70 |
| LnOwners | ? | -0.0055 | -5.43 | -0.0057 | -7.57 |
| MB | ? | -0.0001 | -0.26 | -0.0005 | -2.30 |
| LnMV | ? | -0.0003 | -0.10 | 0.0021 | 0.82 |
| NSIC | - | -0.1189 | -0.71 | -0.1173 | -1.14 |
| MMRs _q | - | -0.0985 | -4.36 | -0.0957 | -4.40 |
| NSEGS | ? | -0.0037 | -6.80 | -0.0032 | -4.72 |
| AccRs _q | ? | 0.0005 | 3.65 | 0.0058 | 4.91 |
| LnAnalyst | ? | 0.0049 | 0.89 | 0.0018 | 0.48 |
| GNEWS | ? | -0.0162 | -7.72 | -0.0147 | -5.89 |
| Adjusted R ² | | 1.97% | 4.40 | 2.43% | 5.85 |

r_ indicates that the variable is assigned a number of 0, 1, or 2 on the basis of ranking each year all firm-year observations for the variable into three equal portfolios, and

Fitted(.) indicates predicted values produced by models 2 and 3.

Table 4
Return Reversal Tests

This table presents the time-series means of coefficients, t-statistics for the averages of the coefficients, and average adjusted R²s from 16 quarterly cross-sectional regressions from 1996 to 1999 using the models below. Total number of forecast revision date observations underlying these regressions is 278,540.

$$\text{SRET}_1 = \alpha + \beta_1 \text{SRET} + \beta_2 (\text{LnMV} \times \text{SRET}) + \beta_3 (\text{Q1mAI} \times \text{SRET}) + \beta_4 (\text{Q5mAI} \times \text{SRET}) + \varepsilon_1 \quad \text{Model 1}$$

$$\text{SRET}_1 = \alpha + \beta_1 \text{SRET} + \beta_2 (\text{LnMV} \times \text{SRET}) + \beta_3 (\text{mAI} \times \text{SRET}) + \varepsilon_2 \quad \text{Model 2}$$

| Independent Variables | Model 1 | | Model 2 | |
|--|-------------|--------|-------------|--------|
| | Coefficient | t-stat | Coefficient | t-stat |
| Panel B: Three-day return windows | | | | |
| SRET | -0.071** | -1.88 | -0.095** | -2.47 |
| LnMV x SRET | 0.004 | 1.42 | 0.005 | 1.81 |
| Q1_AI x SRET | -0.012 | -0.90 | | |
| Q5_AI x SRET | -0.006 | -0.56 | | |
| AvgAI x SRET | | | 0.003 | 1.22 |
| Adjusted R ² | 0.001 | 3.99 | 0.001 | 3.34 |
| Panel B: Five-day return windows | | | | |
| SRET | -0.094** | -2.21 | -0.106** | -2.62 |
| LnMV x SRET | 0.006 | 1.84 | 0.006 | 1.89 |
| Q1_AI x SRET | -0.006 | -0.45 | | |
| Q5_AI x SRET | 0.014 | 1.27 | | |
| AvgAI x SRET | | | 0.007 | 2.79 |
| Adjusted R ² | 0.001 | 4.00 | 0.001 | 3.79 |

Variable Definitions

| | |
|-------|--|
| SRET1 | compounded size adjusted return for event days +3 to +5 where event day 0 is the analyst forecast revision date, |
| SRET | compounded size adjusted return for event days -1 to +1, |
| AI | is the sum of absolute size-adjusted returns on analyst earnings forecast revision dates for a firm in year t divided by the sum of absolute size-adjusted returns for the firm in year t, all divided by the number of analyst revision dates for the firm in year t, |
| LnMV | log of market value of equity at the beginning of year t, |

| | |
|-------|--|
| Q1_AI | is a dummy variable with value equal to 1 if a firm belongs to the lowest quintile of stocks ranked on the basis of each firm's average AI, calculated using the firm's AI values for all years prior to the year of the forecast revision date, |
| Q5_AI | same as Q1_AI except that it is for the highest quintile, and |
| AvgAI | average AI calculated for each firm using its AI values for all years prior to the year of the forecast revision date. |