Determinants of the Informativeness of Analyst Research

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Abstract
Analyst research helps prices reflect information about a security’s fundamentals. However, analysts’ private incentives potentially contribute to misleading research that might distort prices. 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 on or over- or under-reaction to analyst reports.

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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

Offsetting forces influence the extent to which analyst research conveys information to capital markets. The strength of these forces varies across firms, thus generating cross-sectional variation in the firms’ stock price reactions to analyst research or analyst reports. We provide an econometric analysis of the determinants of the magnitude (i.e., absolute value) of the stock price reaction to analyst reports. The average magnitude of a firm’s stock price reaction to analysts’ reports is defined as the informativeness of an analyst report.

Our measure of informativeness is similar to the variance measure of informativeness of earnings reports as pioneered by Beaver (1968) and repeatedly used in subsequent research (see Landsman and Maydew, 2002, and Francis, Schipper, and Vincent, 2002, for recent applications). 1 The goal of our paper is to understand the factors that affect the equilibrium in the market for information supplied by analysts. That is, we seek to explain cross-sectional variation in the average magnitude of news in analyst reports. Why is the average magnitude of news in analyst reports greater for some firms and smaller for others? This is similar to understanding why some firm’s returns are more volatile than others. Clearly event-specific

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1 An alternative measure of the informativeness of analyst reports is the correlation between the stock price reaction to and the surprise in an analyst forecast (i.e., analyst forecast minus the market expected forecast at the time). This measure is also appealing and has been used in the literature (e.g., Lys and Sohn, 1990, and Mikhail, Walther, and Willis, 1997). However, unless the market’s earnings expectation is known accurately at the time of each analyst report, estimation of the correlation as a measure of informativeness is fraught with problems. We discuss these problems later in the paper.
factors cause price movements and therefore return volatility, but in explaining differences in volatility one seeks to understand why news comes in larger doses for some firms and in smaller doses for others.

Informativeness of analyst reports is of great interest to the academic and investment communities. Previous research has typically studied the determinants of analyst following under the assumption that analyst following proxies for the resources devoted to information collection and thus the informativeness of prices with respect to potentially costly, but publicly available information about a firm (e.g., Bhushan, 1989a, O’Brien and Bhushan, 1990, Lang and Lundholm, 1996, and Hong, Lim, and Stein, 2000). That is, the greater the analyst following for a firm, the richer the information set that is assumed to be reflected in the firm’s stock prices. In contrast, we by-pass this assumption and focus directly on the informativeness of analyst reports for a firm and thus on the nature of analysts’ output and its impact on the firm’s security prices. In this analysis, the richness of the information set being reflected in a firm’s stock prices is not automatically an increasing function of additional analyst following a firm. Instead, we study various determinants of analyst informativeness for a firm, where one of the determinants is analyst following, which might positively or negatively influence the informativeness of analyst reports. The analysis incorporates the endogenous relation between analyst informativeness and various firm characteristics.

While analysts in a capital market are typically viewed as enhancing the information set reflected in prices, 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 measures like analyst informativeness and analyst following would be imperfect and/or biased indications of the degree of informational efficiency of the firm’s stock prices. Instead, in an inefficient market, high informativeness and analyst following would make the firm’s stock returns predictable. We test for this implication.

**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 abnormal absolute stock price reaction on the dates that analysts release forecast revisions for a firm. Analyst informativeness is calculated for each firm in each year by averaging the absolute stock price reaction to all the analyst forecast revisions for the firm in a given year. We find analyst research, on average, is significantly informative and the informativeness exhibits substantial cross-sectional variation in our sample. Two-stage-least-squares regression results show that, as predicted, analyst informativeness increases in return volatility. Since average informativeness per analyst report is positive, aggregate informativeness for a firm grows with the number of analysts following a firm (assuming the number of reports per analyst is constant across firms). However, we find the marginal effect of analyst following on the informativeness of analysts’ research reports is not statistically distinguishable from zero. One might have suspected that competition among analysts would 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. That is, the ability to supply information is an important impetus for an analyst when deciding to follow a company.
We also find that analyst informativeness and the timeliness of financial information (measured as the contemporaneous association between security prices and financial information) are substitutes. Thus, timely financial information appears to preempt the information content of analyst reports. The substitution effect of the timeliness of financial reports with respect to analyst informativeness is predicted in a Bayesian model where investors’ reaction to the analyst report decreases in the quality of other information (e.g., accounting information) available to the market participants (see Holthausen and Verrecchia, 1984, Demski and Feltham, 1994, and Subramanyam, 1996, for examples). Our finding is at odds with Francis, Schipper, and Vincent (2002, p. 317) who conclude that their results “do not in general support the predicted substitution relation between earnings announcements and competing information sources...” However, there are important differences between Francis et al. study and our research. Specifically, they examine the relation between reactions to earnings announcements and analyst reports, whereas we analyze the endogenous relation between annual information content of accounting information and informativeness of analyst reports. These differences in analyses lead to the differences in the conclusions reached in the two studies.

Finally, our results show that analyst research is far more informative when analysts issue a negative forecast revision than positive. This finding implies the market has advance knowledge of much of the information in analysts’ positive forecast revisions, but it is surprised by negative forecast revisions. The result lends support to Hong, Lim, and Stein (2000) hypothesis that bad news propagates more slowly than good news.

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 we observe it in
any period, not just around analyst forecast revision dates. Controlling for these effects, we do not observe a difference between return predictability for firms with high and low analyst informativeness. Thus, our evidence is inconsistent 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. Background and hypothesis development

In this section we discuss competing hypotheses about the role of analysts in capital markets, the effect of analysts’ incentives on the contents of analyst reports, and the likely impact of analyst research on security prices. This discussion provides a foundation for the econometric analysis of the determinants of analyst informativeness presented in the next section.

*Analysts as enhancing the informational efficiency of security prices.* Analysts are dominant information intermediaries in capital markets. They engage in private information search, perform prospective analysis aimed at forecasting a firm’s future earnings and cash flows, and conduct retrospective analysis that interprets past events (Beaver, 1998, p. 10). Regulators and other market participants view analysts’ activities and the competition among analysts as enhancing the informational efficiency of security prices.\(^2\) The importance of analysts’ role in capital markets has spurred research showing that analysts influence 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). Prior research (e.g., Givoly and Lakonishok, 1979, Lys and Sohn, 1990, Francis and Soffer, 1997) also shows analyst reports, on average, convey information to the capital market.\(^3\) Finally, considerable research focuses on the relation between analyst following and firm characteristics (e.g., Bhushan, 1989a, O’Brien and Bhushan,

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\(^2\) Justice William O. Douglas is an early believer of analysts’ activities making markets efficient. Douglas (1933) observes, “Even though an investor has neither the time, money, or intelligence to assimilate the mass of information in the registration statement, there will be those who can and who will do so, whenever there is a broad market. The judgment of those experts will be reflected in the market price.”

\(^3\) 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.
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 Stoher, 1999), or because analysts’ costs decrease in disclosure quality (e.g., Bhushan, 1989a, and Healy and Palepu, 2001).

**Offsetting factors influencing the informativeness of analyst research.** Analyst research may not entirely represent the flow of value relevant information to the market. 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 an input into investment decisions. Thus, some analysts might follow companies or produce additional research reports even when they are unable to provide information beyond 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.

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4 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. Also see Schipper (1991) and Beaver (1998).
Second, other analysts and timely (voluntary or mandated) corporate disclosures are likely to serve as partial substitutes for the informativeness of an individual analyst’s research by preempting their analysis (e.g., Bhushan, 1989b, Beaver, 1998, 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.

*Analysts as misinforming the market.* 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, Dechow, Hutton, and Sloan, 2000, Bradshaw, Richardson, and Sloan, 2003, and Lin, McNichols, and O’Brien, 2003). 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. A less harmful outcome compared to the market’s fixation on misinformative analyst reports is that market participants would ignore analysts’ reports because they are perceived to be tainted by analysts’ conflict of interest. Consistent with the notion that market participants ignore analyst reports, 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.

3. 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 likely yields 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).

**Endogenous determinants of 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 endogenous, whereas the remaining variables are econometrically modeled as exogenous. Our treatment of certain variables as exogenous reflects our belief (as articulated later in the paper) that the simultaneity between those variables and the dependent variable, AI, is at best weak and therefore can be ignored in the econometric analysis. 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 increase in a security’s trading volume. Brokerage houses compete for trading volume and offer analyst research as a service to their clients in generating trading business and commissions. A brokerage firm’s success in generating trading volume is likely to be positively influenced by the informativeness of their analysts’ research.
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 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 reason corporations promote 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 literally exogenous, *a priori* the degree to which these variables and informativeness are likely to be jointly determined appears negligible.

**Number of shareholders.** The relation between number of shareholders and analyst informativeness is ambiguous. The number of shareholders should increase the demand for analyst research 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. We expect a positive influence of the number of shareholders on analyst informativeness because the brokerage business would be more successful as their analysts’ research becomes more informative. However, an offsetting negative effect of the number of shareholders on informativeness arises because as demand drives more analysts to follow a company, they are less likely to be able to individually produce informative research.
Another factor influencing the relation between number of shareholders and informativeness is investors’ interest in a security as a function of analyst informativeness. While informative research might attract investors to a security, its net effect 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 (net) 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.\(^5\)

**Number of analysts.** We include number of analysts following a firm to differentiate analyst informativeness, AI, from number of analysts, a proxy often used in prior research (e.g., Brennan and Subramanyam, 1995). Number of analysts is perhaps the most extensively

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\(^5\) One might argue that institutional ownership is endogenous with respect to analyst informativeness. Analysts’ informative research in a security likely stimulates institutional investors’ interest and provides 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.
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 following a firm as a proxy for the informativeness of their research as reflected in the firm’s prices, i.e., aggregate 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.  

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. 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 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 informativeness is distinct from analyst following. Since previous research uses analyst following as a proxy for analysts’ informativeness about a firm,

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6 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.
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. Thus, 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. 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. Alternatively, fewer analyst reports reduce competition and lessen preemption of information, making each research report more informative. Therefore, the net effect on analyst informativeness is ambiguous.

**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,
Therefore, management is more likely to pre-empt bad news from analyst reports and bad news analyst reports’ informativeness will be muted.

**Growth opportunities.** A firm’s growth and/or investment opportunities are reflected in the market-to-book ratio. The effect of growth opportunities on analyst informativeness is unclear. Growth firms have more unrecorded, intangible assets and their valuation depends heavily on future profitability and growth. Forecasting future prospects requires 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.7

4. **Data, regression model, and results**

This section describes data sources and sample, descriptive statistics for the data, econometric specification of the model, and results. Section 4.1 presents data sources and sample. Section 4.2 presents the econometric model. We discuss the descriptive statistics and cross-correlations in the data in section 4.3. Section 4.4 contains our main results.

4.1 **Data**

*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

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7 We acknowledge an additional determinant of informativeness, namely 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 are unable to 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.
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 (or reiteration) 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 follows. We first sum the absolute size-adjusted returns on all the forecast revision dates for a firm in a given calendar year. We then divide it by the sum of absolute size-adjusted returns for all trading days for the firm for the calendar year. Finally, we divide this ratio by the number of forecast revision dates in a given calendar year. Specifically,

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8 If multiple forecast revisions are issued on the same day for a firm, our informativeness measure treats the collection of reports as one report. We cannot infer from any given day’s stock price movement the price reactions to the individual reports issued on the same day.
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AI = \frac{\sum_{\tau = 1}^{\text{NREVS}} |R_{\tau,s} - RS_{\tau}|}{\left( \sum_{t = 1}^{250} |R_{t,s} - RS_{t}| \right) \times \text{NREVS}}
\]

where

- \( R_{\tau,s} \) is a firm’s stock return on day \( \tau \) and the firm belongs to the NYSE size decile portfolio \( s \),
- \( \tau = 1 \) to \( \text{NREVS} \) are analyst forecast revision dates for the firm in a given year with 250 trading days,
- \( \text{NREVS} \) is the number of unique days on which at least one analyst forecast appears on the I/B/E/S detail tape, where the analyst forecast can be a revision or a reiteration, and
- \( RS_{\tau} \) is the return on the NYSE decile portfolio \( s \) on day \( \tau \).

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, \( 1/250^{th} \) of the sum of the absolute returns and thus \( AI \) would equal 0.004.

Our analyst informativeness measure is similar to the variance measure of information content first used in Beaver (1968). The difference between our measure and a variance measure is that we use the average absolute stock price reaction, not the square of the reaction. Average absolute value, however, is highly positively correlated with the variance, especially when the distribution is symmetric. One alternative to the \( AI \) measure is to use the stock price reaction itself and gauge the information content of an analyst report on the basis of the correlation between the unexpected component of an analyst’s forecast and the stock return for the day of the forecast (e.g., Lys and Sohn, 1980). The correlation measure of informativeness captures the magnitude of the news content, i.e., some analyst forecasts might have a large surprise to the market, which would generate a correspondingly large stock price reaction. Fortunately, this property is not lost when using our \( AI \) measure. Large forecast surprises generate large absolute stock price reaction and thus the \( AI \) measure is positively affected by the content of the analyst
forecast. In section 4.5 we present evidence consistent with this intuition. Additional reasons for measuring analyst informativeness using absolute stock price reactions are as follows.

First, our AI measure does not require specifying the market’s forecast of earnings, which is needed to calculate the unexpected component of each analyst’s forecast. While it is possible to estimate the unexpected component of the forecast, such measurement is noisy, and, perhaps more importantly, the noise is likely to be correlated with many of the determinants of informativeness like firm size, and analyst following. Since the noise in a measure of the unexpected component of an analyst’s forecast biases its estimated correlation with the return on the day of the forecast, the subsequent analysis of the informativeness and its determinants suffers from an errors-in-variables problem in which the estimation error in the dependent variable (informativeness) is correlated with its determinants.

Second, we face a practical problem in estimating a firm-specific measure of informativeness each year. Consider the estimation of the analyst informativeness of firm XYZ in year 1997. If we were to correlate returns on analyst forecast revision dates for the firm with the unexpected components of the forecasts on those dates, we might have only a few observations from the dates when analysts issued forecasts for the firm. A correlation estimated using the small number of observations measured with error is likely to be quite noisy. For these reasons we prefer our informativeness measure over a correlation measure.

4.2 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):

\[
AI = \alpha + \beta_1 \text{Fitted}(\sigma^2(R)) + \beta_2 \text{Fitted}(\text{LnVOL}) + \beta_3 \text{INST} + \beta_4 \text{LnOwners} + \beta_5 \text{MB} + \beta_6 \text{LnMV} + \beta_7 \text{NSIC} + \beta_8 \text{MMRsq} + \beta_9 \text{NSEGS} + \beta_{10} \text{AccRsq} + \beta_{11} \text{LnAnalyst} + \beta_{12} \text{GNEWS} + \varepsilon_1
\]  (1)
\[ \sigma^2(R) = \alpha + \beta_1 \text{INST} + \beta_2 \text{LnOwners} + \beta_3 \text{MB} + \beta_4 \text{LnMV} + \beta_5 \text{NSIC} + \beta_6 \text{MMRsq} + \beta_7 \text{NSEGS} + \beta_8 \text{AccRsq} + \beta_9 \sigma^2(R) + \varepsilon_2 \]

\[ \ln \text{VOL} = \alpha + \beta_1 \text{INST} + \beta_2 \text{LnOwners} + \beta_3 \text{MB} + \beta_4 \text{LnMV} + \beta_5 \text{NSIC} + \beta_6 \text{MMRsq} + \beta_7 \text{NSEGS} + \beta_8 \text{AccRsq} + \beta_9 \sigma^2(R) + \varepsilon_3 \]

where

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

\[ \ln \text{VOL} \] is the natural log of total trading volume for firm i in year t (Compustat #28),

\[ \text{INST} \] 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),

\[ \ln \text{Owners} \] is the natural log of the number of thousands of shareholders of firm i in year t (Compustat #100),

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

\[ \ln \text{MV} \] is the natural log of the market value of firm i at the end of year t (CRSP),

\[ \text{NSIC} \] 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,

\[ \text{MMRsq} \] is the \( R^2 \) from firm i’s market-model regression in year t (CRSP),

\[ \text{NSEGS} \] is the number of industry segments on the Compstat business information file in year t,

\[ \text{AccRsq} \] 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.

\[ \text{AccRsq} \] 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-

\[ \text{AccRsq} \]
GNEWS is an indicator variable equal to 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).

We next explain the 2SLS procedure to address endogeneity. Specifically, we explain our use of the fitted values of return volatility and trading volume in eq. (1) and portfolio ranks of these two variables in equations (2) and (3) as instrumental variables. As discussed above, we treat volume and return variance as endogenous with respect to analyst informativeness in this model and the rest of the variables are deemed exogenous.\(^{10}\) However, all three equations contain large subsets of the variables such that 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. We summarize the econometric approach below.

\(^{10}\) We reiterate that 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 be included in some equations and excluded from others can be problematic. As in any econometric formulation, we exercise judgment and hope to circumvent the problem by treating all the variables except analyst informativeness, volatility, and trading volume as exogenous.
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. That is, we assume that whether a stock is in the low, medium, or high return volatility portfolio is unlikely to be due to the endogenous relation between analyst informativeness and return volatility. However, the variation in return volatility among the stocks within the portfolio of high volatility stocks might be endogenously determined by the analyst informativeness of the stocks in the high volatility portfolio of firms. The volatility rank therefore meets the properties of a good instrument. The same logic applies to trading volume. We use the portfolio rank values instead of actual volatility or trading volume in equations (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. Under the assumptions about the properties of the instruments described above, the use of the fitted values circumvents the endogeneity problems of estimation.

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

[Table 1]

We next 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 the 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. Approximately eight percent of the forecast revision dates are lost, and the mean (median) average analyst informativeness measure is reduced to 0.0043 (0.0042) but remains significantly greater than 0.004. The p-values for the t-statistic and the rank sign test are less than 0.001.

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.

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 small firms have weaker price-earnings relation than large firms, perhaps because of the higher frequency of losses among small firms.

Table 2

4.4 Results

Table 3 reports results of estimating the two-stage-least-squares (2SLS) regression model (i.e., the system of equations 1-3) of 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 time series 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.

All, the results are largely consistent with the predicted relations between analyst informativeness and its determinants. Return volatility positively influences the informativeness
of analyst research, but the effect of trading volume is insignificant.\textsuperscript{11} 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.

We believe an important result in table 3 is that the number of analysts, LnAnalysts, does not significantly impact informativeness, which is consistent with the supply of analyst reports increasing until the marginal benefit (i.e., price impact) is reduced to zero. The zero coefficient suggests that analyst following and analyst reports rise as prices react to analyst reports, where price reaction to analyst reports is indicative of opportunities for analysts to convey new information to the market through their reports. However, the supply ceases to go beyond the point when the marginal report fails to generate a price reaction. The fact that the relation between the number of analysts and informativeness is not significantly negative implies competition among analysts does not result in a negative marginal price effect of an additional analyst.

At the risk of stating the obvious, we note that the zero coefficient on LnAnalysts should not be construed as analyst reports lack informativeness. Summary statistics in table 1 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 the average report is informative. Since the average report is informative, analysts’ aggregate informativeness for a firm increases in total number of analyst reports for the firm.

\textsuperscript{11} 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.
In other results in table 3, we find that analyst informativeness significantly declines in both market model r-square (MMRsq) and number of segments (NSEGS). The result of reduced informativeness for firms with multiple segments suggests investors seeking guidance from analyst reports in cases where information analysis is likely to be costly are not helped much by analysts’ research. 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 MMRsq, NSEGS, and the number of shareholders on analyst informativeness 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) is included in the estimation.

We find that analyst informativeness decreases in the strength of the association between accounting information and security prices, AccRsq. Our result is consistent with the investors’ Bayesian updating of their beliefs as modeled in Holtausen and Verrecchia (1988), Demski and Feltham (1994), and Subramanyam (1996). Investors are expected to place lower weight on analyst reports in setting prices when corporate accounting information is timely, i.e., contemporaneously highly associated with security price movements. The substitution effect we observe contradicts the findings in previous research. Specifically, Francis et al. (2002) conclude that the information in earnings announcements does not decrease in competing information sources like the information in analyst reports. Similarly, Lang and Lundholm (1996) and others find that timely (often interpreted as high quality) accounting disclosures, i.e., high AccRsq, and analyst following are complements (e.g., Lang and Lundholm, 1996). We show that accounting reports’ informativeness and information in analyst reports are substitutes. The result is
consistent with high AccRsq reducing the demand for analyst informativeness, without a commensurately offsetting reduction in analysts’ cost of supplying informativeness. The differences between our results and the results in previous research likely arise because of differences in research design. Lang and Lundholm (1996) and others study analyst following, not analyst informativeness. As discussed earlier, the two are not the same. Francis et al. (2002) analyze the price reactions to earnings announcements, whereas we examine whether analysts’ informativeness declines in the strength of the association between accounting information and prices using annual data.

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 significant and negative. This result implies bad news analyst forecasts have greater price impact than an upward forecast revision. The result suggests market having greater foreknowledge of the information in analysts’ positive forecast revisions, perhaps because management has an incentive to disseminate good news to the market through financial reports and/or voluntary formal and informal disclosures. The evidence is also consistent with the Hong, Lim, and Stein (2000) hypothesis that bad news travels more slowly than good news, so the market is surprised by analysts’ negative forecast revisions.

4.5 Sensitivity Analysis

Because AI is a measure first derived in this paper, we perform additional analysis to add to the intuitive appeal of our measure and to demonstrate robustness of the results. As noted earlier, previous research shows a positive relation between the surprise in analyst forecast revisions and stock returns (see Lys and Sohn, 1990). Therefore, if our measure of analyst informativeness, i.e., the absolute stock price reaction to an analyst’s forecast revision, is well
specified, then we expect it to be increasing in the surprise in the analyst’s forecast revision. As a proxy for this surprise, for each analyst forecast on the IBES detail tape, we compute the surprise, UAF, as

$$\frac{AF_{im} - \text{Consensus Forecast}_{m-1}}{P_{m-1}}$$

where $AF_{im}$ is analyst i’s forecast in month m, Consensus Forecast$_{m-1}$ is the consensus forecast reported on IBES in month m-1, and $P_{m-1}$ is share price for the previous month. Since more than one analyst might have issued a forecast revision on any given date, for each firm we calculate the average absolute value of the surprises in analysts’ forecasts, UAFs. We delete observations with share price below $2 to avoid the potential undue impact of a small denominator. We rank the absolute values of the surprise in analyst forecasts and place them into three portfolios. As a result, not all of the forecast revisions for a firm in a given year are assigned to the same portfolio. For example, a firm year containing five forecast revision dates might have three assigned to the portfolio of smallest forecast surprises and two to the portfolios consisting of largest absolute forecast surprises. We recalculate the analyst informativeness measure (defined earlier) using the firm-year forecast revision observations in each portfolio.

Table 3a reports average absolute surprise and average AI for the three portfolios ranked on the basis of absolute forecast surprise. As expected, AI increases in the surprise in analyst forecasts. The mean (median) AI for the lowest absolute forecast surprise portfolio is 0.0043 (0.0040) compared to 0.0051 (0.0044) for the portfolio comprising the largest absolute forecast surprises. The results in table 3a are consistent with the market’s reaction (as captured in AI) to the surprise in analysts’ forecast revisions is proportional to the magnitude of the surprise.

[Table 3a]
4.6 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.

5. Return reversal tests

The previous section provides evidence that analyst informativeness can be an outcome of investors rationally processing information in analyst reports and pricing stocks on the basis of economic fundamentals of the companies. Alternatively, 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 our results on analyst informativeness.

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 the association between the narrow-window price reaction to analyst reports and the returns for the window spanning three to five days after the report is released. We test whether firms that have more informative analyst reports (measured using AI) are more likely to have a return reversal. That is we test whether the market’s reaction to analysts’ reports is permanent, or suggestive of over- or under-reaction. In the second half of this section we examine whether returns exhibit reversal on the earnings announcement date.

The goal of the return-reversal tests is to examine 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 is fixated on analysts’ optimistic reports and therefore does it reverse itself subsequently when the optimism in the analyst forecasts becomes public? 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 offers conflicting explanations for the observed apparent 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 frictions. 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:

\[ SRET1 = \alpha + \beta_1 SRET + \beta_2 (\text{LnMV} \times SRET) + \beta_3 (Q1_{AI} \times SRET) + \beta_4 (Q5_{AI} \times SRET) + \epsilon_1 \]  

\[ SRET1 = \alpha + \beta_1 SRET + \beta_2 (\text{LnMV} \times SRET) + \beta_3 (\text{AvgAI} \times SRET) + \epsilon_2 \]  

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,
- \( \text{LnMV} \) 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
- \( \text{AvgAI} \) 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.
The intuition for interacting SRET with Q1_AI and Q5_AI is as follows. Under the market inefficiency hypothesis, the quintile ranking is a firm characteristic signifying the extent to which the market overreacts to (or is fixated on) analyst reports. The highest quintile stocks, Q5_AI, are those that historically have responded the most to analyst reports and are thus predicted to be the most likely candidates to exhibit return reversals in future around analyst report release dates. Therefore, under the hypothesis that stock price reactions to analyst reports indicate investor overreaction, we expect the coefficient on Q5_AI interaction variable to be more negative than that on the Q1_AI interaction variable in eq. (4). The regression enables us to test whether the degree of return reversals is greater for the stocks in Q5_AI compared to those in Q1_AI. Similarly, the coefficient on AvgAI interacted with SRET is expected to be negative under the investor overreaction hypothesis because the higher the AI measure, the greater the tendency of the investors to overreact to analyst reports.

The predictions are the same as above if the market were to be fixated on (as opposed to overreacting to) optimistic or misleading analyst forecasts, although the reversal might not occur in a short period of three days following the forecast revision. In contrast to the reversal predictions under market inefficiency, in an efficient market analyst informativeness indicates an appropriate reaction to information in analyst reports, and therefore coefficients on the Q5_AI and Q1_AI interaction variables are not expected to be different from each other.

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 R²’s 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

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12 Analyst forecast dates for firms that have many analysts are likely to be clustered. This weakens our ability to detect return reversals because clustering makes it likely that SRET for one analyst forecast date is SRET1 for another analyst forecast date.
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 $\beta_1$ 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 $\beta_1$ 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.

Given that the reversal story is based on investor irrationality, we have diffuse priors regarding the return reversal window. However, research suggests that if investors overweight the information contained in analyst reports, returns should reverse as investors receive additional information. For example, in the model of Daniel, Hirshleifer, Subrahmanyam, (1998) biased self attribution leads investors to overweight their private signal. These beliefs are gradually revised as additional public information is released. Therefore we examine returns around the quarterly earnings-announcement date that immediately follows the analyst report
The regression specification of these reversal tests is similar to the previous reversal tests. However, in these reversal tests we substitute EARET (i.e., the return around the earnings announcement date that immediately follows the analyst release date) for SRET1 (i.e., the return around the days immediately following the analyst release date).

[Table 5]

The results, given in Table 5, show little relation between returns surrounding the release of an analyst report and those surrounding the subsequent earnings announcement. In fact, the coefficient on SRET is no longer significantly negative as in Table 4. Thus we find no evidence that returns surrounding analyst report dates reverse around subsequent earnings announcement dates. As in Table 4, we interact analyst report date returns with a firm specific variable measuring the firm’s average AI in years prior to the given analyst report date. The coefficient ($\beta_3$) in Model 2 on the interaction between AI and SRET is insignificant indicating no evidence of a relation between the strength of the reversal/continuation effect and Analyst Informativeness.

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); (ii) The marginal impact of an (additional) analyst report on informativeness is indistinguishable from zero; (iii) Analyst informativeness is negatively related to variables that

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13 By increasing the separation between the analyst report return window and the subsequent return window, these return tests also mitigate potential difficulties caused by clustering of analyst forecast revisions.
proxy for analysts’ information processing costs; (iv) Consistent with investor rationality, the market’s short-horizon reaction to analyst research does not reverse; and (v) Analysts are less informative when financial statements are more highly related to prices, which is consistent with analysts providing information to market participants in cases where financial statements are less informative.

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 analysts 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).
References


Bradshaw, M., Richardson, S., Sloan, R., 2003,


Douglas, W., 1933, Protecting the investor, Yale Review 21, 523-524.


Landsman, W., Maydew, E., 2002, Has the information content of quarterly earnings announcements declined in the past three decades? Journal of Accounting Research 40, 797-808.


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.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>Std. dvn.</th>
<th>Q1</th>
<th>Median</th>
<th>Q3</th>
</tr>
</thead>
<tbody>
<tr>
<td>AI</td>
<td>0.0045</td>
<td>0.0015</td>
<td>0.0038</td>
<td>0.0043</td>
<td>0.0051</td>
</tr>
<tr>
<td>$\sigma^2(R)$</td>
<td>0.0016</td>
<td>0.0026</td>
<td>0.0005</td>
<td>0.0010</td>
<td>0.0020</td>
</tr>
<tr>
<td>LnVOL</td>
<td>3.32</td>
<td>1.64</td>
<td>2.16</td>
<td>3.26</td>
<td>4.41</td>
</tr>
<tr>
<td>INST</td>
<td>0.44</td>
<td>0.24</td>
<td>0.24</td>
<td>0.44</td>
<td>0.63</td>
</tr>
<tr>
<td>LnOwners</td>
<td>1.42</td>
<td>1.25</td>
<td>0.47</td>
<td>1.10</td>
<td>2.03</td>
</tr>
<tr>
<td>MB</td>
<td>3.84</td>
<td>7.73</td>
<td>1.12</td>
<td>1.94</td>
<td>3.87</td>
</tr>
<tr>
<td>LnMV</td>
<td>12.77</td>
<td>1.86</td>
<td>11.39</td>
<td>12.59</td>
<td>13.91</td>
</tr>
<tr>
<td>NSIC</td>
<td>0.0071</td>
<td>0.0021</td>
<td>0.0008</td>
<td>0.0021</td>
<td>0.0072</td>
</tr>
<tr>
<td>MMRsq</td>
<td>0.07</td>
<td>0.08</td>
<td>0.01</td>
<td>0.04</td>
<td>0.10</td>
</tr>
<tr>
<td>NSEGS</td>
<td>1.78</td>
<td>1.33</td>
<td>1.00</td>
<td>1.00</td>
<td>2.00</td>
</tr>
<tr>
<td>AccRsq</td>
<td>23.00</td>
<td>20.97</td>
<td>26.42</td>
<td>30.99</td>
<td>31.40</td>
</tr>
<tr>
<td>LnAnalyst</td>
<td>1.68</td>
<td>0.93</td>
<td>1.10</td>
<td>1.61</td>
<td>2.40</td>
</tr>
<tr>
<td>GNEWS</td>
<td>0.38</td>
<td>0.49</td>
<td>0.00</td>
<td>0.00</td>
<td>1.00</td>
</tr>
<tr>
<td>NREVS</td>
<td>31.20</td>
<td>29.00</td>
<td>10.00</td>
<td>22.00</td>
<td>42.00</td>
</tr>
</tbody>
</table>

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 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,

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

LnVOL is the natural log of total trading volume in year t-1 (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 shareholders of firm i in year t (Compustat #100),

MB is the market-to-book ratio for firm i in year t ([Compustat #24 x Compustat #25] / 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 using CRSP daily returns,

NSEGs is the number of industry segments on the Compustat 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 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 t,

GNEWS is an indicator variable equal to one 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, and

NREVS is the number of unique analyst earnings forecast revision dates from I/B/E/S for firm i in year t.
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.

<table>
<thead>
<tr>
<th></th>
<th>AI</th>
<th>σ²(R)</th>
<th>LnVOL</th>
<th>INST</th>
<th>Ln Owners</th>
<th>MB</th>
<th>LnMV</th>
<th>NSIC</th>
<th>MMRsq</th>
<th>NSEGS</th>
<th>AccRsq</th>
<th>LnAnalyst</th>
<th>GNEWS</th>
</tr>
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<tbody>
<tr>
<td>AI</td>
<td></td>
<td>0.01</td>
<td>0.01</td>
<td>0.02</td>
<td>-0.06</td>
<td>0.03</td>
<td>-0.03</td>
<td>0.05</td>
<td>-0.04</td>
<td>-0.03</td>
<td>0.04</td>
<td>-0.02</td>
<td>-0.05</td>
</tr>
<tr>
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<td></td>
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<td>-0.27</td>
<td>-0.17</td>
<td>0.08</td>
<td>-0.31</td>
<td>0.23</td>
<td>-0.16</td>
<td>-0.12</td>
<td>-0.28</td>
<td>-0.23</td>
<td>-0.08</td>
</tr>
<tr>
<td>LnVOL</td>
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<td>-0.07</td>
<td></td>
<td>0.42</td>
<td>0.50</td>
<td>0.24</td>
<td>0.74</td>
<td>0.14</td>
<td>0.55</td>
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<td>0.18</td>
<td>0.70</td>
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<td>0.45</td>
<td></td>
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<td>-0.03</td>
<td>0.55</td>
<td>-0.12</td>
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<td>0.18</td>
<td>0.36</td>
<td>0.54</td>
<td>0.21</td>
</tr>
<tr>
<td>Ln Owners</td>
<td>-0.04</td>
<td>-0.40</td>
<td>0.43</td>
<td>0.26</td>
<td>0.04</td>
<td>0.62</td>
<td>-0.11</td>
<td>0.42</td>
<td>0.31</td>
<td>0.15</td>
<td>0.51</td>
<td>0.08</td>
<td></td>
</tr>
<tr>
<td>MB</td>
<td>0.03</td>
<td>0.08</td>
<td>0.44</td>
<td>0.07</td>
<td>0.12</td>
<td>0.13</td>
<td>0.20</td>
<td>0.11</td>
<td>-0.04</td>
<td>0.00</td>
<td>0.07</td>
<td>0.05</td>
<td></td>
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<tr>
<td>LnMV</td>
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<td>0.60</td>
<td>0.53</td>
<td>0.32</td>
<td>-0.10</td>
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<td>0.39</td>
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<tr>
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<td>-0.11</td>
<td>0.22</td>
<td>-0.13</td>
<td>-0.03</td>
<td>-0.16</td>
<td>-0.08</td>
<td>-0.06</td>
<td>-0.00</td>
<td></td>
</tr>
<tr>
<td>MMRsq</td>
<td>0.02</td>
<td>-0.27</td>
<td>0.57</td>
<td>0.43</td>
<td>0.34</td>
<td>0.26</td>
<td>0.65</td>
<td>-0.02</td>
<td>0.21</td>
<td>0.20</td>
<td>0.51</td>
<td>0.17</td>
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</tr>
<tr>
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<td>0.14</td>
<td>0.18</td>
<td>0.27</td>
<td>-0.04</td>
<td>0.31</td>
<td>-0.19</td>
<td>0.18</td>
<td>0.12</td>
<td>0.24</td>
<td>0.00</td>
<td></td>
</tr>
<tr>
<td>AccRsq</td>
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<td>-0.54</td>
<td>0.23</td>
<td>0.44</td>
<td>0.27</td>
<td>0.11</td>
<td>0.58</td>
<td>-0.21</td>
<td>0.30</td>
<td>0.20</td>
<td>0.34</td>
<td>0.08</td>
<td></td>
</tr>
<tr>
<td>LnAnalyst</td>
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<td>-0.39</td>
<td>0.69</td>
<td>0.56</td>
<td>0.45</td>
<td>0.20</td>
<td>0.79</td>
<td>-0.05</td>
<td>0.54</td>
<td>0.21</td>
<td>0.45</td>
<td>0.12</td>
<td></td>
</tr>
<tr>
<td>GNEWS</td>
<td>-0.05</td>
<td>-0.13</td>
<td>0.16</td>
<td>0.21</td>
<td>0.08</td>
<td>0.15</td>
<td>0.24</td>
<td>-0.01</td>
<td>0.19</td>
<td>0.00</td>
<td>0.13</td>
<td>0.12</td>
<td></td>
</tr>
</tbody>
</table>
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 $R^2$s 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.

$$\text{AI} = \alpha + \beta_1 \text{Fitted}(\sigma^2(R)) + \beta_2 \text{Fitted}(\text{LnVOL}) + \beta_3 \text{INST} + \beta_4 \text{LnOWNERS} + \beta_5 \text{MB} + \beta_6 \text{LnMV} + \beta_7 \text{NSIC} + \beta_8 \text{MMRsq} + \beta_9 \text{NSEGs} + \beta_{10} \text{AccRsq} + \beta_{11} \text{LNANALYST} + \beta_{12} \text{GNEWS} + \epsilon_1$$ \hspace{1cm} \text{Eq. 1}

$$\sigma^2(R) = \alpha + \beta_1 \text{INST} + \beta_2 \text{LnOWNERS} + \beta_3 \text{MB} + \beta_4 \text{LnMV} + \beta_5 \text{NSIC} + \beta_6 \text{MMRsq} + \beta_7 \text{NSEGs} + \beta_8 \text{AccRsq} + \beta_9 r \text{_LnVOL} + \epsilon_2$$ \hspace{1cm} \text{Eq. 2}

$$\text{LnVOL} = \alpha + \beta_1 \text{INST} + \beta_2 \text{LnOWNERS} + \beta_3 \text{MB} + \beta_4 \text{LnMV} + \beta_5 \text{NSIC} + \beta_6 \text{MMRsq} + \beta_7 \text{NSEGs} + \beta_8 \text{AccRsq} + \beta_9 r \sigma^2(R) + \epsilon_3$$ \hspace{1cm} \text{Eq. 3}

<table>
<thead>
<tr>
<th>Independent Variables</th>
<th>Predicted sign</th>
<th>Coefficient</th>
<th>t-stat</th>
<th>Coefficient</th>
<th>t-stat</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fitted (\sigma^2(R))</td>
<td>+</td>
<td>0.18878</td>
<td>4.18</td>
<td>0.21182</td>
<td>2.81</td>
</tr>
<tr>
<td>Fitted (LnVOL)</td>
<td>+</td>
<td>-0.00003</td>
<td>-0.45</td>
<td>-0.00007</td>
<td>-0.15</td>
</tr>
<tr>
<td>INST</td>
<td>+</td>
<td>0.00044</td>
<td>1.66</td>
<td>0.00046</td>
<td>1.75</td>
</tr>
<tr>
<td>LnOwners</td>
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<td>-0.00005</td>
<td>-6.12</td>
<td>-0.00005</td>
<td>-7.24</td>
</tr>
<tr>
<td>MB</td>
<td>?</td>
<td>0.00000</td>
<td>-0.63</td>
<td>0.00000</td>
<td>-2.83</td>
</tr>
<tr>
<td>LnMV</td>
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<td>2.55</td>
<td>0.00009</td>
<td>1.40</td>
</tr>
<tr>
<td>NSIC</td>
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<td>-1.01</td>
<td>-0.00235</td>
<td>-1.37</td>
</tr>
<tr>
<td>MMRsq</td>
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<td>-0.00101</td>
<td>-3.91</td>
<td>-0.00089</td>
<td>-3.39</td>
</tr>
<tr>
<td>NSEGs</td>
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<td>-7.48</td>
<td>-0.00003</td>
<td>-3.95</td>
</tr>
<tr>
<td>AccRsq</td>
<td>?</td>
<td>-0.00001</td>
<td>-4.66</td>
<td>-0.00001</td>
<td>-5.51</td>
</tr>
<tr>
<td>LnAnalyst</td>
<td>?</td>
<td>0.00000</td>
<td>0.02</td>
<td>0.00009</td>
<td>0.85</td>
</tr>
<tr>
<td>GNEWS</td>
<td>?</td>
<td>-0.00017</td>
<td>-10.06</td>
<td>-0.00017</td>
<td>-11.88</td>
</tr>
<tr>
<td>Adjusted $R^2$</td>
<td></td>
<td>2.32%</td>
<td>9.96</td>
<td>2.71%</td>
<td>19.44</td>
</tr>
</tbody>
</table>

$r_-$ 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 3a
Forecast Revision and Analyst Informativeness

This table gives means and medians of AI and FOREV. For each fiscal-year-one forecast on the I/B/E/S detail tape 1995 and 1999 we compute FOREV as

\[
\frac{\text{individual\_forecast} - \text{prior\_month\_consensus}}{\text{prior\_month\_share\_price}}.
\]

where individual\_forecast is an analyst’s forecast on a given date, the prior\_month\_consensus is the consensus forecast taken from the I/B/E/S summary tape. We rank all observations by the absolute values of forecast revisions (FOREV) and place them into three portfolios. We compute AI for each of the three forecast revision portfolios where computation of AI is described in the notes to table 1.

<table>
<thead>
<tr>
<th>Forecast Revision (FOREREV) Rank</th>
<th>AI Mean (Obs.)</th>
<th>FORREV Mean (Obs.)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0.0043 (15,308)</td>
<td>0.0006 (15,308)</td>
</tr>
<tr>
<td>1</td>
<td>0.0040 (17,278)</td>
<td>0.0030 (17,278)</td>
</tr>
<tr>
<td>2</td>
<td>0.0046 (15,642)</td>
<td>0.0385 (15,642)</td>
</tr>
<tr>
<td>3</td>
<td>0.0043 (48,228)</td>
<td>0.0138 (48,228)</td>
</tr>
<tr>
<td>All</td>
<td>0.0042 (48,228)</td>
<td>0.0030 (48,228)</td>
</tr>
</tbody>
</table>
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 $R^2$'s 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.

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

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

<table>
<thead>
<tr>
<th>Independent Variables</th>
<th>Coefficient</th>
<th>t-stat</th>
<th>Coefficient</th>
<th>t-stat</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Panel B: Three-day return windows</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>SRET</td>
<td>-0.071**</td>
<td>-1.88</td>
<td>-0.095**</td>
<td>-2.47</td>
</tr>
<tr>
<td>LnMV x SRET</td>
<td>0.004</td>
<td>1.42</td>
<td>0.005</td>
<td>1.81</td>
</tr>
<tr>
<td>Q1_AI x SRET</td>
<td>-0.012</td>
<td>-0.90</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Q5_AI x SRET</td>
<td>-0.006</td>
<td>-0.56</td>
<td></td>
<td></td>
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<tr>
<td>AvgAI x SRET</td>
<td></td>
<td></td>
<td>0.003</td>
<td>1.22</td>
</tr>
<tr>
<td>Adjusted $R^2$</td>
<td>0.001</td>
<td>3.99</td>
<td>0.001</td>
<td>3.34</td>
</tr>
<tr>
<td><strong>Panel B: Five-day return windows</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>SRET</td>
<td>-0.094**</td>
<td>-2.21</td>
<td>-0.106**</td>
<td>-2.62</td>
</tr>
<tr>
<td>LnMV x SRET</td>
<td>0.006</td>
<td>1.84</td>
<td>0.006</td>
<td>1.89</td>
</tr>
<tr>
<td>Q1_AI x SRET</td>
<td>-0.006</td>
<td>-0.45</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Q5_AI x SRET</td>
<td>0.014</td>
<td>1.27</td>
<td></td>
<td></td>
</tr>
<tr>
<td>AvgAI x SRET</td>
<td></td>
<td></td>
<td>0.007</td>
<td>2.79</td>
</tr>
<tr>
<td>Adjusted $R^2$</td>
<td>0.001</td>
<td>4.00</td>
<td>0.001</td>
<td>3.79</td>
</tr>
</tbody>
</table>

**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.
Table 5
Tests of Return Reversal at Subsequent Earnings Announcement Dates

This table presents the time-series means of coefficients, t-statistics for the averages of the coefficients, and average adjusted R²'s 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 232,037.

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

$$EASRET = \alpha + \beta_1 SRET + \beta_2 (\text{LnMV} \times SRET) + \beta_3 (mAI \times SRET) + \varepsilon_2$$  \hspace{1cm} \text{Model 2}

<table>
<thead>
<tr>
<th>Independent Variables</th>
<th>Model 1</th>
<th></th>
<th>Model 2</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Coefficient</td>
<td>t-stat</td>
<td>Coefficient</td>
<td>t-stat</td>
</tr>
<tr>
<td>Panel A: One-day return analyst return window, three-day earnings announcement date return window</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>SRET</td>
<td>0.002</td>
<td>0.04</td>
<td>-0.031</td>
<td>-0.69</td>
</tr>
<tr>
<td>LnMV \times SRET</td>
<td>0.001</td>
<td>0.18</td>
<td>0.005</td>
<td>0.77</td>
</tr>
<tr>
<td>Q1_AI \times SRET</td>
<td>-0.032</td>
<td>-1.45</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Q5_AI \times SRET</td>
<td>-0.022</td>
<td>-0.84</td>
<td></td>
<td></td>
</tr>
<tr>
<td>AvgAI \times SRET</td>
<td></td>
<td></td>
<td>0.001</td>
<td>0.13</td>
</tr>
<tr>
<td>Adjusted R²</td>
<td>0.000</td>
<td>3.29</td>
<td>0.000</td>
<td>1.92</td>
</tr>
<tr>
<td>Panel B: Three-day return analyst return window, three-day earnings announcement date return window</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>SRET</td>
<td>0.084</td>
<td>1.89</td>
<td>0.053</td>
<td>1.28</td>
</tr>
<tr>
<td>LnMV \times SRET</td>
<td>0.005</td>
<td>-1.61</td>
<td>0.003</td>
<td>-1.10</td>
</tr>
<tr>
<td>Q1_AI \times SRET</td>
<td>-0.022</td>
<td>-1.52</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Q5_AI \times SRET</td>
<td>-0.023</td>
<td>1.51</td>
<td></td>
<td></td>
</tr>
<tr>
<td>AvgAI \times SRET</td>
<td></td>
<td></td>
<td>-0.001</td>
<td>-0.15</td>
</tr>
<tr>
<td>Adjusted R²</td>
<td>0.001</td>
<td>4.34</td>
<td>0.000</td>
<td>4.25</td>
</tr>
</tbody>
</table>

Variable Definitions

EASRET  compunded size adjusted return for the three-day window surrounding the earnings announcement date following the release of the analyst report.

SRET   compounded size adjusted return for analyst report release event window. The window includes the day of the report (i.e., day t) release in Panel A and includes days -1 and +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.