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Publication Date
2004-08-23

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August 2004

*Corresponding author. We thank IBES/Firstcall for providing IBES analyst recommendations. We also thank an anonymous reviewer and workshop participants at the 2002 American Accounting Association Annual Meeting, UCLA, University of Chicago, the 2002 London Business School Summer Symposium, University of Iowa, and University of North Carolina for helpful comments. We appreciate funding from the Center for Finance and Accounting Research at UNC-Chapel Hill.

How do Analyst Recommendations Respond to Major News?

Abstract

This study examines how analysts respond to public information when setting their stock recommendations. Specifically, for a sample of stocks that experience large stock price movements, we model the determinants of analysts' recommendation changes. Using an ordered probit model based on all available IBES stock recommendations from 1993 to 1999, we find evidence of an asymmetry following large positive and negative returns. Large stock price changes are associated with more frequent changes in analyst's recommendations. Following large stock price increases, analysts are equally likely to upgrade or downgrade. Following large stock price declines, however, analysts are much more likely to downgrade the company's stock. This asymmetry exists even after accounting for investment banking relationships and herding behavior. Further, this asymmetry cannot be explained by differences in the predictability of future returns. This result suggests that recommendation changes are "sticky" in one direction, with analysts reluctant to downgrade securities. Moreover, this result implies that analysts' optimistic bias is not static, but varies through time.

Key words: Analyst recommendations.
JEL classifications: G14, M41.

1. Introduction

Unlike analysts' earnings forecasts, which are short-term point estimates, analysts' recommendations can be considered more analogous to capital budgeting decisions. For instance, Womack (1996) states that stock recommendations are akin to an analyst concluding that, "I have analyzed publicly available information, and the current stock price is not right" (p. 164). This suggests that analysts develop explicit (or implicit) valuation models. If the market price is sufficiently below the true value indicated by the model, the stock is accorded a buy recommendation; when the market price is above the model value, the stock is given a sell recommendation.

Both academics and practitioners have questioned the view that analysts' recommendations are simple valuation decisions. First, as Lin and McNichols (1998) stress, investment banking relationships can potentially bias analyst recommendations. Consistent with this, Barber, Lehavy and Trueman (2004) show that independent research analysts tend to outperform analysts employed by investment banks, and that a large source of the investment banks' underperformance is a reluctance to downgrade stocks that had recently issued equity. These papers suggest that analysts have mixed incentives. On the one hand, they want to produce accurate reports to satisfy investors. On the other hand, they have an incentive to produce positive reports to generate (or retain) investment banking business from the companies being evaluated. One indication of these conflicting interests is the well-known upward bias in the distribution of recommendations documented by Stickel (1995) and others. Following the collapse of technology stock prices in 2000, the conflict of interest issue became the focus of intense debate in the financial press.[1] Several Wall Street firms and their analysts were sued by investors who claim to have relied on misleadingly optimistic recommendations produced by analysts who the plaintiffs claim had a conflict of interest. In addition, this perceived conflict of interest has led to increased scrutiny of analysts' investment practices by the Securities and Exchange Commission and states' attorneys general.[2]

Second, some empirical research contradicts the view that analyst recommendations are based primarily on fundamental valuation models. Bradshaw (2004) examines the correlation between analyst recommendations and the ratio of fundamental firm value to market price. Bradshaw calculates fundamental value by substituting analysts' consensus earnings forecasts into the residual income version of the discounted cash flow model developed by Ohlson (1995). Surprisingly, he finds that analysts' recommendations are more (less) favorable for stocks with *low* (*high*) value relative to price. This finding is the reverse of what the capital budgeting interpretation predicts. However, Bradshaw's results are consistent with the survey work of Block (1999). Based on a survey of analysts, Block reports extremely low reliance on valuation methods in the formation of stock recommendations.[3]

Individual case studies point to a possibly complex relation between the arrival of market information and *changes* in analyst recommendations. For instance, Cornell (2001) finds a puzzling relation between the innovations in market value and changes in analyst recommendations. Cornell examines the market reaction to an apparently minor news

1 See, for example, Tully (2001).

2 See, for example, Opdyke (2001) and *New York Times*, May 24, 2002.

3 Interestingly, although Bradshaw (2004) finds that fundamental valuation models are not reliable predictors of analyst recommendations, he does find that *heuristic* valuation models have significant explanatory power. In particular, he finds that the PEG ratio, defined as the P/E ratio divided by the long-term growth rate, is correlated with the level of analyst recommendations. This result holds, furthermore, despite the fact that rankings of stock based on PEG ratios are often quite different than rankings based on the ratio of fundamental value to price and despite the fact that PEG ratios are no better predictors of future returns than value to price ratios.

announcement by Intel that, nonetheless, resulted in a 30 percent drop in the company's stock price and destroyed $125 billion in shareholder wealth. Following the news announcement and the subsequent price drop, many analysts revised their recommendations *downwards*, some by several rating classifications. Not one analyst increased his or her recommendation. If analyst recommendations were based on a comparison of value to price, this reaction implies that all analysts believed that fundamental value fell by more than the $125 billion drop in market capitalization. However, Cornell argues that there was "not enough information" in the news release to justify the observed drop in price; that is, he argues that the change in fundamental value was less than the drop in price. As with Bradshaw and Block, Cornell's conclusion would suggest that in downgrading the company following the price decrease, Intel analysts did not rely on present value models.

To date, there has been little research on the determinants of analysts' recommendation *changes*, and this work has tended to focus on the relation between earnings announcements and recommendation changes (see, e.g., Bradshaw (2004) and Finger and Landsman (2003)). In terms of setting recommendation levels, findings in Hong and Kubik (2003) show that analysts are rewarded for both optimism and accuracy, which suggests that analysts tradeoff reputation (which is based on accuracy) and bias. Presumably, anything that affects the comparison of public price and private value will cause the analyst to change her recommendation while maintaining the optimal tradeoff. However, if the analyst perceives the market price as too high relative to her private valuation, she may be reluctant to downgrade the stock (because of pressure from her company), causing the optimistic bias inherent in her recommendation to become larger. That is, there could be a dynamic component to the tradeoff between accuracy and optimism. In this example, the dynamic component depends on the sign of the difference between her private valuation and market price. As market prices change in response to positive and negative information shocks, the analyst may change her recommendation to reflect a new optimal optimism/accuracy tradeoff.

In this study, we examine how analysts' recommendations respond to public information shocks, using large price changes as a proxy for the shocks (Ryan and Taffler, 2004). In doing so, we develop hypotheses based on various assumptions regarding the information analysts possess and the incentives they face. We then estimate empirical models of recommendation changes, partitioning on the sign of information shock, to determine which hypothesis is most consistent with the data. The hypotheses we consider begin with the assumption that analysts' recommendations reflect price-to-value comparisons and a belief that the market is efficient. In the first hypothesis (hypothesis 1), analysts are unbiased but have no informational advantage relative to the market, in which case we predict they will have no reason to change their recommendation in reaction to a stock price shock. In the second and third hypotheses, analysts have private information relative to the market, but may have conflicts of interest (pressure from their firms) that affect their recommendations. Where no conflict of interest exists (hypothesis 2), we predict that, on average, analysts will downgrade (upgrade) in response to positive (negative) price shocks, assuming that their private information is at least partially revealed by the price movement. However, although there is a predicted difference in the direction of the response, we predict no difference in the magnitude of the response to positive and negative stock price shocks under this hypothesis.

Conversely, a conflict of interest can exist if the analyst receives negative private information (hypothesis 3). That is, the analyst would ordinarily prefer to downgrade the stock to maintain the optimal level of optimism and accuracy, but is prevented from doing so because of business pressure. A sufficiently large negative shock may relieve the conflict of interest because the market price reveals a portion of the analyst's private information, thereby permitting the analyst to downgrade while still maintaining an optimistic bias. No conflict of interest exists if the analyst received positive private information. Thus, if hypotheses 1 or 2 are correct, then recommendation changes will be symmetric following positive and negative information shocks, although hypothesis 1 would also be consistent with no response. Only if hypothesis 3 is correct do we predict the possibility of an asymmetric response.

In robustness checks, we test the assumption that analysts believe markets are efficient. We also permit recommendations to reflect dimensions beyond value-to-price fundamentals. For example, following a large stock price decline, if the analyst believes the market under-reacted to negative information, she may downgrade the stock. Conversely, if the analyst believes the market over-reacts, then the analyst may upgrade following a sharp stock price drop. We test whether there is systematic evidence of price continuations or reversals, which bring prices back in line with fundamental values, following the recommendation changes that accompany the price shocks. Womack (1996) and Jegadeesh, Kim, Krische, and Lee (2004) also study the relation between stock price movements and analyst recommendations. However, whereas these studies focus on measuring how recommendation changes affect subsequent market prices, we include price prediction tests for purposes of buttressing our understanding of how analyst recommendation changes respond to large information shocks.

The results clearly demonstrate that analysts respond to large price changes by changing their recommendations. That is, among the sample of recommendation changes, we are much more likely to see a revision occur in the three days following a stock price event. These results are not consistent with hypothesis 1, i.e., with analysts behaving as if they have no private information. Second, following large stock price increases, analysts are equally likely to upgrade or downgrade, that is, on average the analysts react as if fundamental values and market prices move in tandem. Following large stock price declines, however, analysts are much more likely to downgrade the company's stock (as they did in the case of Intel). These results are not specific to the recommendation level prior to the stock price change, i.e., the asymmetry is present after controlling for the level of initial recommendation. The asymmetry is also present when we examine only "interior" recommendation levels, from which analysts can either upgrade or downgrade securities. The observed asymmetry is consistent with analysts' recommendations before the public information shock being attributable, at least in part, to some other force such as pressure from their employers.

Analysts' recommendation changes following negative return events also are consistent with the theory of information cascades. In this case, the negative return event shatters the optimistic consensus (Bikhchandani, Hirshleifer, and Welch, 1992). However, the asymmetry in the analysts' responses to negative return events cannot be simply attributable to analysts herding. In particular, the evidence reveals that these negative return events are significant determinants of analysts' recommendation changes even after controlling for the tendency of analysts to respond following other analysts' recommendation changes. Overall, the findings suggest that recommendations are differentially "sticky" in that analysts appear to use large stock price drops to realign their optimal level of optimism and accuracy.

We also conduct a number of robustness checks on our results. First, an examination of returns data commencing immediately after the three-day price shock event shows no systematic evidence of price continuation or reversals. This suggests that the price responses preceding the analyst recommendation changes are not an under- or over-reaction. Thus, the asymmetry does not appear to be related to a differential over (under) price reaction. Second, we examine a subset of recommendation changes following earnings announcements and find that the asymmetry is present in this subsample. In particular, controlling for earnings surprises, downgrades are more likely to follow negative price shocks, but upgrades and downgrades are equally likely to follow positive price shocks.

We also find that upgrades are more likely if there is an investment banking relationship between the brokerage firm making the recommendation and the firm for which the recommendation is issued. Analysts also tend to respond in the same direction as other analysts who recently changed their recommendations. However, these results do not explain the asymmetry since their effects are present in both the positive and negative return samples.

The remainder of the paper is organized as follows. The next section lays out the hypotheses we test, discusses the nature of the data, the sample selection criterion and the empirical framework. Because analyst recommendations are coded into five discreet categories, ordered probit analysis is employed. The empirical results are presented in section three. Section four discusses the implications of the results. In particular, we offer a possible explanation for the pronounced asymmetry described above. Section five examines post-event returns. The paper is summarized in the final section.

2. Hypotheses

In our hypotheses we maintain market efficiency, i.e., observed price responses accurately reflect the information revealed to the market.[4] In the first hypothesis, H1, we consider the possibility that analysts have no private information, and consequently make no

[4] We test this assumption in our sample of large stock price change events in robustness tests discussed in section 5 below.

value-to-price comparisons when setting recommendations.[5] In this setting, a sharp change in stock price can neither reflect analyst private information nor have any systematic effect on analysts' recommendations.

In the second and third hypotheses, H2 and H3, we assume that analysts have private information and use value-to-price comparisons when setting recommendations. Following Hong and Kubik (2003), we also assume that analysts are rewarded based on accuracy and optimism. As a result, analysts set recommendations in a way that reflects an optimal tradeoff between those two competing objectives. In H2, we assume that observed stock price changes are the result of revelation of at least a portion of analysts' private information. As a consequence, when a portion of an analyst's private information is revealed, she may reset the recommendation to reflect the new value-to-price comparison. Under this hypothesis, therefore, we expect to see a downgrade following a price increase, and an upgrade following a price decrease. In addition, under H2, we assume that the well known (Stickel, 1985) recommendation bias is time invariant. As a result, the magnitude of any recommendation changes should be symmetric in the sign of the price shock.[6]

In the third hypothesis, H3, we assume that the optimistic bias in analysts' recommendations can change through time. In particular, because of conflicts of interest arising from pressure from the analyst's employer, the optimistic bias may be more severe when the analyst has negative private information. In this case, the private information of the analyst and the subsequent value-to-price comparison suggests that she downgrade the stock, but she cannot.

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5 In the absence of private information, recommendations may serve the purpose of generating goodwill among the firm's clients and potentially investment banking business from the covered firms. For example, the Wall Street Journal quoted Mary Meeker (an analyst at Morgan Stanley Dean Witter) as saying "my highest and best use is to help MSDW win the best Internet IPO mandates…and then to let them work their way through our powerful research and distribution system."

6 Stock price change events do not necessarily comprise the full extent of analysts' private information. Only if the price movement is sufficiently large will it cause the analyst to change her recommendation.

That is, the optimistic bias has become larger—in fact, unacceptably so in the absence of the conflict of interest. If enough of the analyst's private information is revealed so as to result in a sufficiently large negative stock price revision, this may relieve the conflict of interest. Indeed, the analyst may be able to maintain an optimistic bias relative to the new valuation while still downgrading the stock.

When the analyst receives positive private information, the subsequent value-to-price comparison suggests that she upgrade the stock, and because there is no conflict of interest, she is free to do so. Thus, as in H2, when the analysts' private information is subsequently revealed, causing a positive stock price revision, the analyst will either take no action if her information is incompletely revealed or downgrade if it is fully revealed. Thus, relative to the first two hypotheses, H3 is the only one that predicts the possibility of an asymmetric response on the part of analysts in terms of changing recommendations following negative and positive stock price events. The asymmetry is attributable to a "stickiness" in the downgrades that is the result of a conflict of interest.

3. Sample Selection and Research Design

3.1 *Construction of sample*

Construction of the sample begins with the IBES U.S. Recommendations database, which spans the years 1993-2000.[7] Each observation in the database represents the issuance of a

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[7] We considered the use of changes in analysts' target prices rather recommendations as our dependent variable. For our sample, we examined the relation between changes in analysts' recommendation and percentage changes in corresponding target prices in the interval +/- 15 days surrounding the recommendation change. Untabulated findings indicate a strongly positive and significant correlation between the two. Pearson and Spearman correlations are 0.37. This suggests that there is a common element to these measures of analyst activity. However, the use of target prices would require a minimum of two adjustments: horizon and required return. Analyst reports provide little information on either dimension. Moreover, in our sample, there are many cases where analysts simultaneously upgrade (downgrade) and decrease (increase) target prices. Consequently, we use analyst recommendations as the indicator of analyst sentiment regarding a stock's valuation.

recommendation by a particular brokerage firm for a specific company. For instance, one observation would be a recommendation by Merrill Lynch regarding Intel. Therefore, there is no distinction in this sample between “analyst” recommendations and “brokerage firm” recommendations. Recommendations in the IBES database are coded as follows: 1 = Strong Buy, 2 = Buy, 3 = Hold, 4 = Sell, 5 = Strong Sell. It should be noted that the individual analyst responsible for the Merrill Lynch recommendation may change over time. If that is the case, and if the new Merrill Lynch analyst has a different recommendation, the result would be coded as a change in the Merrill Lynch recommendation. There are a total of 234,159 observations in the IBES file. Of these observations 90,777 represent initializations in the data set.[8]

For each available broker-firm combination, daily recommendation changes are constructed from the IBES dataset. Recommendation changes can be upgrades, downgrades, initializations, affirmations, or no changes. Both upgrades and downgrades can be from 1 to 4 recommendation grades. By convention, and consistent with prior research, we sign increases (decreases) in recommendation grades positively (negatively). For example, an increase from a “sell” (grade = 4) to “buy” (grade=2) is coded as a plus 2–grade recommendation change. Affirmations represent broker recommendation announcements confirming prior recommendations. No changes, which represent the overwhelming majority of the observations, are constructed by “filling in the holes” between each of the 234,159 brokerage recommendations listed on the IBES database. That is if there is no new information from a given brokerage on a given day for a given firm, the recommendation is assumed to remain unchanged.

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[8] Initializations may not actually represent when coverage by the particular broker began, but instead may only represent the first observation for the particular broker/firm combination in the data set.

Because the focus of this study is determining how individual analysts respond to public information, we require a proxy for information that can be applied to a large sample of stocks without having to identify any particular information event. We choose price movements as a sufficient statistic for information events. The linkage that we presume between large stock price movements and information events is supported by evidence presented in Ryan and Taffler (2004) which finds that 65% of price changes can be accounted for by the release of public information. For computational reasons, we select a subsample of firms for which there is some evidence of a significant news shock, i.e., a large price shock, during the sample period.[9]

We begin by determining for each firm in the recommendations database the beginning and end dates for which the firm is followed by at least one brokerage firm. Using these dates to define the time period for the firm, we construct a vector of returns for this period, beginning immediately before the start of the recommendations in the database. The vector is based on three-day compounded returns on the grounds that some information events may affect the market for more than one day. To illustrate how the vector of three-day returns is computed, consider a hypothetical firm, XYZ, Inc., which first appears in the recommendations database on July 11, 1996, and remains in the database until the end of 2000. The first three-day return for this firm is constructed from July 8 through July 10, the second is from July 9 through July 11, etc., until the last return from December 28 through December 30, 2000. The next step is to select an appropriate sample of extreme returns. Here an extreme return is defined as one in the top or bottom 1% tail of the distribution of three-day returns subject to two adjustments. First,

[9] An alternative method of capturing "news shocks" is to use actual information releases, estimated from the unexpected components of the information released, and examine analysts' behavior around those dates. However, this requires a robust and feasible method of identifying important announcements *ex ante*, and measuring the unexpected components of those announcements *ex post*; this would obviously also entail measurement problems. In section 5.2 below, we use a subsample of earnings announcements for which we can measure the unexpected component of the announcement.

each three-day return, r_{it}, is netted against the contemporaneous CRSP three-day value-weighted market return, r_{mt}. Second, to control for differences in sample firms' return volatilities along with possible changes in volatilities over time, each resulting net-of-market return, $r_{it} - r_{mt}$, is scaled by the standard deviation of three-day net-of-market returns, $\sigma_{it}(r_{it} - r_{mt})$, calculated using a sample of non-overlapping three-day net-of-market returns prior to day *t*, i.e., those running from day –3 to day –249 relative to each day's return. A vector of market-adjusted returns, $ADJRET3_{it}$, is computed simply as the ratio $[r_{it} - r_{mt}] / \sigma_{it}(r_{it} - r_{mt})$.

It is this sample of market-adjusted returns that is utilized to calculate upper and lower 1% tail cutoff points of the distribution of normalized 3-day returns aggregated across all firms. By assumption, any firm exhibiting a stock return that falls outside these cutoffs has experienced a significant public information event in relation to both its own performance and the sample as a whole. When calculating the cutoff points only non-overlapping returns are used. The resulting upper and lower 1% cutoff points for the $ADJRET3_{it}$ distribution are –2.59 and 3.06.

We select the final sample of extreme 1% return events for each firm by comparing the full vector of market-adjusted three-day returns to the cutoff points calculated from the overall sample. We avoid selecting overlapping returns as extreme events. That is, once a three-day period is flagged as an extreme return event, we do not select the next two (overlapping) three-day return events as extreme. We considered, but rejected, selecting the largest three-day return event in any overlapping period since this would result in a "look-ahead bias." For example, suppose the first three-day return for XYZ that meets one of these criteria is July 15, 1996. The three-day returns ending on July 16 and 17 would be deleted from the dataset and we would continue chronologically beginning on July 18 to search for the next return observation that meets the cutoff criteria.

This procedure, which is repeated for each firm in the IBES sample, results in 40,458 and 41,481 return events, respectively, in the lower and upper 1% tails. The larger number of return events in the upper 1% tail reflects the fact that lower tail events are associated with more overlapping returns that are eliminated when the samples are constructed.[10] Our sample period for these 81,939 return events extends from 20 days prior to the return event to 20 days after the return event, centered on day +1 relative to the last day of the 1% three-day return event.[11] The reason for extending the event period +/-20 days is to provide a more accurate assessment of the probability of a recommendation change. While recommendation changes do not occur frequently, they are particularly clustered around large return events for our sample (see discussion of table 1 below). Thus, the additional days add cross sectional variation in returns without which the power of our tests would be limited. That is, if we limited sample observations to include only large stock returns then the effect of returns on recommendation changes would be estimated with less precision.

For our sample of firms with identified public information events, and for each day in the 41-day event window, we analyze how recommendation changes can be explained by variables

[10] For a random sample of 500 large return events, we searched for news releases surrounding each event to understand better the potential source of the price movement. Not surprisingly, many large price movements occur close to announcements regarding earnings or preliminary earnings news (162), merger and acquisition activity (76), dividends (14), share repurchases (16), and product information (e.g., successful drug trials) (40). For some large return events, we could find no proximate announcement; in fact, in some cases, there were related disclosures by the firm which state that they have no information regarding the price movement. We find little evidence that a single type of announcement was associated with our return events, although earnings are clearly the most important announcement; we examine earnings announcements separately in section 5 below. Overall, the random sample provides strong evidence that these return events are generally associated with “news”. Furthermore, recommendation changes are 5 times more likely to occur after identifiable news events relative to unidentifiable ones, which suggests that our research design is biased against finding results.

[11] Because large return events sometimes occur within 40 days of one another, our procedure of including observations for the probit analysis in the period +/–20 days surrounding each identified public information event results in duplicate observations for certain firm/broker/date combinations. To avoid counting some observations multiple times, we remove duplicate entries, leaving a single observation for each firm/broker combination on any individual day.

that are publicly available as of the previous day. As described section 2.3, we use ordered probit which allows for discreteness in individual analysts' recommendation changes.

3.2 *Univariate analysis*

Table 1, panels A through D, provides a variety of descriptive statistics for the 9,050,560 recommendation change/days used in the probit analysis. Panel A, which also provides summary data for the full sample of recommendation changes on the IBES database, indicates that the probit sample is dominated by no changes, amounting to 9,000,482 observations. Downgrades occur more frequently than upgrades (24,581 versus 17,610) and, because recommendation changes are undefined for initializations, there are no initializations in the sample. Panel B, which provides an industry breakdown, indicates no obvious clustering of recommendation change observations across industries. Likewise, panel C, which provides a breakdown of recommendations by year, indicates no obvious clustering of recommendation change observations across time. The relatively small number of observations in 1993 is the result of the IBES database starting in the fourth quarter of that year.

Panel D, which breaks down the recommendation changes by number of grades, indicates that among downgrades, recommendation changes of multiple grades are approximately twice as common as they are among upgrades. The fact that downgrades are more common than upgrades, particularly for large changes, is consistent with the positive bias in the level of recommendations mentioned earlier. In our sample, the average recommendation is 2.1, which is approximately a buy. The fact that the level of recommendations already clusters at the optimistic end of the range provides less room for future upgrades, particularly by more than one rating category. In the probit analysis, a recommendation level variable is used to take account of this "congestion" at the high end.

Panel D also demonstrates that analyst activity is much greater following large return events. The frequency of upgrades is higher by a factor of 3 and the frequency of downgrades is higher by a factor of 4 compared with the overall sample. The fact that there are relatively few changes in the recommendations but analysts are more likely to change recommendations following the large stock price events suggests that analysts have private information. That is, analysts' recommendations are based on value-to-price comparisons; a change in the market price may cause a change in their value-to-price comparison and hence a related change in their recommendations.

If analysts' recommendations are upwardly biased (Stickel, 1995), then the arrival of negative information may precipitate a greater response from analysts than good news. That is, there may be some circumstances in which accuracy is deemed more important than optimism, just as Hong and Kubik (2003) find that there are some analysts for whom optimism may be more important than accuracy. The findings in table 1, which indicate a larger proportion of downgrades relative to upgrades, could be indicative of such an asymmetric response. The most direct way to assess the empirical validity of this conjecture is to split the sample based on the sign of the information shock. Table 2 partitions the data in table 1, panel A, based on the sign of the three-day standardized market-adjusted return preceding each recommendation event, and also includes summary statistics for the return. Table 2 indicates that the proportion of upgrades and downgrades following positive and negative returns differs dramatically. In particular, whereas there are relatively equal numbers of upgrades and downgrades following positive returns (9,163 versus 9,446) there is nearly twice the number of downgrades than upgrades following negative returns (15,135 versus 8,447). The accompanying return information suggests that this asymmetrical analyst response cannot be explained by differences in return magnitudes preceding the response.

Table 3 extends the analysis of analysts' responses to price changes to include information about the analysts' level of initial recommendation. The sample comprises all observations, including those for which analysts made no change in recommendation level. In panel A, we examine negative return shocks; in Panel B, positive return shocks are considered. Comparing the two matrices, the asymmetry in analyst response is apparent. There are many more downgrades (represented in the upper right portion of the matrix) associated with negative return shocks in Panel A. The ratio of the total number of downgrades to the total number of upgrades in Panel A is 1.79, while the ratio of downgrades to upgrades is 1.03 for positive return shocks in Panel B. This difference in analyst response across positive and negative returns is consistent with the evidence presented in Boni and Womack (2004), and suggests that the multivariate analysis should be conducted separately for positive and negative return observations.

2.2 Multivariate analysis

Since recommendations are coded into five discreet categories, changes in recommendations are constrained to fall into one of nine categories (-4 through +4, inclusive.) This constraint suggests the use of ordered probit analysis, with recommendation level changes as the dependent variable and market movements as the key independent variable. Because recommendation levels are presumably affected by other variables, we include additional independent variables as controls.

In particular, we seek to explain changes in recommendations made by specific analysts in the 40 trading days surrounding the large return event, i.e., in the 1% upper and lower return tails. The values of recommendation changes, *RECCH*, are limited dependent variables, in that the true recommendation changes, $RECCH^*$, are unobservable. Under the assumption of a standardized unit normal distributed error term, i.e., $\varepsilon \sim N(0,1)$, ordered probit can be used to estimate the underlying latent relation,

$$RECCH^* = \beta' X + \varepsilon \, . \qquad (1)$$

We use maximum likelihood estimation to estimate the vector of model parameters, β, which represent the marginal effects of changes in regressors, *X*, on the probabilities, Prob(*RECCH* = *k*), *k* = –4, –3,…, 0, +1,…,+4. In addition, cutoff points μ_κ, are imputed where

$$\begin{aligned} RECCH &= -4 \quad \text{if } RECCH^* \le \mu_0 \qquad (2) \\ &= -3 \quad \text{if} -\mu_0 < RECCH^* \le \mu_1 \\ &. \\ &. \\ &. \\ &= +4 \quad \text{if } \mu_8 < RECCH^* \, . \end{aligned}$$

Note that except for the endpoints, *k* = –4 and *k* = +4, the signs of the changes in probabilities as a function of changes in the regressors are ambiguous. That is, although individual regressors can be evaluated for significance, the signs of estimated model parameters do not necessarily correspond in sign to changes in probabilities in response to marginal changes in the regressors. However, partial derivatives for Prob(*RECCH* = *k*) with respect to each of the regressors evaluated at sample means can be computed using estimated model parameters.[12] For example, for a particular continuous variable, X_j, we can compute the change in Prob(*RECCH* = *k*) from $X_j = \overline{X}_j + \sigma_j$ to $X_j = \overline{X}_j - \sigma_j$, holding all other variables constant at their sample means. For a particular discrete 0/1 variable, X_j, we can compute the difference in Prob(*RECCH* = *k*) for

12 See Green (1997), pp. 926-931, for a more complete description of ordered probit.

X_j = 1 and X_j = 0, again holding all other variables constant at their sample means. At a practical level, because our sample is dominated by no change observations, the computed changes are all going to be relatively small. As a result, we report changes in probabilities as probability ratios evaluated at each of the nine recommendation change levels. Note that if these probability ratios vary monotonically across the recommendation change categories, then we can interpret the sign of the coefficient as having the same influence on the dependent variable as in an ordinary regression.

The ordered probit model used here is given by (3). Observations are time-indexed from day –20 to day +20, where day 0 is the day following the end of the extreme 1% three-day return event that caused a firm to be included in the sample. For each day *t*, the change in the recommendation for firm *i* by brokerage firm *j* is denoted by the variable $RECCH_{ijt}$.

$$\begin{aligned}RECCH_{ijt} = {} & \alpha_0 + \alpha_1 ADJRET3_{it} + \alpha_2 ADJRET10_{it} + \alpha_3 AFIL_{ij} + \alpha_4 AGE_i + \\ & \alpha_5 MVE_{it} + \alpha_6 LMNREC3_{it} + \alpha_7 LMNREC10_{it} + \alpha_8 NUMREC_{it} + \alpha_9 LPERC3_{it} + \\ & \alpha_9 LPERC10_{it} + \alpha_{10} LREC_{ijt} + \alpha_{11} AFIL_{ij}*ADJRET3_{it} + \alpha_{12} AFIL_{ij}*ADJRET10_{it} + \\ & \alpha_{13} PRICE_{it} + \alpha_{14} SMALL_{it} + \alpha_{15} SMALL_i*ADJRET3_{it} + \varepsilon_{ijt}, \qquad (3)\end{aligned}$$

where

$RECCH_{ijt}$	=	Recommendation change for firm *i* by analyst *j* on day *t*, *t* = –20,…,+20;
$ADJRET3_{it}$	=	Standardized market-adjusted return for firm *i* for the three days preceding analyst *j*'s recommendation change at day *t*;
$ADJRET10_{it}$	=	Standardized market-adjusted return for firm *i* for the 10 days commencing 13 days before and ending 4 days before analyst *j*'s recommendation change at day *t*;
$AFIL_{ij}$	=	One if analyst *j*'s firm has an investment banking relationship with firm *i* as of day *t*, and zero otherwise;
AGE_i	=	Number of years between current year and year firm *i* first appears on CRSP;
MVE_{it}	=	Equity market value on day *t* for firm *i*;

$LMNREC3_{it}$	=	Mean recommendation change for firm *i* for the three days preceding analyst *j*'s recommendation change at day *t*;
$LMNREC10_{it}$	=	Mean recommendation change for firm *i* for the 10 days commencing 13 days before and ending 4 days before analyst *j*'s recommendation change at day *t*;
$NUMREC_{it}$	=	Number of analysts following firm *i* at time *t*;
$LPERC3_{it}$	=	Percentage of analysts following firm *i* at time *t* that change their recommendation during the three days preceding analyst *j*'s recommendation change at day *t*;
$LPERC10_{it}$	=	Percentage of analysts following firm *i* at time *t* that change their recommendation during the 10 days commencing 13 days before and ending 4 days before analyst *j*'s recommendation change at day *t*;
$LREC_{ijt}$	=	Recommendation for firm *i* by analyst *j* on day $t-1$, $t = -20,\ldots,+20$;
$PRICE_{it}$	=	Stock price for firm *i* on day *t*;
$SMALL_{i}$	=	1 if firm is in the smallest equity market value decile for all sample observations within the quarter in which day *t* falls, and zero otherwise.

The primary empirical question of this study is whether analysts change their recommendations in response to major news, with large stock price events serving as our proxy for news shocks. Our purpose for expanding the event window to +/–20 days surrounding the end of the 1% tail three-day return interval is to estimate more accurately the probability of making a recommendation change by including "non-event" days surrounding the large return event days.[13] By construction, because the return interval associated with *ADJRET3* ends before *RECCH* occurs, *ADJRET3* should not be affected by *RECCH*. However, to allow for the possibility that events prior to the immediate three days could affect the probability of a recommendation change, we include an additional explanatory variable, *ADJRET10*, which extends the return event interval back an additional ten days.[14]

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[13] Note we may also be including in our non-event period large return event days that were excluded in the construction of the sample to avoid overlapping returns. If return events are important in determining analysts' recommendation changes, this will bias against our finding a significant relation between the return events and recommendation changes.

[14] *ADJRET10* is computed analogously to *ADJRET3*, with the ten-day compounded net-of-market return scaled by the standard deviation of prior period net-of-market ten-day returns.

To determine whether investment banking relationships can possibly affect the probability of a recommendation change, we include *AFIL*, an indicator variable that equals one if the analyst's firm has an investment banking affiliation and zero otherwise.[15] It is important to note, in this regard, that affiliation can bias the level of recommendation, as previous research shows, and still not bias the recommendation changes. To allow for the possibility that affiliation affects the probability of the analyst changing his recommendation in response to stock price movements, we also include the interaction of *AFIL* with *ADJRET3* and *ADJRET10*. To allow for the possibility that the probability of an analyst response to large returns is greater for small firms, we also allow both the intercept and the return response to vary with the market capitalization of the firm. That is, we include an indicator variable, *SMALL*, if a firm is in the smallest size decile, as well as a variable interacting *SMALL* with *ADJRET3*.

It is possible that analysts respond not just to the return event but also to actions taken by their peers following the same stock during the same three-day period. Such a response would occur if analysts have a tendency to "herd" (e.g., Welch (2000)). To test for this, we include *LMNREC3* and *LPERC3*, which are the mean recommendation change for firm *i* and percentage of analysts following firm *i* that change their forecasts in the three days preceding analyst *j*'s recommendation change on day *t*. As with the return variables, to allow for the possibility that events prior to the immediate three days could affect the probability of a recommendation change, we include additional explanatory variables, *LMNREC10* and *LPERC10*, which extends the event interval back an additional ten days.

[15] To determine whether an analyst's firm had an investment banking relationship with the firm for which he supplied a recommendation, using CUSIP, we matched firms common to the IBES and Securities Data Corporation datasets. We assume an investment banking relationship exists if the SDC dataset indicates there were any debt or equity offerings or merger and acquisition activity sponsored by the analyst's firm any time during the IBES sample period.

The censored nature of analysts' recommendations imply that it is impossible to observe an upgrade from a strong buy, or a downgrade from a strong sell. We use two methods of controlling for this potential source of bias induced by this feature of the data. First, we include *LREC*, analyst *j*'s recommendation (lagged one day) to permit recommendation changes to depend on the initial recommendation level, i.e., to control for the fact that when recommendations are high there is little or no room to upgrade and when they are low there is little or no room to downgrade. The inclusion of *LREC* also permits the ordered probit to calculate different empirical probabilities for recommendation changes of equivalent magnitudes but with different initial recommendation levels. Second, we conduct a separate probit analysis of the subsample of recommendations for which the starting recommendation level is not at a boundary (i.e., strong buy or sell). We continue to include *LREC* as a control variable in this estimation, as well.

We include several variables that capture the amount of public information, interest or following that a firm might have. First, we include *NUMREC*, the number of analysts following the firm. Other variables that might capture the amount of publicly available information on the firm include *MVE* and *AGE*.[16] Finally, we include, *PRICE*, the firm's stock price on the event day as an additional control. This variable is typically considered as a proxy for liquidity, and hence may control for the incentive to collect (and profit from) private information about a firm.

We estimate equation (3) by pooling observations across $i = 1, ..., I$ firms and $j = 1, ..., J$ analysts during the +/–20 day window surrounding the large stock return event on a calendar quarter-by-quarter basis during the sample period. We do this partly for computational

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[16] In unreported estimations, we also included indicator variables that permitted the probability of a recommendation change to differ based on a firm's industry membership. No systematic differences were detected, nor are any inferences based on reported findings affected by inclusion/exclusion of the industry indicators.

reasons and also to permit coefficients to vary over time. The coefficient estimates for each regressor are averaged across the 25 quarters of data. In addition, as noted above, we also estimate equation (3) by dividing the observations into positive and negative returns to allow for the possibility that probabilities are dependent on the sign of the return.

2.4 <u>*Data*</u>

Table 4, panels A and B, presents sample summary statistics for all variables used in the probit analysis for negative and positive return subsamples. Negative and positive return observations represent firms with similar mean market capitalization, *MVE*, and years listed on an exchange, *AGE*, and mean number of analysts following the firm, *NUMREC*. In addition, both subsamples have identical percentage of analysts whose brokerages have investment banking relationships with the firm, *AFIL*. The mean percentages of analysts that change their recommendations in the three-days preceding the recommendation change, *LPERC3*, and ten days before that, *LPERC10*, are identical for both subsamples, at approximately 1% and 5%, respectively. In addition, the mean recommendation on the day before the recommendation change, *LREC*, of 2.1(approximately a "buy,") also is identical for the subsamples. The mean recommendation changes in the three- and ten-day periods prior to each analyst's recommendation change, *LMNREC3* and *LMNREC10*, are both near zero, reflecting the fact that analysts rarely change recommendations.

Although the mean standardized three-day return preceding a recommendation change, *ADJRET3*, is similar in absolute magnitude for both negative and positive return subsamples, −0.93 and 1.01, respectively, the mean standardized ten-day return preceding the three-day return, *ADJRET10*, indicates there is modest evidence of price reversals for the positive return events, −0.11, and a virtually flat price movement for negative return events, −0.02. Since these two return measures share a common price (i.e., the ending price used to calculate *ADJRET10* is also the beginning price for *ADJRET3*), this effect may be attributable to bid-ask bounce (see, e.g., Blume and Stambaugh, 1983).

3. <u>Probit Results</u>

Table 5, panels A and B, presents the ordered probit summary statistics for equation (3) corresponding to negative and positive return observations. Following Fama and MacBeth (1973) we report mean coefficient estimates from 25 calendar quarter probit regressions along with significance tests based upon the time-series standard deviation of the parameter estimates.[17] To aid in interpreting the probit results, as described in section 2.2, for each independent variable, table 6 presents changes in probability ratios evaluated at sample means of the other independent variables based on probit results for a representative quarter (1996Q1).

Table 5 reveals that for both positive and negative return observations, the coefficient on *AFIL* is generally positive and statistically significant.[18] The positive sign suggests that the probability of an upgrade (downgrade) is greater if there is (is not) an investment banking relationship between the brokerage firm making the recommendation and the firm for which the recommendation is issued. This is confirmed in table 6—the evidence indicates that for *AFIL*, the ratio of probabilities exceeds 1 for each of the four upgrades categories, and is less than 1 for each of the four downgrade categories. Table 5 also indicates that the coefficients on *LMNREC3* and *LMNREC10* are positive and significant. As the probability ratios in table 6 confirm, this is

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[17] We also conducted tests separately for observations that do and do not fall within a firm's fiscal year-end quarter to allow for the possibility that analyst behavior differs depending on whether the large return event corresponds to the release of fiscal year-end earnings (Cornell and Landsman, 1989). Results from unreported analyses indicate that for 13% (50%) of sample firms, event day 0 is within three (seven) trading days of the release of quarterly earnings. However, the fiscal year-end quarter distinction does not have a significant effect on any of the inferences relating to reported probit results and therefore these results are not reported.

[18] Throughout the paper, we use a five percent criterion for assessing statistical significance.

consistent with the probability of an upgrade (downgrade) being higher if other analysts following the same firm also upgraded (downgraded) the stock in the prior three and ten day periods. This finding also provides some added support for the notion of herding among analysts studied by Welch (2000), among others.

Table 5 also shows a strong and highly significant positive relation between the probability of an upgrade (downgrade) and the initial recommendation, *LREC*. This result is expected; irrespective of the return sign, at the extreme, when recommendations are high (low) there is little or no room to upgrade (downgrade).[19]

Turning to the key variable of interest, *ADJRET3*, the findings in tables 5 and 6 indicate that analysts respond to large price shocks, rejecting the H1 prediction that because analysts do not have private information, they will not respond to public information. However, the findings indicate that analysts systematically respond only to large negative price shocks. This asymmetry in the analyst response to large price shocks is evidence supportive of the H3 prediction that analysts possess private information but their recommendations are "sticky" downwards. These results hold even after controlling for the censored nature of the recommendations, and hence the changes in recommendations.

In particular, for positive return observations, *ADJRET3*'s coefficient in table 5, panel B, is negative but statistically insignificant. In contrast, for negative return observations, *ADJRET3*'s coefficient in table 5, panel A, is positive and statistically significant, with p-values less than 0.0001. The probability ratios in table 6 confirm that this translates into the probability of a downgrade (upgrade) being substantially higher (lower) the more negative (less negative) is the three-day return before the recommendation change. That is, analysts appear to be

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[19] Recall that we sign increases (decreases) in recommendation grades positively (negatively), but leave the lagged recommendation level *LREC* unchanged, which ranges from 1 (Strong Buy) to 5 (Strong Sell).

responsive only to large negative stock price events. The positive and generally significant coefficient on the interaction of *SMALL* with *ADJRET3* for the negative return sample suggests that analysts are more responsive to large negative returns for small firms.

Although we include the initial recommendation level in our estimation to address the censored nature of our data, the possibility remains that our results are biased by the fact that analysts who have already rated a stock a "strong buy" ("strong sell") cannot upgrade (downgrade). We perform additional analyses considering only the "interior" initial recommendation levels (2, 3 or 4) at which the analyst could either upgrade or downgrade. Untabulated findings support the asymmetry result obtained for the full sample. For example, in univariate results, one can focus on the middle three rows of the matrices in table 3, where we continue to see a significant difference in the proportion of total downgrades to total upgrades for positive and negative return shocks: in Panel A, the ratio is 0.86, while in Panel B the ratio is 0.49. When the probit model is re-estimated for the interior initial recommendation levels 2, 3, and 4, untabulated findings show a continued asymmetry in the *ADJRET3* coefficients for the positive and negative return sub-samples. Although the magnitude of the asymmetry declines, the difference in the coefficients remains statistically significant.[20]

Among the remaining explanatory variables, the only systematically significant relation between the probability of a recommendation change and a change in the variable obtains for *LPERC10*, which has a negative coefficient. Thus, it appears that the probability of an upgrade

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[20] As another robustness check on the results, we calculate the average (across the 25 quarters of our sample period) aggregate probability of observing an upgrade (downgrade) following positive and negative returns, for both the full sample and the subsample of interior recommendation levels. Since these results are aggregated across the entire sample (or subsample), they are not conditional on any initial recommendation level. The aggregate probability of an upgrade is, as one would expect, higher in the subsample of observations where the initial recommendation level is 2, 3 or 4, for both negative and positive returns. However, the asymmetry in the response to negative and positive returns is still present. In particular, in the subsample of interior recommendation levels, we observe a ratio of upgrades to downgrades of 2 for positive returns, and 1.2 for negative returns. Overall, for negative returns, the aggregate probability of a downgrade increases by 41% for *both* the full sample, and the restricted interior sample, of recommendation levels. .

(downgrade) is lower (higher) the greater is the percentage of analysts that follow the same stock that change their recommendation in the ten day period before the three days preceding the recommendation change.

4. Discussion of results

The most striking result to emerge from the probit analysis is the asymmetry between the results for positive and negative returns. For the positive return sample, the results suggest that, on average, analysts react as if prices and fundamental values move in concert—the average investment rating of the companies is largely unchanged. More specifically, following large positive returns, the number of upgrades and downgrades are about equal. Following price increases, analysts do not simply follow up with upgrades, as they would if they consistently believed the market underreacts, nor do they behave as if the market systematically overreacts. Consistent with this interpretation, the estimated coefficient of *ADJRET3* is insignificant in the ordered probit regressions for the positive return sample. This finding is potentially consistent with any of the three hypotheses

The picture for large negative changes is markedly different. The number of downgrades is twice the number of upgrades following large stock price drops. In addition, the z-statistics for coefficients of *ADJRET3* are large for the sample in general and are even more significant for small firms. This asymmetry is inconsistent with the both the first two hypothesis. Furthermore, if recommendations are interpreted as comparisons of fundamental value with price, these results appear to imply that analysts believe that the market underreacts on average to bad news, but not good news.

It seems unlikely that analysts believe in such an asymmetric underreaction; indeed, we test whether prices in this sample behave in a manner consistent with underreaction in Section 5, and find no evidence of it. Thus, it appears that forces other than direct price-to-value comparisons have an impact on analyst recommendations. Hypothesis 3 offers one interpretation that is consistent with the data, namely that business pressure causes analysts to trade-off accuracy and optimism. Given this pressure, negative stock price movements serve as catalysts that allow analysts to downgrade their recommendations without necessarily eliminating the optimistic bias.

Note that our results are also consistent with the literature on information cascades. Suppose that analysts are under pressure to rate companies highly and not to downgrade for fear of insulting potential clients. This effect, furthermore, may well extend beyond clients with which a particular investment bank is currently affiliated. Given this pressure, analysts need unambiguous external cues (with which management of potential clients cannot quarrel) to help them cut ratings. According to this interpretation, analysts recognize that their recommendations are too optimistic. The arrival of bad news makes it possible to downgrade the company without fear of retribution. This interpretation is consistent with predicted behavior in models examining informational cascades (Bikhchandani, Hirshleifer, and Welch, 1992) as well as the empirical evidence presented in Lin, McNichols and O’Brien (2004), which finds that analysts take longer to downgrade versus upgrade in a duration analysis framework. It is important to note that the return event cue is important even after controlling for the effect of other analysts’ recommendation changes, suggesting that the cue is the primary motivating force behind the recommendation change rather than herding behavior.

5. Additional Tests

5.1 *Post-Event Returns*

The asymmetrical analyst response to large negative and positive return events does not rule out the possibility that analysts possess superior information. If analysts do have private information and their recommendations reflect it, then stock prices should adjust accordingly—on announcement of the recommendation change if markets are efficient, and in future periods if markets react to this information with a lag. We are particularly interested in determining whether analysts exhibit differential ability to predict future returns after downgrading following large negative news relative to other news/recommendation change combinations.

Table 7, panel A, presents unscaled mean and median equally weighted buy-and-hold market-adjusted returns following the 40,458 and 41,481 large negative and positive events. Returns are presented separately for recommendation changes of +1 and –1, changes greater than (less than) or equal to 2 (–2), and for no changes and affirmations, and over two different horizons, 20 days, and 60 days. Returns are computed as buy and hold returns on the day following the observed recommendation changes.[21] Panel B presents a test of differences of mean returns following negative and positive return events for the same analyst response category.[22]

The general picture that emerges is that stock prices continue to fall following downgrades—both observed and unexpected—regardless of whether the downgrade was preceded by a large positive or negative return event. For example, panel A reveals that median

[21] We also examined post-event returns conditioning on the sign of unexpected recommendation changes computed using fitted values from the probit model. Untabulated findings reveal no observable pattern in post-event returns that cannot be garnered from the tabulated results in table 7.

[22] Related research (e.g., Womack (1996)) documents the contemporaneous price response to analysts' recommendation changes. The post-event returns examined here begin the day after the relevant recommendation change.

returns for stocks that are downgraded one category, which comprise more than two-thirds of the downgrades, are significantly negative over the 20-day and 60-day horizons following both negative and positive return events.[23] Similar findings obtain for stocks that are downgraded two or more categories. There is no systematic stock price movement following upgrades preceded by either large positive or negative return events.[24] The tests for differences in mean returns in panel B indicate that, if anything, negative price reactions are stronger following downgrades preceded by positive return events than negative return events.

Taken together, the evidence in Table 7 seems to provide support for the notion that analyst recommendation changes (more specifically the downgrades) following large stock price movements are informative to the market. Thus, the findings are further evidence that analysts possess private information. However, the future return data fail to account for asymmetrical response of analysts in response to large negative and positive stock price events.[25] That is, for our sample of large stock price events, we find no evidence that the market consistently under- or over-reacts to public information.

5.2 *Earnings Announcement Events*

As an additional robustness check, we re-estimated a probit equation on a subsample of earnings announcement events.[26] That is, instead of using large price changes to define our sample, we use the sample of all earnings announcement events for firms in our sample. Our

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[23] Insignificance in some of the mean returns is likely attributable to positive return skewness. Extant research (Kothari and Warner [1997]) suggests that skewness is not peculiar to our sample, but is endemic to buy-and-hold returns.

[24] One interesting finding is that stock prices appear to fall for "no change" observations preceded by both large positive and negative return events. One explanation for this is that the market expected most of these stocks to have been upgraded. That is, the fact that such stocks were not upgraded was regarded as bad news by the market.

[25] Untabulated findings from additional analyses provide some evidence that controlling for analyst activity during *future* return event horizons accounts for part of the returns following the recommendation change events.

[26] Our review of 500 random large stock return events indicates that approximately 20 percent correspond to earnings announcements.

purpose in conducting this test is to choose a sample of price movements for which we know there is a corresponding information event. We record all analyst recommendation changes in the fifteen days following each earnings announcement. We record a recommendation change of zero if no change occurs in these fifteen days. For the earnings announcement sub-sample, 58 percent of recommendation changes occur in the three days immediately following the earnings announcement.

In untabulated probit estimations we control for the sign and magnitude of the earnings surprise measured for each individual analyst. We also interact the extent of the earnings surprise with the related price response. Our results indicate that analysts are still more likely to downgrade following a large negative stock price shock. That is, controlling for the sign and magnitude of the earnings surprise has no effect on inferences from our main findings reported in tables 5 and 6.

6. Conclusion

This study examines how analysts respond to public information when setting their stock recommendations. Specifically, we test empirically different hypotheses regarding analyst information and incentives using a sample of stocks that experience large stock price movements, and analyst recommendation changes for those stocks. Using an ordered probit model based on all available IBES stock recommendations from 1993 to 1999, we find evidence of an asymmetry between the results for positive and negative returns, even after controlling for the initial recommendation level. Following large positive returns, the number of upgrades and downgrades are about equal. In contrast, following large negative returns, analysts are much more likely to downgrade than upgrade the company's stock.

Our findings are consistent with the hypothesis that analysts have private information, and set recommendations comparing private values to market price. That is, they respond to public information events using large price shocks as a proxy for news. However, the asymmetrical response is further consistent with a dynamic component to the analyst's optimism when setting recommendations. The results suggest stickiness in recommendations induced by reluctance to downgrade, possibly because of conflicts of interest or information cascades. Relatedly, there is also evidence that upgrades are more likely if there is an investment banking relationship between the brokerage firm making the recommendation and the firm for which the recommendation is issued. In addition, there is evidence that analysts tend to respond in the same direction as other analysts who recently changed their recommendations, which adds some support for the notion of herding among analysts. This finding obtains for the full sample of recommendation changes, and (as a control for the censored nature of the recommendation levels, and changes in levels) for a subsample which includes only "interior" recommendation levels of 2, 3 or 4.

Findings from analysis of future stock returns indicate that analysts' recommendation changes are useful in explaining future stock returns. However, the findings fail to provide an explanation for the observed asymmetry in the response of analysts following large negative and positive return events. Specifically, we find no evidence that the market consistently under- or over-reacts to public information. We also examine a subset of recommendation changes following large stock price movements that are associated with earnings announcements and find the asymmetry is present in this subsample. That is, after controlling for earnings surprises, downgrades are more likely to follow negative price shocks, but upgrades and downgrades are equally likely to follow positive price shocks. Overall, our findings suggest that the bias in recommendations changes through time, and that the bias may decrease conditional on a significant public information shock.

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TABLE 1

Recommendation Change Descriptive Statistics

Panel A

	All Firms	1% Sample +/- 20 Days	Large Return Event Sample
Total observations	29,257,042	9,050,560	214,084
Upgrades	53,956	17,610	1,158
Downgrades	63,377	24,581	2,449
Initializations	90,777	0	0
Affirmations	26,049	7,887	361
No Changes	28,989,279	9,000,482	210,116

Panel B
Industry Composition

Industry	Upgrades	Downgrades	Affirmations	No Changes	Total
Mining and construction	27	35	10	4,905	4,977
Food	41	66	11	5,887	6,005
Textiles, printing & publishing	42	104	15	9,744	9,905
Chemicals	35	52	8	5,812	5,907
Pharmaceuticals	60	106	16	8,243	8,425
Extractive industries	50	67	11	12,805	12,933
Durable manufacturers	240	433	61	35,856	36,590
Computers	190	421	59	27,198	27,868
Transportation	84	116	32	13,295	13,527
Utilities	36	81	8	11,404	11,529
Retail	113	364	52	23,137	23,666
Financial institutions	107	213	24	22,985	23,329
Insurance and real estate	38	105	24	12,409	12,576
Services	92	273	29	15,886	16,280
Other	3	13	1	550	567
Total	1,158	2,449	361	210,116	214,084

Industry definitions based upon methodology in Barth, Beaver and Landsman (1998).

All recommendations are between 1 (Strong Buy) and 5 (Strong Sell). Upgrades are recorded as positive changes (i.e. a move from 3 to 1 is recorded as Upgrade +2) and downgrades as negative changes (i.e. a move from 1 to 3 is recorded as Downgrade -2). The All Firms sample represents the total number of observations after filling in the days between IBES recommendation dates as No Changes. The Large Return Event Sample represents recommendation changes on the day following a standardized CRSP 3-day market adjusted return within the 1% tails of the distribution for sample firms. The 1% Sample represents the recommendation changes in the ± 20 days surrounding event dates identified in the Large Return Event Sample. We identify 81,393 large return events resulting in 214,084 recommendation changes (including No Changes). The difference represents the fact that multiple analysts cover a stock at any point in time. See Table 4 for average analyst coverage.

TABLE 1, Continued

Recommendation Change Descriptive Statistics

Panel C
Yearly Composition

Year	Upgrades	Downgrades	Affirmations	No Changes	Total
1993	1	5	0	1,136	1,142
1994	108	204	30	25,707	26,049
1995	162	325	52	35,243	35,782
1996	184	387	71	35,039	35,681
1997	176	390	67	39,476	40,109
1998	247	593	74	45,324	46,238
1999	280	545	67	28,191	29,083
Total	1,158	2,449	361	210,116	214,084

Panel D
Recommendation Change Categories

	1% Sample OBS	Percentage of Total	Return Event Sample OBS	Percentage of Total
Upgrade +1	12,918	0.14%	874	0.41%
Upgrade +2	4,446	0.05%	268	0.13%
Upgrade +3	131	0.00%	11	0.01%
Upgrade +4	115	0.00%	5	0.00%
Downgrade -1	16,864	0.19%	1,647	0.77%
Downgrade -2	7,263	0.08%	760	0.36%
Downgrade -3	259	0.00%	28	0.01%
Downgrade -4	195	0.00%	14	0.01%
No Changes	9,000,482	99.45%	210,116	98.15%

All recommendations are between 1 (Strong Buy) and 5 (Strong Sell). Upgrades are recorded as positive changes (i.e. a move from 3 to 1 is recorded as Upgrade +2) and downgrades as negative changes (i.e. a move from 1 to 3 is recorded as Downgrade -2). The Large Return Event Sample represents recommendation changes on the day following a standardized CRSP 3-day market adjusted return within the 1% tails of the distribution for sample firms. The 1% Sample represents the recommendation changes in the ± 20 days surrounding event dates identified in the Large Return Event Sample. We identify 81,393 large return events resulting in 214,084 recommendation changes (including No Changes). The difference represents the fact that multiple analysts cover a stock at any point in time. See Table 4 for average analyst coverage.

TABLE 2

Recommendation Change and Return Descriptive Statistics based upon Sign of Standardized Market Adjusted Return

Panel A
1% Sample

Return Sign	Grade	obs	Mean Return	Median Return	Maximum Return	Minimum Return
Negative	Upgrade	8,447	-1.24	-0.85	0.00	-13.92
Negative	Downgrade	15,135	-1.83	-1.11	0.00	-19.86
Negative	Affirm	4,251	-1.19	-0.81	0.00	-12.19
Negative	No Change	4,792,321	-0.93	-0.69	0.00	-23.14
Positive	Upgrade	9,163	1.46	1.02	20.45	0.00
Positive	Downgrade	9,446	1.50	0.85	43.61	0.00
Positive	Affirm	3,636	1.15	0.77	27.39	0.00
Positive	No Change	4,208,161	1.00	0.70	175.10	0.00
Total observations		9,050,560				

Panel B
Large Return Event Sample

Return Sign	Grade	obs	Mean Return	Median Return	Maximum Return	Minimum Return
Negative	Upgrade	546	-3.60	-3.19	-2.59	-10.45
Negative	Downgrade	1,882	-4.42	-3.73	-2.59	-19.86
Negative	Affirm	229	-3.79	-3.17	-2.59	-11.65
Negative	No Change	111,292	-3.25	-2.97	-2.58	-19.86
Positive	Upgrade	612	4.23	3.74	16.66	3.06
Positive	Downgrade	567	5.35	4.10	43.61	3.07
Positive	Affirm	132	4.05	3.69	11.52	3.09
Positive	No Change	98,824	3.78	3.51	76.98	3.06
Total observations		214,084				

The Large Return Event Sample represents recommendation changes on the day following a standardized CRSP 3-day market adjusted return within the 1% tails of the distribution for sample firms. The 1% Sample represents the recommendation changes in the ± 20 days surrounding event dates identified in the Large Return Event Sample. Standardized returns are calculated utilizing 3-day market adjusted returns scaled by the standard deviation of 3-day market adjusted returns over day -3 to -249.

TABLE 3

Recommendation Changes by Lagged Recommendation Level

Panel A
1% Negative Returns

	New Recommendation					
LREC	**1**	**2**	**3**	**4**	**5**	***Downgrades***
1	1,407,187	4,129	3,926	65	102	***8,222***
2	2,977	1,778,547	5,819	159	92	***6,070***
3	1,788	2,898	1,494,386	403	418	***821***
4	21	53	290	59,249	22	***22***
5	54	34	311	21	57,203	
Upgrades	***4,840***	***2,985***	***601***	***21***		

Panel B
1% Positive Returns

	New Recommendation					
LREC	**1**	**2**	**3**	**4**	**5**	***Downgrades***
1	1,241,847	2,639	2,345	54	93	***5,131***
2	2,880	1,567,111	3,588	93	48	***3,729***
3	1,925	3,551	1,304,530	251	322	***573***
4	31	90	284	49,907	13	***13***
5	61	45	279	17	48,402	
Upgrades	***4,897***	***3,686***	***563***	***17***		

The 1% Negative (Positive) Returns sample represents recommendation changes following negative (positive) 3-day standardized returns within the ± 20 days surrounding Large Return Events defined in Table 1. LREC is the recommendation level on the day prior to the recommendation change (i.e. the lagged recommendation) where 1 represents Strong Buy and 5 represents Strong Sell.

TABLE 4

1% Sample Summary Statistics

Panel A
1% Negative Returns

Variable	Mean	Median	Max	Min
MVE (000)	6,668,831	1,249,060	608,560,448	1,102
AGE	16	12	37	0
RECCH	0.002	0	4	-4
ADJRET3	-0.93	-0.69	0	-23
ADJRET10	-0.02	-0.09	227	-24
LMNREC3	0.01	0.00	5	-4
LMNREC10	0.01	0.00	6	-4
LPERC3	1%	0%	100%	0%
LPERC10	5%	0%	100%	0%
LREC	2.1	2	5	1
NUMREC	9	7	37	1
AFIL	0.03	0	1	0
PRICE	34	27	78,500	0

Panel B
1% Positive Returns

Variable	Mean	Median	Max	Min
MVE (000)	7,516,770	1,410,607	614,687,978	1,110
AGE	16	12	37	0
RECCH	0.0002	0	4	-4
ADJRET3	1.01	0.71	175	0
ADJRET10	-0.11	-0.14	37	-19
LMNREC3	0.00	0	4	-4
LMNREC10	0.01	0	6	-4
LPERC3	1%	0%	100%	0%
LPERC10	5%	0%	100%	0%
LREC	2.1	2	5	1
NUMREC	10	8	37	1
AFIL	0.03	0	1	0
PRICE	38	29	80,900	0

The 1% Negative (Positive) Returns sample represents recommendation changes following negative (positive) 3-day standardized returns within the ± 20 days surrounding Large Return Events defined in Table 1.

Variable Definitions
MVE is the market value of equity on day t. AGE represents the number of years between current calendar year and year first recorded on CRSP. RECCH is the recommendation change on day t. ADJRET3 is the standardized CRSP 3-day market adjusted return from day t-3 to t-1. ADJRET10 is the standardized CRSP 10-day market adjusted return from day t-13 to t-4. LMNREC3 is summation of the lagged 3-day (t-3 to t-1) mean recommendation changes for $firm_i$. LMNREC10 is the summation of the lagged 10-day (t-13 to t-4) mean recommendation changes for $firm_i$. LPERC3 is the percentage of analysts covering the stock that changed

recommendations in the lagged 3-day period (t-3 to t-1). LPERC10 is the percentage of analysts covering the stock that changed recommendations in the lagged 10-day period (t-13 to t-4). LREC is the lagged (t-1) recommendation level, which ranges from 1 (Strong Buy) to 5 (Strong Sell). NUMREC is the number of analysts covering the stock on day t. AFIL is an indicator variable equal to 1 if broker covering firm had an investment banking relation with the firm at any point in the sample period, 0 otherwise. PRICE is the CRSP closing stock price on day t.

TABLE 5

Probit Analysis Summary Statistics

Panel A
1% Negative Returns

Variable	Mean Coefficient Estimate	Z-Statistic	P-Value
AFFIL	0.035	1.80	0.04
AGE	-0.002	-4.48	0.00
MVE	0.000	1.71	0.04
LMNREC3	0.186	3.26	0.00
LMNREC10	0.076	2.30	0.01
NUMREC	-0.003	-3.11	0.00
LPERC3	0.016	0.44	0.33
LPERC10	-0.097	-4.25	0.00
ADJRET3	0.102	24.25	0.00
ADJRET10	0.015	3.87	0.00
LREC	0.308	69.57	0.00
INTER3	-0.010	-0.63	0.27
INTER10	-0.010	-0.92	0.18
PRICE	0.001	4.58	0.00
SMALL	-0.056	-3.46	0.00
SMALLRET	0.056	5.84	0.00
Adjusted R-Square		0.05	
Average N		192,806	

Panel B
1% Positive Returns

Variable	Mean Coefficient Estimate	Z-Statistic	P-Value
AFFIL	0.088	2.81	0.00
AGE	-0.002	-5.45	0.00
MVE	0.000	1.06	0.15
LMNREC3	0.352	5.46	0.00
LMNREC10	0.125	4.99	0.00
NUMREC	-0.001	-0.79	0.22
LPERC3	-0.203	-6.12	0.00
LPERC10	-0.140	-5.30	0.00
ADJRET3	-0.008	-1.48	0.07
ADJRET10	0.002	0.41	0.34
LREC	0.318	64.63	0.00
INTER3	-0.010	-0.41	0.34
INTER10	-0.002	-0.22	0.41
PRICE	0.000	3.24	0.00
SMALL	-0.066	-4.81	0.00
SMALLRET	0.029	2.82	0.00
Adjusted R-Square		0.05	
Average N		169,216	

The 1% Negative (Positive) Returns sample represents recommendation changes following negative (positive) 3-day standardized returns within the ± 20 days surrounding Large Return Events defined in Table 1. Mean coefficient estimates are obtained by averaging 25 calendar quarter estimates beginning with Q4 1993 and ending in Q4 1999. Z-statistics are computed using time series standard deviations of coefficient estimates obtained from the 25 quarterly probit regressions (Fama and MacBeth, 1973).

Variable Definitions

AFIL is an indicator variable equal to 1 if broker covering firm had an investment banking relation with the firm at any point in the sample period, 0 otherwise. AGE represents the number of years between current calendar year and year first recorded on CRSP. MVE is the market value of equity on day t. LMNREC3 is summation of the lagged 3-day (t-3 to t-1) mean recommendation changes for $firm_i$. LMNREC10 is the summation of the lagged 10-day (t-13 to t-4) mean recommendation changes for $firm_i$. NUMREC is the number of analysts covering the stock on day t. LPERC3 is the percentage of analysts covering the stock that changed recommendations in the lagged 3-day period (t-3 to t-1). LPERC10 is the percentage of analysts covering the stock that changed recommendations in the lagged 10-day period (t-13 to t-4). ADJRET3 is the standardized CRSP 3-day market adjusted return from day t-3 to t-1. ADJRET10 is the standardized CRSP 10-day market adjusted return from day t-13 to t-4. LREC is the lagged (t-1) recommendation level, which ranges from 1 (Strong Buy) to 5 (Strong Sell). INTER3 is the interaction of AFIL and ADJRET3. INTER10 is the interaction of AFIL and ADJRET10. PRICE is the CRSP closing stock price on day t. SMALL is an indicator variable designated 1 if a firm's MVE falls within the smallest decile for sample firms, 0 otherwise. SMALLRET is the interaction of SMALL and ADJRET3.

TABLE 6

Ratios of Probabilities of One Standard Deviation Movements Around the Mean For a Representative Quarter, Q1 1996

Panel A
1% Negative Returns

Variable	Dwn -4	Dwn -3	Dwn -2	Dwn -1	No Change	Up +1	Up +2	Up +3	Up +4
AFIL	0.71	0.72	0.76	0.79	1.00	1.14	1.15	1.15	1.14
AGE	0.94	0.94	0.94	0.94	1.00	1.13	1.15	1.18	1.20
MVE	0.64	0.68	0.72	0.75	1.00	1.42	1.49	1.63	1.69
LMNREC3	2.13	1.83	1.54	1.42	1.00	0.78	0.76	0.71	0.69
LMNREC10	1.24	1.21	1.16	1.13	1.00	0.91	0.90	0.88	0.87
NUMREC	1.08	1.07	1.06	1.04	1.00	1.03	1.05	1.08	1.09
LPERC3	1.58	1.44	1.29	1.23	1.00	0.96	0.97	1.00	1.01
LPERC10	0.98	0.98	0.98	0.98	1.00	1.06	1.08	1.11	1.13
ADJRET3	0.41	0.46	0.54	0.59	1.00	1.63	1.73	1.93	2.01
ADJRET10	0.82	0.84	0.87	0.89	1.00	1.09	1.09	1.10	1.10
LREC	0.06	0.09	0.13	0.17	1.00	8.03	10.98	20.00	25.72
INTER3	1.35	1.33	1.27	1.23	1.00	0.90	0.90	0.90	0.91
INTER10	0.61	0.62	0.65	0.68	1.00	1.46	1.54	1.68	1.73
PRICE	0.68	0.71	0.76	0.79	1.00	1.24	1.27	1.31	1.32
SMALL	1.79	1.67	1.52	1.44	1.00	0.70	0.67	0.62	0.60
SMALLRET	0.50	0.54	0.61	0.65	1.00	1.53	1.61	1.76	1.82

Panel B
1% Positive Returns

Variable	Dwn -4	Dwn -3	Dwn -2	Dwn -1	No Change	Up +1	Up +2	Up +3	Up +4
AFIL	0.57	0.59	0.65	0.70	1.00	1.22	1.23	1.24	1.24
AGE	0.98	0.97	0.96	0.95	1.00	1.11	1.12	1.15	1.15
MVE	1.12	1.11	1.09	1.07	1.00	1.01	1.03	1.06	1.08
LMNREC3	1.50	1.44	1.32	1.25	1.00	0.86	0.84	0.81	0.80
LMNREC10	0.92	0.92	0.92	0.93	1.00	1.13	1.15	1.19	1.21
NUMREC	0.96	0.96	0.96	0.96	1.00	1.12	1.14	1.18	1.20
LPERC3	1.20	1.17	1.12	1.09	1.00	0.99	1.00	1.02	1.02
LPERC10	1.20	1.19	1.15	1.13	1.00	0.94	0.94	0.95	0.95
ADJRET3	1.23	1.21	1.17	1.15	1.00	0.88	0.87	0.85	0.83
ADJRET10	0.86	0.87	0.90	0.91	1.00	1.08	1.09	1.11	1.12
LREC	0.08	0.09	0.13	0.17	1.00	7.25	9.74	16.49	20.92
INTER3	0.57	0.59	0.66	0.70	1.00	1.22	1.23	1.23	1.24
INTER10	1.13	1.13	1.11	1.10	1.00	0.88	0.86	0.83	0.81
PRICE	0.98	0.97	0.98	0.98	1.00	0.99	0.99	0.97	0.96
SMALL	1.10	1.09	1.07	1.06	1.00	1.00	1.01	1.03	1.04
SMALLRET	1.03	1.03	1.02	1.01	1.00	1.05	1.07	1.10	1.13

The 1% Negative (Positive) Returns sample represents recommendation changes following negative (positive) 3-day standardized returns within the ± 20 days surrounding Large Return Events defined in Table 1.

Variable Definitions

AFIL is an indicator variable equal to 1 if broker covering firm had an investment banking relation with the firm at any point in the sample period, 0 otherwise. AGE represents the number of years between current calendar year and year first recorded on CRSP. MVE is the market value of equity on day t. LMNREC3 is summation of the lagged 3-day (t-3 to t-1) mean recommendation changes for $firm_i$. LMNREC10 is the summation of the lagged 10-day (t-13 to t-4) mean recommendation changes for $firm_i$. NUMREC is the number of analysts covering the stock on day t. LPERC3 is the percentage of analysts covering the stock that changed recommendations in the lagged 3-day period (t-3 to t-1). LPERC10 is the percentage of analysts covering the stock that changed recommendations in the lagged 10-day period (t-13 to t-4). ADJRET3 is the standardized CRSP 3-day market adjusted return from day t-3 to t-1. ADJRET10 is the standardized CRSP 10-day market adjusted return from day t-13 to t-4. LREC is the lagged (t-1) recommendation level, which ranges from 1 (Strong Buy) to 5 (Strong Sell). INTER3 is the interaction of AFIL and ADJRET3. INTER10 is the interaction of AFIL and ADJRET10. PRICE is the CRSP closing stock price on day t. SMALL is an indicator variable designated 1 if a firm's MVE falls within the smallest decile for sample firms, 0 otherwise. SMALLRET is the interaction of SMALL and ADJRET3.

TABLE 7

Future Market Adjusted Returns Following Recommendation Changes
Large Return Event Sample

Panel A
Future Market Adjusted Returns Conditioning on Recommendation Changes

Return Sign	Rec Change	OBS	Post 20 Days mean	Post 20 Days median	Post 60 Days mean	Post 60 Days median
Negative	Down =< -2	594	-0.2%	** -2.1%	** -3.0%	** -3.9%
Negative	Down -1	1,288	** -1.3%	** -2.2%	** -3.3%	** -3.9%
Negative	Up +1	424	0.4%	-0.1%	* -2.4%	** -2.6%
Negative	Up >= +2	122	0.7%	0.8%	2.3%	0.8%
Negative	Affirm	229	-1.2%	-1.3%	-2.5%	** -3.8%
Negative	No Change	111,292	** -0.3%	** -0.5%	** -1.1%	** -1.7%
Negative	All	113,949	** -0.3%	** -0.6%	** -1.1%	** -1.7%
Positive	Down =< -2	208	** -2.7%	** -2.1%	** -5.6%	** -5.4%
Positive	Down -1	359	-1.0%	** -1.7%	0.2%	** -2.3%
Positive	Up +1	450	* 1.4%	0.6%	* 3.1%	1.5%
Positive	Up >= +2	162	1.8%	* 1.5%	0.0%	-0.6%
Positive	Affirm	132	-0.3%	-0.6%	-1.1%	-1.9%
Positive	No Change	98,824	** -0.5%	** -0.9%	** -0.6%	** -2.2%
Positive	All	100,135	** -0.5%	** -0.9%	** -0.6%	** -2.2%
All	All	214,084	** -0.4%	** -0.7%	** -0.9%	** -1.9%

Panel B
Test of Differences between Returns of Different Signs, but Equal Recommendation Changes

Return Sign	Rec Change	Post 20 Days mean	Post 20 Days t-stat	Post 60 Days mean	Post 60 Days t-stat
Neg vs Pos	Down =< -2	2.5%	** 2.6	2.7%	0.0
Neg vs Pos	Down -1	-0.3%	-0.4	-3.5%	* -2.3
Neg vs Pos	Up +1	-1.0%	0.0	-5.5%	** -3.2
Neg vs Pos	Up >= +2	-1.1%	-0.7	2.3%	0.7
Neg vs Pos	Affirm	-0.9%	-0.6	-1.5%	-0.5
Neg vs Pos	No Change	0.2%	** 4.2	-0.5%	** -4.3
Neg vs Pos	All	0.1%	** 3.9	-0.5%	** -4.8

* Significantly different from zero at the 5% level.
** Significantly different from zero at or below the 1% level.

The Large Return Event Sample represents recommendation changes on the day following a standardized CRSP 3-day market adjusted return within the 1% tails of the distribution for sample firms. We identify 81,393 large return events resulting in 214,084 recommendation changes (including No Changes). The difference represents the fact that multiple analysts cover a stock at any point in time. See Table 4 for average analyst coverage.