"Self-Fulfilling" Stock Recommendations

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Abstract

This paper tests the hypothesis that analysts report biased earnings estimates in order to enhance their stock recommendation performance. In particular, we argue that analysts with optimistic (pessimistic) stock recommendations tend to issue negatively (positively) biased earnings forecasts so that the underlying firms are more likely to beat (miss) the consensus forecasts and thus have higher (lower) stock returns after these recommendations are issued. Consistent with this hypothesis, we find that average stock recommendations prior to earnings announcements significantly and positively predict subsequent earnings surprises. In addition, the predictability is substantially stronger when the net benefits associated with such strategic behavior are larger, for example, among firms with lower analyst coverage.

JEL Classification: G12, G14, G23

Keywords: Biased earnings forecasts, Return predictability, Strategic behavior.

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1 Introduction

Sell-side analysts play an integral role in financial markets. They collect, process, and transmit information to market participants, who in turn use analysts' research to guide their investment decisions.[1] Understanding how sell-side analysts are motivated and how incentive contracts in place affect their forecasting behavior is thus of significant importance both to academics and practitioners.

In this paper, we identify and test an important form of bias in analysts' earnings forecasts. We hypothesize that current incentive structures in the financial industry induce analysts to strategically issue biased earnings forecasts in the direction that enhances the subsequent performance of their stock recommendations. More specifically, we predict that analysts with more optimistic (pessimistic) recommendations report negatively (positively) biased earnings estimates relative to their true beliefs, so that the underlying firm is more (less) likely to meet/beat the consensus forecast and, hence, experience higher (lower) stock returns after these recommendations are issued.

Our hypothesis is motivated by two sets of empirical findings. First, we add to prior literature that studies the determinants of analyst career outcomes by providing evidence that stock recommendation performance has an important impact on analysts' future career.[2] In particular, we suggest that analysts in the bottom quintile of recommendation performance are substantially more likely to leave the profession. Moreover, we find that, in terms of economic significance, recommendation performance has a stronger effect on analyst career outcomes than earnings forecast accuracy.[3] These results imply that analysts are motivated to care about their stock recommendation performance, and perhaps more so than their earnings forecast accuracy.

The second building block of our hypothesis is that analysts have the capacity to influence stock returns, at least temporarily. Prior studies detect a strong positive relation between

[1]Prior literature documents significant market reactions to (revisions in) analysts' earnings forecasts and stock recommendations. For instance, Stickel (1995), Womack (1996), and Jegadeesh et al. (2004) provide evidence that stocks experiencing a recommendation upgrade subsequently outperform stocks experiencing a recommendation downgrade. Moreover, financial analyst earnings forecasts appear, on average, to be more accurate than forecasts generated by statistical models (e.g., Kothari (2001)).

[2]Recommendation performance for each analyst is computed as the difference in the average characteristics-adjusted returns of securities with strong-buy/buy recommendations and those with strong-sell/sell/hold recommendations. We classify "hold" as a negative recommendation as analysts rarely issue strong sell/sell recommendations.

[3]Prior studies provide evidence that earnings forecast accuracy is closely tied to the firing of analysts by brokerage houses (see, for example, Mikhail et al. (1999); Hong et al. (2000); Hong and Kubik (2003)).

earnings surprise and stock returns around earnings announcements.[4] These studies further document that the market reaction to earnings surprises is significantly stronger than the reaction to earnings forecast revisions.[5] Together, these findings imply that analysts with optimistic (pessimistic) recommendations can exploit investors' differential reaction by strategically lowering (increasing) their earnings forecasts (and thus the consensus forecasts) and benefiting from the resulting higher (lower) earnings surprise. We label this hypothesis "self-fulfilling stock recommendations," in the sense that part of the subsequent stock returns associated with these recommendations is driven by analysts' strategic behavior rather than value-relevant information.

To test our hypothesis, we obtain data on earnings forecasts and stock recommendations from the IBES database. We then examine whether the average recommendation of a firm prior to its earnings announcement is related to its subsequent earnings surprise, defined as the difference between the reported earnings and the most recent consensus forecast (based on earnings forecasts issued within three months of the announcement), scaled by lagged price-per-share.

Our results are consistent with sell-side analysts exhibiting strategic forecasting behavior. The average recommendation issued prior to an earnings announcement is a positive and signficant predictor of the subsequent earnings surprise. Specifically, sorting firms into terciles based on their average outstanding recommendation level, we find that firms with more optimistic recommendations experience substantially more positive earnings surprises than firms with more pessimistic recommendations; the difference in price-scaled earnings surprise between the top and bottom terciles of firms ranked by their average recommendations prior to earnings announcements is 0.002 (t=5.15), more than half of the interquartile range of earnings surprise in our sample. Taking the long-term average stock price of $35 per share from Weld, Thaler, and Benartzi (2009), the 0.002 difference in price-scaled earnings surprise translates to a 7.5 cents per share difference in earnings surprise. This result continues to hold within a regression framework and the inclusion of various controls for growth opportunities and earnings management.

We also observe that recommendations predict stock returns in a three-day window around earnings announcement. Specifically, the average market-adjusted earnings an-

[4]See, for example, Patell (1976); Kasznik and McNichols (2002); Bartov et al. (2002); Bhojraj et al. (2009).

[5]The differential market reaction may be due to earnings announcements receiving more investor attention than forecast revisions.

nouncement day return of the tercile with the most optimistic recommendations is 44 basis points higher than that of the tercile with the most pessimistic recommendations. Moreover, the difference in earnings announcement day returns largely evaporates within months of the earnings announcement as stock prices subsequently revert. This is consistent with part of the earnings announcement day return being induced by analysts' strategic behavior, which in turn causes a reversal effect in the long-run.

To further explore the "self fulfilling stock recommendation" hypothesis, we analyze recommendation revisions subsequent to earnings announcements. If analysts were truly issuing biased earnings forecasts to enhance their recommendation performance, we would expect them to partially reverse their recommendations shortly after the earnings announcement (before stock prices subsequently reverse). We find evidence consistent with this prediction. Specifically, for firms with the most optimistic recommendations outstanding, recommendations issued within the first three months after the earnings announcement are significantly lower than the average recommendation before the earnings announcement; similarly, for firms with the most pessimistic recommendations outstanding, recommendations issued within the first three months after the earnings announcement are substantially above the average pre-announcement recommendation. The reversal pattern in recommendation revision we document cannot be explained by mechanical mean reversion in recommendation and is consistent with our hypothesis that analysts are aware of the return effect induced by their strategic behavior and time their recommendations accordingly.

To further pin down the mechanism at work, we exploit cross-sectional variation in the potential benefits and costs associated with analysts' strategic behavior. Under the "self-fulfilling stock recommendations" hypothesis, analysts are confronted with the following cost-benefit analysis: By issuing biased earnings estimates, analysts benefit from higher stock recommendation performance and possibly brighter career outcomes; at the same time, they sacrifice part of their earnings forecast accuracy and risk damaging their reputation, as their self-serving behavior may be exposed to the public. The magnitude and frequency of such distortions in reported earnings forecasts are determined jointly by both the benefits and the costs.

We focus on two sets of firm characteristics that likely vary with the benefits and costs associated with analysts' strategic behavior. The first characteristic is the firm's analyst coverage. Any strategic deviation by a single analyst in his reported earnings forecast has a larger impact on the consensus forecast when analyst coverage is low.[6] We thus predict that analysts are more likely to report distorted earnings estimates when a firm is followed by fewer analysts. The second set of firm characteristics captures the difficulty in stock valuation. We argue that analysts are more likely to distort their earnings estimates for harder-to-value-stocks, as they have weaker convictions about their recommendations for these securities. Specifically, we predict more severe distortions for firms with lower market capitalization and higher stock-return volatility.[7] Our predictions are borne out by the data. The association between the average recommendation and subsequent earnings surprise significantly decreases with analyst coverage and firm size, and increases with stock return volatility.

To complement the tests on earnings surprise and stock returns, we also analyze investor trading behavior around earnings announcements. In order for analysts to benefit from strategic distortions in their earnings forecasts, some investors must be unaware of (or fooled by) the manipulation in forecasts. In particular, we predict that retail investors, naive about incentives, take analyst reports at face value, while institutional investors account for distortions in earnings forecasts and adjust their trading decisions accordingly (e.g., Daniel et al. (2002); Schotter (2003); Malmendier and Shanthikumar (2007)). Consistent with this prediction, using detailed trading records from TAQ, we provide evidence that high stock recommendations lead to increased buying around subsequent earnings announcements among retail investors (i.e., small trades), yet increased selling among institutional investors (i.e., large trades).

Overall, the findings presented in this paper are consistent with the "self-fulfilling stock recommendations" hypothesis. Analysts, induced by their career concerns, report biased earnings forecasts in the direction that improves the subsequent performance of their stock recommendations. Retail investors, unaware of the potential agency problems in the financial industry, take analysts' earnings forecasts at face value, and therefore help fulfill analysts' recommendations ex-post.

This paper is related to the growing body of research that studies how analysts may compromise their objectivity and issue biased research reports in order to curry favor with

[6]A related issue is the free-rider problem. If an analyst chooses to report biased earnings estimates, he is indirectly helping his fellow analysts with similar stock recommendations. Since the analyst with distorted earnings forecasts is the only one to bear the cost, the more analysts that are covering a firm, the less likely any one of them chooses to report distorted earnings forecasts.

[7]We also explore alternate measures of valuation uncertainty (firm age, cash flow volatility, number of industry segments), with very similar results.

firm managers. For instance, Richardson et al. (2004) provide evidence that analysts on average walk down their earnings forecasts to beatable levels. Lin and McNichols (1998), Michaely and Womack (1999), and Malmendier and Shanthikumar (2009), among others, suggest that analysts from brokerage firms with underwriting relations tend to issue more optimistic recommendations than their peers. This paper adds to prior literature in that it proposes a heretofore unexplored form of strategic behavior among analysts that arises from current incentive structures in the financial industry.

The paper proceeds as follows. Section 2 summarizes our data collection and screening procedures. Section 3 develops our hypothesis. Section 4 reports the test results of our main hypothesis. Section 5 discusses a number of alternative hypotheses, and section 6 concludes.

2 Data

We obtain sell-side analyst recommendation- and earnings forecast-information from the Institutional Brokers Estimate System (IBES) detail recommendation file and the IBES unadjusted U.S. detail history file, respectively. The IBES recommendation file tracks each recommendation made by each analyst, where recommendations are standardized and converted to numerical scores ranging from 1 (strong buy) to 5 (strong sell). In order to facilitate interpretation of our results, we reverse the IBES coding to 5 (strong buy), 4 (buy), 3 (hold), 2 (sell), and 1 (strong sell). A high value, thus, indicates a more bullish view. The IBES unadjusted detail history file tracks each EPS forecast made by each analyst (among others). Following prior literature (e.g., Teoh et al. (1998a,b)), we define the consensus forecast as the *average* annual EPS forecast; in robustness tests, we also use the *median* earnings forecast and obtain very similar results. The sample period spans from 1994 to 2009 and is determined by the availability of recommendation data in the IBES dataset.

We augment the IBES file with financial-statement and financial-market data from COMPUSTAT and the Center for Research in Security Prices (CRSP), respectively. We also obtain quarterly institutional holdings from THOMPSON. Appendix A and B provide a full description of the variables used in this study.[8]

[8] In a recent study, Ljungqvist, Malloy and Marston (2009) detect that the IBES recommendations database downloaded at different points in time (but for the same sample period) yields different observations. Thomson Financial has for the most part purged the data. As of February 12th 2007, the data on WRDS reflect the corrections (Glushkov, 2007).

In our analysis, we exclude firm observations with the most extreme one percent of standardized earnings surprise, i.e. we exclude observations for which the absolute value of (actual EPS minus consensus EPS forecast scaled by lagged price-per-share) is above the 99th percentile of its distribution.[9] In an attempt to remove market microstructure effect, in our stock return analysis, we follow prior literature (e.g., Jegadeesh and Titman (2001), Avramov et al. (2007)) and also exclude firm observations with prices below $5 a share and market capitalization that would place them in the bottom NYSE decile. Our final sample comprises around 33,000 firm-year observations.

Table I presents summary statistics of our main variables of interest. Consistent with prior literature, the median firm in our sample meets or beats its most recent consensus earnings forecast. In addition, the distribution of scaled earnings surprise (i.e., actual earnings per share minus the most recent consensus earnings forecast scaled by lagged price per share) is significantly negatively skewed, consistent with prior findings that firms sometimes choose to take earnings baths when they are unable to meet the consensus forecast. Firms that meet or beat their consensus earnings forecast outperform those that miss their consensus by a significant margin in a three-day window around earnings announcement (1.48% vs. -1.89%).

The median firm in our sample is covered by 8 analysts, and the average firm is covered by 10.82 analysts, in line with the numbers reported in related studies. The average firm size in our sample is $4.18 billion, the average book-to-market ratio is 0.55, and the average institutional ownership is 60%. Compared to the CRSP-sample averages, these figures indicate that firms covered by analysts tend to be larger, more growth-oriented, and held more by institutional investors. This is consistent with analysts' incentives to cover firms that are more visible to and favored by institutional investors.

3 Hypothesis Development

3.1 Determinants of Analysts' Career Outcomes

Given the crucial information-intermediary role played by sell-side analysts in financial markets, it has long been of great interest, both to academics and practitioners, to understand

[9] Including outliers increases the standard errors of the coefficient estimates in our regressions analysis; however, the tenor of the results remains.

how analysts are compensated and motivated to provide accurate and unbiased information. Prior research (e.g., Mikhail et al. (1999), Hong et al. (2000), and Hong and Kubik (2003)) argues that analysts' compensations and career outcomes are closely tied to their earnings forecast accuracy. In this section, we complement this literature by suggesting another performance metric by which analysts likely are evaluated– the subsequent returns to stocks they recommend be bought, held, and sold.

There is reason to believe that brokerage firms consider individual analysts' stock recommendation performance when evaluating and compensating their analysts. First, stock recommendations are effectively summary statistics of analysts' available information about individual stocks.[10] Stock returns subsequent to the issuance of these recommendations thus provide a quantifiable measure of analysts' ability and effort to collect and process information. Second, existing evidence suggests that analyst recommendations, on average, have investment values for their clients and that investors respond strongly to (changes in) these recommendations, in particular to those they deem to be more informative (e.g., Womack (1996); Jegadeesh et al. (2004); Jegadeesh and Kim (2010)). Therefore, sell-side analysts with superior stock recommendation performance may be in a better position to generate brokerage business from clients who value analyst research. Moreover, Emery and Li (2009) point out that sell-side research ratings, such as the annual "Best on the Street" report published by the Wall Street Journal (which may affect the brokerage firm's reputation and ability to bring in investment banking business) are based importantly on analysts' recommendation performance. This finding further signifies the importance of analysts' recommendations both to their clients and their employers. Together, these observations suggest that brokerage firms, and analysts themselves, care about the ex-post performance of stock recommendations.

Since the details of analysts' compensation contracts are not publicly disclosed, we follow prior literature that studies the importance of earnings forecast accuracy for analysts' career outcomes (e.g., Mikhail et al. (1999), Hong et al. (2000), and Hong and Kubik (2003)) and analyze how recommendation performance relates to the termination decisions of brokerage firms, as these decisions on the part of brokerage firms can be inferred, albeit imperfectly, from the detailed analyst and brokerage firm data provided by the IBES. Specifically, we estimate the following binary response model based on the logistic function:

$$Termination_{j,t+1} = \alpha + \beta_1 * RP\_B20_{j,t} + \beta_2 * EFA\_B20_{j,t} + \gamma * Control + \varepsilon_{j,t}, \quad (1)$$

[10] More strictly speaking, stock recommendations reflect the divergence between analysts' views and the market view.

where $Termination_{j,t+1}$ is a dummy variable that equals one if analyst j leaves the IBES sample in year t+1. $RP\_B20_{j,t}$ is a dummy variable that equals one if the analyst's recommendation performance is in the bottom quintile across all analysts in year t, and $EFA\_B20_{j,t}$ is defined similarly based on earnings forecast accuracy. We use dummies, rather than the actual raw performance, as the effect of recommendation performance (or earnings forecast accuracy) on subsequent termination decisions is likely to be non-linear.[11]

The subsequent stock return to each recommendation for a given year is calculated as the annualized cumulative DGTW-adjusted stock return from the day after the recommendation issuance to the last trading day of the year. The recommendation performance of each analyst is then defined as the difference between the average annualized stock return of the analyst's outstanding strong-buy/buy recommendations and the average annualized return of the analyst's outstanding hold/sell/strong-sell recommendations, with each recommendation being assigned an equal weight.[12] Earnings forecast accuracy is computed as the average absolute difference between the actual earnings per share (EPS) and the analyst's most recent forecast of EPS, scaled by lagged price per share, across all firms covered by the analyst in year t. The correlation between $RP\_B20_{j,t}$ and $EFA\_B20_{j,t}$ is 0.046 (p-value = 0.00).

Motivated by Hong and Kubik (2003), we include a control variable for valuation uncertainty. For each stock, we first calculate the average absolute earnings-forecast error across all analysts covering the stock in question, $|FE|$; we then construct a measure of the analyst's overall valuation difficulty by taking the average $|FE|$ across all stocks covered by the analyst in question. The idea is that if an analyst covers stocks that are, on average, harder to value (i.e., those with larger absolute forecast errors), his/her employer may be more tolerant of poor performance. Our approach is similar to the one used in Hong and Kubik (2003), except that instead of incorporating the valuation difficulty directly into the analyst

[11]We later provide evidence that the effect of recommendation performance on subsequent job termination is concentrated in extreme poor performing deciles. The nonlinearity may help explain why some prior studies (e.g. Mikhail et al. (1999)) find no statistically significant relation between recommendation performance and subsequent termination and demotion of analysts.

[12]Since the average recommendation is close to a "buy" in our sample period, we classify a "hold" recommendation as conveying negative information. To ensure robustness, we also compute an analyst's recommendation performance as the average return difference between his strong buy/buy recommendations and his strong sell/sell recommendation, with the results unchanged. In additional analyses, we also compute *value-weighted* average annualized stock returns, where the weights are determined by the number of months a recommendation has been outstanding; the results become slightly stronger using this alternate measure of recommendation accuracy. Moreover, we also conduct regression analyses using an alternate measure of analysts' recommendation performance, in which the subsequent return to each recommendation is calculated from the month after the recommendation is issued. The results are very similar.

ranking, we (explicitly) control for this construct in our regression specification.[13] We also control for year-fixed effects and brokerage firm-fixed effects to capture time-series variations in market conditions and unobserved brokerage firm characteristics that may affect analyst career outcomes and compensation.

The regression results, shown in Table II, are consistent with the prediction that stock recommendation performance is an important determinant of analyst career outcomes. As reported in Column 1, the coefficient estimate on $RP\_B20_{j,t}$ equals 0.258 (p-value=0.00), which implies that being in the bottom quintile of prior-year recommendation performance increases the probability of termination by 5.36%. For reference, in any given year, an analyst has a 14.47% chance of leaving the sample.

Consistent with prior findings, earnings forecast accuracy is also significantly related to analysts' termination; the coefficient estimate on $EFA\_B20_{j,t}$ equals 0.179 (p=0.00). Interestingly, in terms of economic significance, the partial effect on career outcomes appears stronger for recommendation performance than for earnings forecast accuracy: The coefficient estimates on $RA\_B20_{j,t}$ and EFA_B12 imply that the effect of recommendation performance on the likelihood of termination is almost one and a half times as large as the effect of earnings forecast accuracy (0.258 vs. 0.179).

In Column 2, we re-estimate the analyst-termination specification, with an additional indicator function, which equals one if the analyst is in the second-to-last quintile based on prior year recommendation performance, and zero otherwise. Analysts in the bottom quintile continue to have a significantly higher chance of experiencing negative career outcomes than their better performing peers; analysts in the second-to-last quintile also are more likely to lose their jobs, but to a lesser extent. In untabulated results, we also examine the likelihood of job termination in other performance quintiles and observe that the effect of recommendation performance and earnings forecast accuracy on future job termination decreases quickly as we move away from the bottom quintile, indicative of a monotonic but non-linear functional form.

The detected link between recommendation performance and earnings forecast accuracy, on one hand, and analyst career outcomes, on the other, need not be causal. Brokerage firms may perfectly infer analysts' true ability through other (to them) observable characteristics.

[13] In untabulated results, we also include interaction terms between valuation difficulty and recommendation performance, and between valuation difficulty and earnings forecast accuracy. The coefficient estimates on the interaction terms are neither statistically significant nor economically meaningful.

Meanwhile, analysts' ability likely affects their recommendation performance and earnings forecast accuracy, thus causing analyst career outcomes and recommendation- and earnings performance to be positively correlated. This alternate view conflicts with our main hypothesis development, as one may argue that in order for analysts to have an incentive to manipulate their recommendation performance, their employers must not perfectly know analysts' ability and only gradually learn about analysts' ability through their recommendation performance. While it is impossible to completely rule out this alternative interpretation, we re-estimate all our regression specifications with analyst-fixed effects, under the assumption that the effect of ability be persistent over time. The results (untabulated) show that, after controlling for analyst-fixed effects, recommendation performance and earnings forecast accuracy continue to be highly statistically significant with coefficient estimates of very similar magnitude to the ones reported in Table II.

3.2 A Stylized Model

In order to illustrate how the findings presented so far relate to our main hypothesis development, we introduce a simple, stylized model. Consider a single analyst whose utility is determined (solely) by his earnings forecast accuracy- and recommendation performance ranking (relative to other analysts).[14] Assume that the analyst has some capacity to improve his ex-post recommendation performance by reporting biased earnings estimates; the increase in recommendation performance comes at the cost of reduced earnings forecast accuracy.

Specifically, our model has the analyst maximize the following objective function:

$$U(x) = g(RANK_{FA} - f(x)) + h(RANK_{RP} + k(x)), \tag{2}$$

where x is the degree of bias in the reported earnings forecast, $f(.)$ and $k(.)$ are both increasing functions describing the loss in (relative) forecast accuracy and the gain in (relative) recommendation performance resulting from the strategic reporting behavior, respectively, $RANK_{FA}$ and $RANK_{RP}$ are the relative rankings based on forecast accuracy (FA) and recommendation performance (RP) in absence of any strategic reporting behavior, and $g(.)$ and $h(.)$ are increasing and concave functions of the effects of (relative) forecast accuracy and recommendation performance on future career outcomes.

[14]For simplicity, we do not model the interactions among analysts that cover the same stocks, nor do we consider other factors that impact analysts' future career.

We make two assumptions: While both forecast accuracy and recommendation performance reflect the analyst's ability to collect and process information, we assume that $RANK_{FA}$ and $RANK_{RP}$ are not perfectly positively correlated. In other words, it is conceivable that an analyst in the bottom quintile of recommendation performance is not necessarily in the bottom quintile of forecast accuracy (but rather in some other forecast accuracy quintile).[15] This is a reasonable assumption given that both realized earnings per share and stock returns are noisy. The second assumption we make is that both $g(.)$ and $h(.)$ are increasing and concave; that is the effect of a drop in $RANK_{FA}$ and $RANK_{RP}$ on the likelihood of termination decreases as we move away from the bottom quintile.

Without loss of generality, we define $f(x) = ax(a > 0, x \geqslant 0)$, $k(x) = bx(b > 0, x \geqslant 0)$, $g(.) = log(.)$, and $h(.) = log(.)$:

$$U(x) = log(RANK_{FA} - ax) + log(RANK_{RP} + bx). \tag{3}$$

The first order condition of equation 3 can then be written as

$$0 = b(RANK_{FA} - ax) - a(RANK_{RP} + bx). \tag{4}$$

Solving for x^* yields:

$$\begin{aligned} x^* &= \tfrac{bRANK_{FA} - aRANK_{RP}}{2ab}, \text{ for } \tfrac{RANK_{FA}}{RANK_{RP}} > \tfrac{a}{b} \\ x^* &= 0, \text{ otherwise.} \end{aligned} \tag{5}$$

The amount of manipulation, x^*, increases in $RANK_{FA}$ and decreases in $RANK_{RP}$; that is the analyst is more likely to bias his earnings forecast in order to boost his recommendation performance when he is in greater need and/or in a better position to do so (poor recommendation performance and/or relatively high forecast accuracy). Further, the higher the cost and/or the lower the benefit associated with biased reporting (i.e., the larger a and/or the smaller b), the fewer analysts exhibit biased forecasting behavior.[16] Moreover, given $max(\frac{RANK_{FA}}{RANK_{RP}}) > \frac{a}{b}$, the average x^* across all analysts is strictly positive. Put differently, under the assumptions that earnings forecast- and recommendation performance are not perfectly correlated and that the performance effect is non-linear, there *must* exist some an-

[15]The correlation between $RANK_{FA}$ and $RANK_{RP}$ in the data is 0.046.

[16]One interpretation of the parameter b is that it captures the market's differential responses to earnings forecast revisions and earnings surprises.

alysts whose forecast accuracy rankings are sufficiently high relative to their recommendation performance rankings, so that issuing biased earnings forecasts can be career-enhancing.

4 Biases in Analysts' Earnings Forecasts

The main prediction of our stylized model is that, on average, analysts with more optimistic (pessimistic) recommendations choose to report negatively (positively) biased earnings estimates – relative to their true beliefs, so that the underlying firms are more (less) likely to meet/beat the consensus forecasts and hence experience higher (lower) subsequent returns. In this section, we take this prediction to the data.

4.1 Empirical Design

Formally, our "self-fulfilling stock recommendations" hypothesis can be stated as follows: Let $e_{i,t+1}$ be the actual earnings per share of firm i in period $t+1$. Analyst j's unbiased estimate of $e_{i,t+1}$(based on all available information in period t) is $\hat{e}_{j,i,t+1}$; his *reported* estimate is $\hat{e}^{rep}_{j,i,t+1}$. Our hypothesis maintains that if analyst j has an optimistic recommendation outstanding, his reported forecast will be lower than his true forecast, i.e. $E\left(\hat{e}^{rep}_{j,i,t+1}\right) < E\left(\hat{e}_{j,i,t+1}\right)$; the reverse applies if analyst j has a pessimistic recommendation outstanding (i.e., $E\left(\hat{e}^{rep}_{j,i,t+1}\right) > E\left(\hat{e}_{j,i,t+1}\right)$).

Empirical tests of this hypothesis face the challenge that we, as econometricians, do no observe analysts' full information sets and thus cannot infer their true earnings estimates for individual stocks (i.e., $\hat{e}_{j,i,t+1}$). Simply examining the correlation between analyst j's recommendation for firm i and the associated earnings forecast error, without properly adjusting for analyst j's true belief, will bias our analysis, as analyst j's true earnings estimate and his stock recommendation are derived from the same information set and hence positively correlated.

In this paper, we take a simple yet novel approach to get around this "lack-of-benchmark" issue. Instead of analyzing the potential bias in individual analysts' earnings forecasts, we aggregate both variables, i.e., analysts' earnings forecast errors and stock recommendations, to firm averages. Doing so, we obtain a natural benchmark against which analysts' reported earnings estimates can be compared: To the extent that analysts form rational expectations, their *true* earnings forecasts will, on average, equal reported earnings.[17] However, if analysts decide to report forecasts that are biased in a direction that helps improve their recommendation performance, their issuing negatively (positively) biased earnings forecasts will result in predictable positive (negative) earnings surprises. Our main (testable) hypothesis (stated in its alternative form), thus, is that a stock's average recommendation level prior to its earnings announcement does not predict its (subsequent) earnings surprise.

More technically speaking, given each analyst's bias in reported forecast, $\hat{e}^{rep}_{j,i,t+1} - \hat{e}_{j,i,t+1}$, the average forecast bias for firm i is defined as:

$$\begin{aligned}\frac{1}{J}\sum\left(\hat{e}^{rep}_{j,i,t+1} - \hat{e}_{j,i,t+1}\right)_j &= \overline{\hat{e}}^{rep}_{i,t+1} - \overline{\hat{e}}_{i,t+1} \\ &= \left(\overline{\hat{e}}^{rep}_{i,t+1} - e_{i,t+1}\right) + \left(e_{i,t+1} - \overline{\hat{e}}_{i,t+1}\right).\end{aligned}$$

Since $\overline{\hat{e}}_{i,t+1}$, the true consensus forecast, is an unbiased estimate of $e_{i,t+1}$, the second term equals zero in expectation (based on all information at time t). We are thus left with the first term, $\left(\overline{\hat{e}}^{rep}_{i,t+1} - e_{i,t+1}\right)$, i.e., the difference between the firm's *reported* consensus forecast and its actual earnings per share. Therefore, by focusing on the reported consensus forecast for each firm and using the actual earnings as a benchmark, we are able to quantify the bias in analysts' earnings forecasts even though we do not directly observe each analyst's true earnings estimate.

The specification for the firm level regression analysis is as follows:

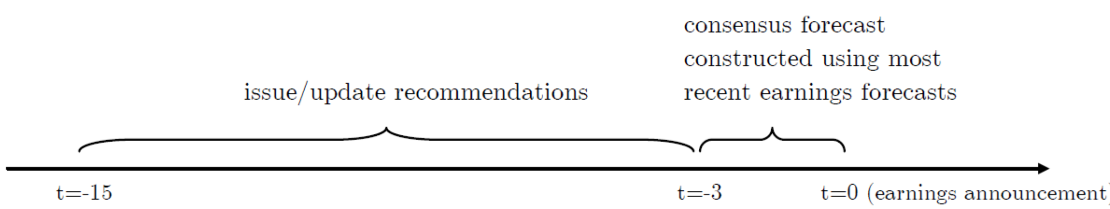
$$\overbrace{e_{i,t+1} - \overline{\hat{e}}^{rep}_{i,t+1}}^{EarningsSurprise} = \alpha + \beta * \overline{rec}_{i,t} + Control * \gamma + \varepsilon_{i,t}, \tag{6}$$

where $\overline{\hat{e}}^{rep}_{i,t+1} = \frac{1}{J}\sum_j\left(\hat{e}^{rep}_{j,i,t+1}\right)$ is the reported consensus earnings forecast for firm i, and $\overline{rec}_{i,t} = \frac{1}{J}\sum_j\left(rec_{j,i,t}\right)$ is the average stock recommendation prior to the earnings announcement. In our regression analysis, we scale *EarningsSurprise* by lagged price per share to address potential heteroscedasticity issues.

To reduce the impact of stale earnings forecasts, we follow prior literature and only consider the most recent earnings forecast issued/updated within a three-month window preceding the earnings announcement; similarly, in constructing the average recommendation outstanding, we use the most recent recommendations issued/updated three to fifteen months

[17] We discuss potential violations of this assumption in Section 5.

prior to the earnings announcement.[18] The fifteen-month filter serves to weed out "stale" recommendations. We impose the three-month filter because analysts may not (yet) feel the need to report biased earnings estimates in order to improve the ex-post performance of their (recently issued) recommendations. The timing of our main variables is shown in the figure below. Note that we do not take a position on when exactly analysts start issuing biased earnings forecasts (for their recommendations issued [-15;-3]). Analysts may do so simultaneous to their issuing the recommendation; alternatively, they may wait a few months whether the realized returns (after recommendation issuance) are in line with those implied by their recommendation in order to (better) evaluate the "need" to report biased earnings forecasts:



The list of control variables in the specification (i.e., *control*) includes lagged firm size, book-to-market ratio, prior year stock returns, and discretionary accruals.[19] We include discretionary accruals in our regression to control for the effect of earnings management on earnings surprises, and, as such, to focus on the part of the earnings surprise that is driven by biases in analyst forecasts. In additional analyses, we include alternative controls for a firm's growth opportunities (investment ratio, the price-to-earnings ratio, and advertising expenditures, as well as past stock returns over various horizons); the results are very similar to the ones reported in this study. Finally, we include year-fixed effects in the regression to deal with changes in overall market conditions.

4.2 Main Results

The results presented in Table III are consistent with the "self-fulfilling stock recommendations" hypothesis. The coefficient estimate on the firm's average recommendation level is both statistically and economically significant. Specifically, a one-notch upgrade in the con-

[18] We observe similar results whether we include earnings forecasts issued four, six or twelve months before the earnings announcement. Our results are also robust to whether we begin with including recommendations issued twelve or fifteen months before the earnings announcement as well as whether we stop including recommendations issued three, four or six months before the earnings announcement.

[19] Appendices A and B provide a detailed discussion of how these variables are constructed.

sensus recommendation prior to the earnings announcement (e.g., from 3 (hold) to 4 (buy)) is associated with a 13-basis-point increase (t=5.14) in scaled earnings surprise, which is about one third of the interquartile range of the earnings surprise-variable in our sample. The coefficient estimates on the control variables indicate that earnings surprises tend to be more positive for firms with more growth opportunities, higher past returns, and more positive discretionary accruals.

Table III also reports coefficient estimates from a binary response model with the logistic function. The dependent variable equals one if a firm meets or beats its consensus earnings forecast, and zero otherwise. The independent variables are the same as in equation (6). The results show a positive relation between the average recommendation level and the propensity to meet or beat consensus earnings forecasts. All else equal, a one-notch increase in the average recommendation level is associated with a 12.56% increase (p=0.00) in the likelihood of meeting or beating consensus forecasts. For reference, in any given year, 50.3% of firms meet or beat their annual consensus earnings forecast. The results are consistent with our prediction that analysts with optimistic (pessimistic) recommendations issue negatively (positively) biased earnings forecasts, relative to their true estimates, in order to enhance their recommendation performance.

To further quantify to what extent analysts with optimistic and pessimistic views are each responsible for the suggested bias in earnings forecasts, we conduct portfolio analyses. Specifically, in each year, we sort all firms into terciles based on their average outstanding recommendation level three months prior to the annual earnings announcement, and report the average earnings surprise for each tercile portfolio. As shown in Table IV, the consensus recommendation of the average firm in the bottom tercile is around three (a "hold"); the consensus recommendation of the average firm in the top tercile is around four and a half (the mid-point between a "buy" and a "strong buy").

Both high-recommendation and low-recommendation groups contribute roughly equally to the observed association between consensus recommendations and subsequent earnings surprises. Specifically, the difference in price-scaled earnings surprise between the high- and low-recommendation group is about 21 basis points (t=5.65), of which roughly 60% can be attributed to the difference between the low- and median-recommendation groups, and the remaining 40% to the difference between the high- and median-recommendation groups. Given the long-term average stock price of $35 per share (in the CRPS universe), the difference in price-scaled earnings surprise between the top and bottom tercile translates to a earnings surprise of 7.5 cents per share, which is economically meaningful relative to the median earnings surprise of 1.5 cents per share in our full sample. Note that the average earnings surprise in all three groups is negative, which is likely due to the negative skewness in earnings surprise caused by some firms taking earnings baths when they are sure to miss earnings targets.

Since the ultimate goal of analysts' forecast manipulation is to influence stock returns around earnings announcements (and thus to enhance the subsequent performance of their stock recommendations), we repeat our analysis, but now replace the earnings surprise variable with earnings announcement day returns. The basic prediction is that, if investors do not fully understand the incentives faced by analysts and mistake the bias in earnings forecasts for a genuine earnings surprise, we expect the average recommendation prior to an earnings announcement to positively relate to earnings announcement day returns. On the other hand, if investors are perfectly aware of potential agency issues among sell-side analysts and thus respond rationally to the bias component in earnings surprise, then we would expect no predictable returns around earnings announcements.[20]

As reported in Panel B of Table IV, recommendation level and subsequent earnings announcement day returns are positively correlated, where earnings announcement day returns are market-adjusted returns in a three day window around the annual earnings announcement. Specifically, the average spread in market-adjusted returns between the top and bottom tercile based on recommendation level is 44 basis points (t=2.72).

In Panel C, we also examine long-run returns. If part of the announcement day returns is due to investors being fooled by analysts' strategic behavior, we would expect some of the so induced return effect to be reversed in the long run. Consistent with this conjecture, we observe a return reversal of 77 basis points in the six-month period following the earnings announcement; specifically, the cumulative six-month DGTW-adjusted return of the top tercile is 77 basis points below that of the bottom tercile in months four to nine following the earnings announcement. However, the difference is only marginally statistically significant (t=-1.57).

The comparatively low statistical significance of the difference in returns is likely due to noise in earnings announcement day returns and long-run returns, in particular. In untabulated analysis, we also compare the difference in the *median* earnings announcement day

[20]Further, we would expect analysts not to engage in this game as their attempt to issue biased earnings forecasts in order to temporarily boost stock prices would be in vein.

return and *median* long-run return between top and bottom tercile based on recommendation level. Here, the difference is 60 basis points (t=4.06) for earnings announcement day returns and -99 basis points (t=-2.58) for long-run returns, respectively, where standard errors are adjusted using the Markov-chain marginal bootstrap method of He and Hu (2002).

Relatedly, one may contend that the spread of 44 basis points reported in Table IV is too small in economic terms to be meaningful for analysts' careers. However, it is important to realize that the here documented spread is the average effect across both analysts playing the strategic distortions-game and those that do not.[21] A more appropriate metric for the potential benefit of reporting distorted earnings forecasts is the average earnings announcement return spread between firms meeting/beating their consensus forecasts and those missing their consensus forecasts, which is close to 3.4% (Table I).

The return predictability of lagged stock recommendations we document is distinct from prior findings that recent *updates* in recommendations can predict future stock returns. As shown in Womack (1996), recommendation revisions have essentially no return predictive power beyond the horizon of three months, whereas in our study we use (levels of) recommendations that are issued at least three months prior to earnings reports. To confirm this conjecture, we conduct a placebo test, in which we use the average recommendation issued in months t-15 to t-3 to predict stock returns in month t. There is no predictive power flowing from lagged recommendation levels to future stock returns *outside* the earnings announcement period. This result further implies that the return predictability around earnings announcements is likely due to analysts' strategic behavior rather than value-relevant information.

If analysts understand the return pattern induced by their distorted earnings forecasts, we would expect (at least some) analysts to revert their recommendations shortly after earnings are announced, as the positive return predictability of their stock recommendations has been realized and future returns are likely to reverse. This conjecture is borne out by the data. Specifically, we compute changes in average recommendations in months one through three after earnings announcements for each of the three terciles ranked by consensus recommendations. To control for any mechanical mean reversion in stock recommendation, we repeat our analysis for all three-month episodes that are *not* preceeded by or coincide with an annual earnings announcement (placebo sample).

[21]It is unreasonable to assume that every single firm with a positive recommendation oustanding will be covered by analysts playing the here proposed strategic game.

Table IV reports the average recommendation revision in the post-announcement quarter relative to the average recommendation level in the pre-announcement period for all three recommendation terciles. In the high-recommendation tercile, recommendations issued within the first three months after an earnings announcement are about 40% of a notch lower than the average recommendation before the earnings announcement; similarly, in the low recommendation tercile, recommendations issued within the first three months after an earnings announcement are about 60% of a notch higher than the average pre-announcement recommendation. The difference in recommendation revision between the two groups is close to a full notch and statistically significant at the 1% level (t=-33.08). In comparison, in our placebo sample, the difference in recommendation revision between the top and bottom tercile is (only) 0.38. Taken together, the evidence suggests that (at least some) analysts are aware of the stock return effect caused by distortions in earnings forecasts and time their recommendations accordingly.

4.3 The Mechanism

In this section, we further explore the mechanisms behind analysts' strategic forecasting behavior. Under our "self-fulfilling stock recommendation" hypothesis, sell-side analysts face the following cost-benefit tradeoff: By strategically issuing biased earnings estimates, analysts enjoy the benefit of higher stock recommendation performance and potentially better career outcomes; at the same time, they suffer from reduced earnings forecast accuracy and risk losing their reputation as their self-serving behavior may be revealed to the public. The magnitude and frequency of distortions in reported earnings estimates should be a function of both perceived benefits and costs.

We focus on two sets of firm characteristics that likely vary with the benefits and costs associated with distortions in earnings estimates. The first variable we examine is a firm's analyst coverage. Intuitively, the more analysts that are following a firm, the less each analyst's earnings forecast weighs in the consensus forecast upon which the earnings surprise is based. Put differently, if an analyst decides to report a biased earnings estimate by a single cent, the same one cent would have a larger effect on the consensus forecast among firms with lower analyst coverage. High analyst coverage also exacerbates the free-rider problem. By reporting biased earnings forecasts, analysts are unintentionally helping their fellow analysts with similar outstanding recommendations. Since analysts are evaluated relative to their peers, the free-rider problem weakens the incentives to distort their forecasts.

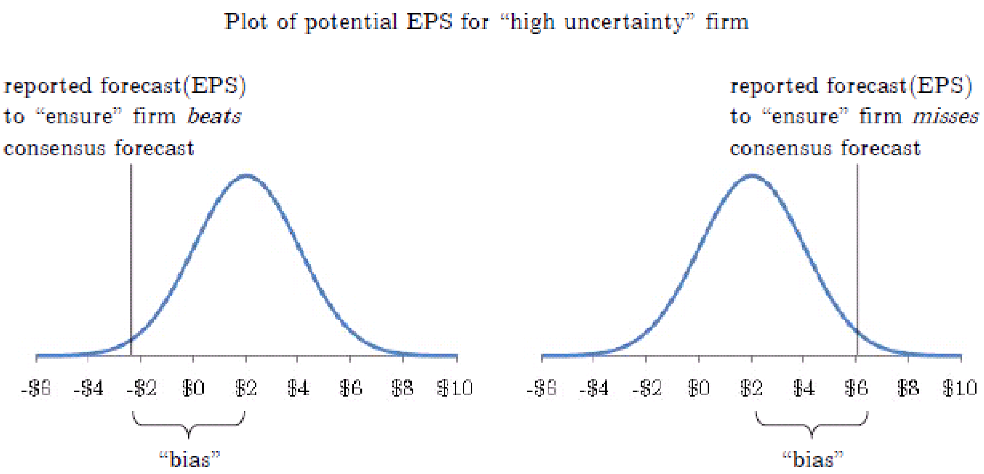
Taken together, we expect analysts to distort their forecasts more frequently and to a larger extent for firms that are covered by fewer analysts.

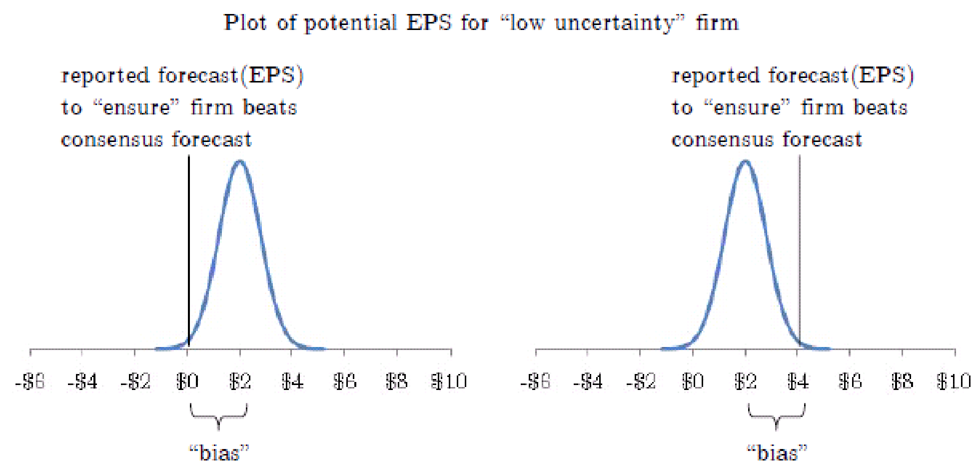
The second set of firm characteristics we examine, the lagged firm size and stock return volatility, are related to a stock's valuation difficulty.[22] Analysts obtain less precise signals on harder-to-value stocks and thus have weaker convictions on their recommendations for these securities. The analyst labor market, however, seems to only partially understand the effect of valuation uncertainty: When re-estimating regression equation (1) (to predict the termination of sell-side analysts) with an interaction term between the poor-recommendation-performance indicator function and valuation uncertainty, we obtain a negative, yet statistically and economically insignificant coefficient estimate on the interaction term.[23] Because some stocks' future returns are more difficult to predict than others' and the financial industry only partially accounts for differences in valuation difficulty across stocks when evaluating analyst performance, we expect analysts to have stronger incentives to report biased earnings forecasts and thus to enhance their subsequent recommendation performance, when valuation uncertainty is high. (The notion is akin to students being more likely to cheat when the exam is very difficult and there is no curve.)

Valuation uncertainty may matter for another reason. Firms with high uncertainty have a wider range of potential earnings realizations. In order to "ensure" that these high uncertainty firms meet (miss) the consensus forecast, analysts therefore have to report more biased forecasts (see figure next page):

[22] We compute stock return volatility as in French et al. (1987): $\sigma_t^2 = \sum_{d=1}^{D_t} r_d^2 + 2\sum_{d=2}^{D_t} r_d r_{d-1}$, where D_t is the number of days in month t and r_d is the return on day d. In untabulated analysis, we explore alternative proxies for valuation difficulty, including firm age, cash flow volatility, and number of industry segments the firm operates in, with very similar results

[23] Our measure of valuation uncertainty in (1) is the standard deviation in signed forecast errors across all analysts. We make similar observations when using firm size and return volatility as alternate measures of valuation uncertainty. (Results are available upon request.) We consider firm size and return volatility as somewhat noisier estimators for valuation uncertainty than the standard deviation in signed forecast errors. We choose to use firm size and return volatility for this part of the analysis because our dependent variable is the unsigned forecast error.





To test our predictions, we re-estimate equation (6), but now include interaction terms between our sets of firm characteristics and the firm's average outstanding recommendation prior to earnings announcements:

$$\left(e_{i,t+1} - \overline{\widetilde{e}}^{rep}_{i,t+1}\right) = \alpha + \beta_1 * \overline{rec}_{i,t} + \beta_2 * \overline{rec}_{i,t} * indicator_{i,t} + Control * \gamma + \varepsilon_{i,j,t}, \qquad (7)$$

where the indicator function equals zero if the respective firm characteristic is in the bottom tercile of its distribution in a given year, one if the respective firm characteristic is in the middle tercile, and two otherwise.

The results are reported in Table V. Consistent with our predictions, the association between the average recommendation and subsequent earnings surprise significantly decreases with analyst coverage and increases with our proxies for valuation difficulty. Specifically, the coefficient estimate on the analyst-coverage interaction term is -0.117 (t=-4.16), the estimate on the firm-size interaction term equals -0.093 (t=-2.88), and the estimate on the return-volatility interaction term is 0.097 (t=2.73). All coefficient estimates are economically meaningful compared to the average effect of 0.134 reported in Table III. In particular, the association between average recommendation level and subsequent earnings surprise is indistinguishable from zero in the tercile with the highest analyst coverage, i.e., among firms that are, on average, followed by more than ten analysts. The same qualification applies to firms in the largest size tercile and lowest return volatility tercile.

To better isolate the residual effect of each of the three variables (i.e., analyst coverage, firm size, and return volatility), we also estimate a regression equation that includes interaction terms between the average recommendation and all three variables in the same specification. The results, presented in the last column of Table V, show that the interaction terms based on analyst coverage and return volatility remain highly significant, with an economic magnitude of -0.101 (t=-3.02) and 0.085 (t=2.39), respectively, while that based on firm size loses its significance.

The perhaps most interesting interaction variable in the context of this study is analyst coverage. To further explore the differential association between earnings surprise and recommendation level across various analyst coverage subsamples, Panel A of Figure I reports the partial correlation coefficient for the subsample of observations where analyst coverage equals one, the subsample where coverage is between two and four, the subsample where coverage is between five and eight, and the subsample where coverage is greater than eight.[24] The coefficient estimates are 0.237 (t=3.15), 0.172 (t=3.93), 0.072 (t=2.21) and 0.028 (t-stat 0.96), respectively. These results are line with those from the regression analysis with interaction terms and further point to the possibility that the strategic distortion game requires coordination and sharing of both costs and benefits to be viable and thus is more likely to be played when a firm is covered by fewer analysts.

To follow up on this logic, we assume that geographic proximity facilitates coordination and further partition the sample based on whether the analysts covering the firm in question are from the same locale. Specifically, we extract brokerage firm names from the *Broker Translation File* and match the names to the brokerage codes in the IBES dataset. We then collect each brokerage firm's location using a combination of *Nelson's Directory of Investment Research*, *Manta*, *D&B Million Dollar Database* and the brokerage firm's website.[25] Each brokerage firm's location is (then) assigned its Metropolitan Statistical Area (MSA) or its

[24]In other words, we plot the coefficient estimate $\hat{\beta}$ on the average recommendation level from our baseline regression (6) estimated for various subsamples.

[25]Here, we make the assumption that analysts are located at the brokerage firm's headquarters.

ISO 3166-1 Country Code, if the brokerage firm is located outside the US. In the end, we are able to determine the brokerage firm's MSA/country for 98% of all observations. A firm is considered to be covered by analysts from the same locale if they all come from the same MSA/non-US-country.

Panel B of Figure I reports the partial correlation coefficient across various analyst coverage/locale-subsamples. In all subsamples for which a comparison can be made (i.e., for which there are both firms covered exclusively by analysts from the same locale and firms covered by analysts from different locales), the coefficient estimates are substantially higher when analysts are from the same locale than when they are not.

We entertain one final prediction of our hypothesis. If analysts are indeed issuing biased earnings forecasts in order to enhance the subsequent performance of their buy/sell recommendations, those analysts whose initial recommendations are disconfirmed by ex-post stock returns should have stronger incentives to behave strategically. More specifically, we predict analysts have stronger incentives to report biased earnings forecasts if they recommend a stock be bought (sold), yet that stock subsequently performs very poorly (well).

We test this prediction by conducting regression analyses that are almost identical to that in Table III Column 1, except that we now replace the recommendation level with four indicator variables: high recommendation/high performance (confirming), high recommendation/low performance (disconfirming), low recommendation/high performance (disconfirming), and low recommendation/low performance (confirming). A firm is considered to have a high (low) recommendation if its recommendation level places it in the top (bottom) tercile. The ex-post performance is defined as the stock's cumulative DGTW-adjusted return from one year to three months prior to the earnings announcement.[26] A high recommendation-firm's performance is considered to be confirming if its performance is in the top tercile; similarly, a low recommendation-firm's performance is considered to be confirming if its performance is in the bottom tercile.

The results presented in Table VI are consistent with our prediction. The observed strategic behavior in Table III appears concentrated in situations where analysts' initial recommendations are disconfirmed by subsequent stock returns. Specifically, for firms with high recommendation levels but low subsequent returns, their average earnings surprise is

[26]We observe very similar results whether we begin our calculation fifteen, twelve, or nine months prior to the earnings announcement as well as whether we end our calculation six or three months prior to the earnings announcement.

0.196 (t=2.92) higher than that of firms in the median recommendation tercile. Similarly, for firms with low recommendation levels but high subequent returns, their average earnings surprise is 0.130 (t=3.14) lower than that of firms in the median recommendation tercile. In contrast, for firms whose recommendations are confirmed by subsequent stock returns, their average earnings surprise is indistinguishable from that of firms in the median recommendation tercile.

Together, the findings presented in this subsection shed light on some of the mechanisms at work: Analysts weigh the costs of distorting their forecasts against the benefits in deciding how frequently and to what extend to report biased earnings estimates. We argue that the benefits (costs) decrease (increase) in analyst coverage, firm size, and institutional ownership, and yet increase (decrease) in return volatility. Consistent with our prediction, the evidence implies that the magnitude and frequency of forecast distortions decrease in analyst coverage, firm size, and institutional ownership, but increase in return volatility.

4.4 Investors' Trading Behavior

Our finding that the average recommendation level can predict both the subsequent earnings surprise and the corresponding earnings announcement day return suggests that (at least some) investors are unaware of the potential bias in analysts' earnings forecasts, and thus take the earnings surprise at face value. In this section, we examine which investor group is more likely to be misled by distortions in analysts' earnings forecasts.

Prior studies (e.g., Daniel et al. (2002); Schotter (2003); Malmendier and Shanthikumar (2007)) suggest that retail investors, naive about incentives, are particularly vulnerable to agents' strategic behavior, while institutional investors, having a better understanding of the incentive structure in financial markets, are likely able to see through such behavior. We therefore expect the association between the average recommendation level and subsequent earnings surprise to weaken with the fraction of institutional holdings. Moreover, for the firms that *are* affected by analysts' strategic distortion game, we expect retail investors to buy on the earnings surprise induced by analysts' strategic behavior and institutional investors to take the other side of unsophisticated demand.

To test our first prediction, we re-estimate (7), but now interact average recommendation level with an institutional holdings indicator. The indicator function equals zero if institutional holdings is in the bottom tercile of its distribution in a given year, one if institutional holdings is in the middle tercile, and two otherwise. Consistent with our conjecture, Column 1 of Table VII reports that the association between the average recommendation and subsequent earnings surprise decreases with institutional holdings; the estimate on the institutional-ownership interaction term equals -0.054 (t=-1.79).

To test our second prediction, we re-estimate equation (6), except that the dependent variable now is the small-trade imbalance (large-trade imbalance) in the three-day window around earnings announcement, $\frac{SmallBuys-SmallSells}{SmallBuys+SmallSells}$ $\left(\frac{LargeBuys-LargeSells}{LargeBuys+LargeSells}\right)$, where "small" orders are those that are below \$5,000 in value and proxy for retail trading, and "large" orders are those that are above \$50,000 in value and proxy for institutional trading (e.g., Barber et al. (2007)).[27] We limit our analyses to the 1994-July 2000 period, as the adoption of decimalization by the NYSE in late 2000 renders identification of retail vs. institutional trading activities using TAQ data impossible.

The results, presented in Columns 2 and 3 of Table VII, are consistent with our prediction. Retail investors submit more buy orders, while institutional investors submit more sell orders around earnings announcements for firms with more optimistic recommendations. Specifically, the coefficient estimate on the average recommendation is 0.029 (t=5.58) for small trade imbalance and -0.367 (t=-2.34) for large trade imbalance. For comparison, institutional investors, on average, are net buyers of stocks with positive earnings surprises (untabulated). Put differently, while institutional investors respond favorably to earnings surprises "unconditionally," they trade in the opposite direction to the part of the earnings surprise that is associated with the average recommendation level prior to the earnings announcement. This is consistent with our prediction that institutional investors understand the potential bias in analysts' forecasts and thus are willing to trade against retail investors when the latter are fooled by analysts' strategic behavior.

4.5 Robustness Checks

We perform a number of additional specification and robustness checks on our results. First, we use an alternative definition of analysts' consensus earnings forecast for each firm. More specifically, following Richardson et al. (2004), among others, we define the consensus earnings forecast as the median (rather than the mean) forecast across all analysts with valid earnings forecasts issued within three months prior to the annual earnings announcement,

[27] Using \$10,000 as an alternate cutoff point for small trades (e.g., Lee, 1992; Bessembinder and Kaufman, 1997) yields very similar results.

and then re-estimate regression equation (6) with this alternative measure. The results reported in Panel A of Table VIII are virtually unchanged from those in Table III.[28] The average recommendation level significantly and positively relates to the subsequent earnings surprise; the coefficient estimate equals 0.133 (t=5.14). In addition, the average recommendation is positively related to the likelihood that the firm meets or beats the median analyst forecast with a point estimate of 0.120 (p=0.00).

We also analyze whether analysts distort their forecasts for quarterly earnings reports. The tests reported in Panel B of Table VIII are identical those in Panel A, except that we replace the dependent variable with the subsequent *quarterly* earnings surprise. The results indicate that analysts issue biased estimates for quarterly earnings as well. Specifically, the average recommendation prior to a quarterly earnings announcement significantly and positively predicts the subsequent quarterly earnings surprise, with a coefficient estimate of 0.092 (t=7.19) when the consensus forecast is defined as the mean forecast across all analysts, and an estimate of 0.089 (t=6.99) when the consensus forecast is defined as the median forecast. Results from logistic regressions based on a binary dependent variable, which equals one if a firm's quarterly earnings report beats/meats its consensus forecast and zero otherwise, are also in line with the results based on annual earnings reports. The point estimates on the average recommendation level are 0.130 (p=0.00) for the mean consensus forecast and 0.165 (p=0.00) for the median consensus forecast.

In additional analysis, we re-estimate both the OLS regression model and the binary response model for the 1994-2001 and 2002-2009 periods. We choose to split our sample around year 2002, as we would like to understand the effect of the Global Settlement (2002) on analysts' strategic forecasting behavior. In the OLS regressions, the coefficient estimate on the average recommendation equals 0.179 (t=4.82) for the 1994-2001 period and 0.121 (t=3.26) for the 2002-2009 period. In the meet-or-beat logistic regressions, the coefficient estimate on recommendation equals 0.162 (p=0.00) in the first half of the sample period and 0.062 (p=0.02) in the second half. The observation that the documented effect is significantly stronger in the first half of the sample than the second half is consistent with the idea that the costs of reporting distorted earnings forecasts rose substantially after the Global Settlement.

[28] For the purpose of comparison, we have also included the results based on the mean forecast in the same Panel.

5 Alternative Interpretations

This section discusses potential alternative interpretations of our findings, namely i) earnings management conducted at the firm level, ii) analysts' tendencies to herd in their stock recommendations and earnings forecasts, iii) analysts' incentives to curry favor with firm management , and iv) analysts' (investors') underreaction to information.

5.1 Earnings Management

Prior studies (e.g., Subramanyam and Wild (1996); Skinner and Sloan (2002); Abarbanell and Lehavy (2003)) document a significantly stronger return response to earnings surprises for growth firms than for value firms. In other words, growth firms are penalized more severely than value firms for missing their respective earnings targets. Consequently, managers of growth firms may have stronger incentives to manipulate their earnings (e.g., through discretionary accruals) to avoid reporting earnings below their consensus forecasts, leading to more positive earnings surprises. In addition, previous research finds that growth firms, on average, receive higher stock recommendations than value firms (see, e.g., Womack (1996); Barber et al. (2001); Jegadeesh et al. (2004)), thus causing stock recommendations and earnings surprises to be positively correlated.

Although we cannot preclude this alternate interpretation, we do not think it fully explains our results. First, we explicitly control for growth opportunities and the results are only marginally affected by these additional controls. Second, we also control for earnings management using discretionary accruals and the inclusion of this variable has virtually no effect on the coefficient estimate on the average recommendation. Moreover, the earnings management interpretation cannot match other aspects of the data, such as the abnormal reversal in recommendations shortly after the earnings announcement.

5.2 Currying Favor with Firm Management

Lin and McNichols (1998), Michaely and Womack (1999), and Richardson et al. (2004), among others, provide evidence that analysts, in particular those from brokerage firms with underwriting businesses with the firm in question, tend to curry favor with management by issuing overly optimistic stock recommendations and beatable earnings forecasts. In particular, Malmendier and Shanthikumar (2009) document that for "affiliated" analysts (i.e., those whose employers have an underwriting relation) ”the more positive the recommendation is relative to the existing consensus, the more negative is the same analyst's same-stock earnings forecast relative to the consensus.” Malmendier and Shanthikumar (2009) find no such association for unaffiliated analysts.

The currying favor mechanism more speaks to analysts' relative views *within the same firm* (i.e., differences in forecasting behavior between affiliated and unaffiliated analysts covering the same firm) as opposed to differences *across firms*. Nevertheless, in additional analyses, we collect data from the SDC New Issues database to determine whether the analyst's employer was a lead or co-underwriter of an IPO in the past five year or of an SEO in the past two years. We (then) re-estimate our baseline regression, but now include the fraction of analysts who are affiliated as an additional independent variable. The inclusion of the affiliation variable does not alter the coefficient estimate on the average recommendation level; the coefficient estimate turns to 0.129 (t=5.11); for comparison, the estimate reported in Table III equals 0.134 (t=5.14). We also explore including an interaction term between the fraction of affiliated analysts and recommendation level; the interaction term is close to zero and not statistically significant.

5.3 Underreaction to Information

Another possible explanation for our findings is that analysts underreact to information. For instance, an analyst with a positive signal on a particular firm may upgrade his recommendation, and still underestimate the firm's (true) earnings per share, thus resulting in subsequent positive earnings surprises. This alternative story does not fit our research design exactly, as we are analyzing the relation between earnings surprise and average recommendation level, as opposed to recommendation changes. In addition, we provide evidence in Section 4 that institutional investors are net sellers around earnings announcements for stocks with optimistic recommendations. If the underreaction mechanism were fully generating our data and the positive earnings surprise associated with optimistic recommendations represented a genuine positive shock, we would expect institutional investors, who likely share similar views as analysts (e.g., Battalio and Mendenhall (2005)), to be net buyers not net sellers. Taken together, the evidence leads us to conclude that any explanation for the positive correlation between the average recommendation level and earnings surprise must include the “self-fulfilling stock recommendations” hypothesis.

6 Conclusion

We study an important yet overlooked agency problem between financial analysts and their clients. We argue that analysts issue biased earnings forecasts in a direction that helps improve their stock recommendation performance. We employ a simple yet novel approach to test this hypothesis. Instead of fixating on individual analysts' recommendations and earnings forecasts (which lack a natural benchmark), we examine, at the firm level, the relation between the average recommendation and subsequent earnings surprise. In doing so, we find ourselves an intuitive benchmark – actual earnings – to quantify the potential bias in earnings forecasts.

The results are consistent with our hypothesis. Firms with optimistic average recommendations prior to earnings announcements experience significantly positive earnings surprises, positive announcement-day returns, and negative long-run returns (albeit only marginally statistically significantly so). Analysts revert their recommendations shortly after the earnings announcement and before the return reversal. In addition, we provide evidence that distortions in forecasts are more prevalent among firms with low analyst coverage, high valuation uncertainty, and low institutional holdings. Combined, these findings suggest that analysts distort their reported earnings estimates and that (some) investors are unaware of such strategic behavior. These findings raise questions about market efficiencies and the financial industry's compensation structure, which is supposed to motivate analysts to dig out more information, rather than encourage them to report biased estimates.

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Appendix A:

Brief Definitions and Sources of Main Variables

Variable Name	Description	Source
Panel A: Variables used in Table II		
Recommendation Accuracy	Holding period return on the analyst's recommendations computed as the annualized difference between the DGTW-adjusted returns of the analyst's outstanding strong-buy/buy recommendations and the DGTW-adjusted returns of the analyst's outstanding hold/sell/strong-sell recommendations as of the end of year *t*.	IBES, CRSP, Russ Wermer's Website[1]
EPS Forecast Accuracy	Analyst's average *EPS* forecast error computed as the average absolute difference between actual *EPS* and the analyst's most recent forecast of *EPS* (scaled by lagged price) across all firms covered by the analyst in year *t*.	IBES, CRSP
Valuation Difficulty	Average absolute forecast error across all analysts covering firm *i* in year *t* (scaled by lagged price), averaged across all firms covered by the analyst in question (in year *t*).	IBES, CRSP
Panel B: Additional Variables used in Table III		
(Actual EPS - EPS Forecast)/Price	Difference between the actual *EPS* and the consensus *EPS* forecast scaled by (lagged) price.	IBES, CRSP
Indicator(Actual EPS ≥ EPS Forecast)	Indicator that actual *EPS* is greater than or equal to the consensus *EPS* forecast.	IBES
Recommendation Level	Analyst's outstanding recommendation level three months before the earnings announcement (but no later than fifteen months).	IBES
Size ($MM)	Firm's market capitalization (in million$), the month prior to the earnings announcement.	CRSP
Book-to-Market Ratio	Firm's book-to-market ratio (of equity), the month prior to the earnings announcement.	CRSP, COMPUSTAT
Past Returns	Firm's cumulative one-year stock return prior to the earnings announcement.	CRSP
Discretionary Accruals	See Appendix B.	COMPUSTAT

[1] http://www.rhsmith.umd.edu/Faculty/rwermers/

Variable Name	Description	Source
Panel C: Additional Variables		
Earnings Announcement Day Return	Cumulative market-adjusted return three days around the earnings announcement.	CRSP
Long-Run Return	Cumulative six-month DGTW-adjusted return from four months to nine months after the earnings announcement.	CRSP, Russ Wermer's Website[2]
Analyst Coverage	Number of analysts providing annual earnings forecasts for the firm in question.	IBES
Return Volatility	Monthly volatility (the month prior to the earnings announcement) calculated as in French, Schwert and Stambaugh (1987): , where D_t is the number of days in month t and r_d is the return on day d. The second term adjusts for serial correlation in daily returns.[3]	CRSP
Institutional Holdings	Institutional holdings.	THOMPSON

[2] http://www.rhsmith.umd.edu/Faculty/rwermers/

[3] In rare cases, the autocorrelation in returns is less than -0.5 and the variance estimate is negative. For these stocks, the variance estimator is the sum of squared daily returns only.

Appendix B:
Discretionary Accruals

We begin with total accruals, calculated as the difference between net income and net cash flow.[4] We decompose total accruals into a discretionary component, *DACCR*, and a non-discretionary component, *NDAACR*. Specifically, we form industry-year clusters of all COMPUSTAT firms using two-digit SIC codes. Then, for each industry-year cluster (j, t) with at least eight firms, we estimate the following firm-level regression for all firms i in industry j in year t:

$$ACCR_{i,j,t} \big/ TA_{i,j,t-1} = \alpha_{0j,t} + \alpha_{j,t}\left[1 \big/ TA_{i,j,t-1}\right] + \beta_{j,t}\left[\Delta REV_{i,j,t} \big/ TA_{i,j,t-1}\right] + \gamma_{j,t}\left[PPE_{i,j,t} \big/ TA_{i,j,t-1}\right] + \varepsilon_{i,j,t}\,, \quad \text{(A1)}$$

where *ACCR* is total accruals, *TA* is total assets, *ΔREV* is the change in net sales, and *PPE* is gross property, plant and equipment. Using the coefficient estimates from equation (A1) and adjusting changes in revenues by changes in accounts receivables to account for the discretion allowed in realizing sales on credit (e.g., Dechow, Sloan, and Sweeney, 1995), we calculate the non-discretionary accruals component:

$$NDACCR_{i,j,t} = \hat{\alpha}_{0j,t} + \hat{\alpha}_{j,t}\left[1 \big/ TA_{i,j,t-1}\right] + \hat{\beta}_{j,t}\left[\left(\Delta REV_{i,j,t} - \Delta AR_{i,j,t}\right) \big/ TA_{i,j,t-1}\right] + \hat{\gamma}_{j,t}\left[PPE_{i,j,t} \big/ TA_{i,j,t-1}\right]. \quad \text{(A2)}$$

Our estimate for the discretionary component in accruals is the difference between total accruals and the non-discretionary accruals component (from equation (A2)):

$$DACCR_{i,j,t} = ACCR_{i,j,t} \big/ TA_{i,j,t-1} - NDACCR_{i,j,t}\,. \quad \text{(A3)}$$

Other studies following this approach include Teoh, Welch, and Wong (1998a; 1998b), Xie (2001), Klein (2002) and Yu (2008).

[4] We truncate at 99th percentile of absolute total accruals to remove extreme outliers.

Table I

Summary Statistics

This table presents summary statistics on various variables used in this study. The sample includes all firms with valid recommendations and *EPS* forecasts in IBES over the period 1994 to 2009. *(Actual EPS - EPS Forecast)/Price* is the difference between the actual *EPS* and the consensus *EPS* forecast scaled by (lagged) price. *Earnings Announcement Returns* is the cumulative market-adjusted return three days around the earnings announcement. *Recommendation Level* is the analyst's outstanding recommendation level three months before the earnings announcement. *Size* is the firm's market capitalization (in million$). *Book-to-Market Ratio* is the firm's book-to-market ratio. *Past Returns* is the firm's cumulative one-year stock return prior to the earnings announcement. *Discretionary Accruals* is as defined in Appendix B. *Analyst Coverage* is the number of analysts providing annual earnings forecasts for the firm in question. *Return Volatility* is the firm's monthly stock return volatility. *Institutional Holdings* is the firm's institutional holdings.

Variables	Mean	25^{th}	Median	75^{th}	Standard Deviation
Panel A: Earnings Surprise and *Market Reaction to Earnings Surprise*					
(Actual EPS - EPS Forecast)/Price	-0.149	-0.126	0.042	0.236	2.627
Earnings Announcement Returns, when Actual EPS ≥ EPS Forecast	1.48%	-3.84%	0.91%	6.26%	10.95%
Earnings Announcement Returns, when Actual EPS < EPS Forecast	-1.89%	-7.25%	-1.65%	3.40%	11.39%
Panel B: Other Variables					
Recommendation Level	3.774	3.267	3.800	4.222	0.674
Size ($MM)	4,175	204	633	2,122	17,684
Book-to-Market Ratio	0.554	0.265	0.443	0.702	0.573
Past Returns	16.00%	-23.26%	4.47%	34.78%	83.00%
Discretionary Accruals	0.049	-0.019	0.033	0.114	0.182
Analyst Coverage	10.816	5.000	8.000	15.000	8.403
Return Volatility	0.030	0.006	0.014	0.032	0.076
Institutional Holdings	0.600	0.406	0.619	0.795	0.264

Table I. Continued.

Panel C: Correlation Matrix (Pearson)

		(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1)	(Actual EPS - EPS Forecast)/Price							
(2)	Recommendation Level	0.037 [0.01]						
(3)	Size ($MM)	0.044 [0.01]	-0.105 [0.01]					
(4)	Book-to-Market Ratio	-0.031 [0.01]	-0.157 [0.01]	-0.248 [0.01]				
(5)	Past Returns	0.047 [0.01]	0.139 [0.01]	-0.143 [0.01]	0.075 [0.01]			
(6)	Discretionary Accruals	0.044 [0.01]	0.031 [0.01]	0.015 [0.01]	-0.049 [0.01]	0.040 [0.01]		
(7)	Analyst Coverage	0.031 [0.01]	-0.063 [0.01]	0.652 [0.01]	-0.155 [0.01]	-0.024 [0.01]	-0.008 [0.01]	
(8)	Institutional Holdings	0.050 [0.01]	-0.005 [0.37]	0.418 [0.01]	-0.050 [0.01]	0.020 [0.01]	0.054 [0.01]	0.276 [0.01]

Table II

Recommendation- and Forecast Accuracy, and Analyst Career Outcomes

This table presents estimates from pooled logistic regressions of financial analyst career outcomes on measures of recommendation and *EPS* forecast accuracy (on an analyst/year-level). The dependent variable is an indicator that the analyst is not in the IBES sample in year *t+1*. The sample includes all analysts with valid recommendations and *EPS* forecasts in IBES over the period 1994 to 2009. The independent variables are: $D_{Bottom20}$ (*Recommendation Accuracy*), defined to be an indicator that the holding period return on the analyst's recommendations is in the bottom quintile of its distribution (in year *t*). The holding period return on the analyst's recommendations is computed as the annualized difference between the DGTW-adjusted returns of the analyst's outstanding strong-buy/buy recommendations and the DGTW-adjusted returns of the analyst's outstanding hold/sell/strong-sell recommendations as of the end of year *t*. $D_{Bottom20}$ (*EPS Forecast Accuracy*) is defined to be an indicator that the analyst's average *EPS* forecast error is in the top quintile of its distribution (in year *t*). The analyst's average *EPS* forecast error is computed as the average absolute difference between actual *EPS* and the analyst's most recent forecast of *EPS* (scaled by lagged price) across the firms covered by the analyst in year *t*. $D_{Bottom20\,-\,Bottom40}$ is defined respectively. *Valuation Difficulty* is defined to be the average absolute forecast error across all analysts covering firm *i* in year *t*, averaged across all firms covered by the analyst in question (in year *t*). *P*-values account for clustering (by brokerage house).

	Coefficient [*p*-value]	
Variables	Probability that Analyst Leaves Profession (1)	Probability that Analyst Leaves Profession (2)
Recommendation Accuracy		
$D_{Bottom20}$	0.258	0.297
	[0.00]	[0.00]
$D_{Bottom20-Bottom40}$		0.160
		[0.00]
EPS Forecast Accuracy		
$D_{Bottom20}$	0.179	0.241
	[0.00]	[0.00]
$D_{Bottom20-Bottom40}$		0.196
		[0.00]
Valuation Difficulty	0.044	-0.158
	[0.94]	[0.81]
Brokerage house effects	Yes	Yes
Year Effects	Yes	Yes
Number of Observations	33,200	33,200
Likelihood Ratio	2,326	2,369

Table III

Recommendation and Earnings Surprise

This table presents estimates from pooled regressions of the difference between actual *EPS* and consensus *EPS* forecasts on recommendation levels (on a firm/year-level). The sample includes all firms with valid recommendations and *EPS* forecasts in IBES over the period 1994 to 2009. In column (1), the dependent variable is the difference between the actual *EPS* and the consensus *EPS* forecast scaled by (lagged) price. In column (2), the dependent variable is an indicator that actual *EPS* is greater than or equal to the consensus *EPS* forecast. The independent variables are: *Recommendation Level*, defined to be the analyst's outstanding recommendation level three months before the earnings announcement; *Size*, defined to be the logarithm of the firm's market capitalization (in million$); *Book-to-Market Ratio*, defined to be the logarithm of the firm's book-to-market ratio; *Past Returns*, defined to be the firm's cumulative one-year stock return prior to the earnings announcement; and *Discretionary Accruals*, as defined in Appendix B. In column (1), the coefficient estimates are multiplied by 100. *T*-statistics and *p*-values account for clustering (by year-month).

	Coefficient (*t*-statistic),[*p*-value]	
Variables	Standardized Earnings Surprise (1)	Probability (Actual $\geq$ Forecast) (2)
Recommendation Level	0.134	0.101
	(5.14)	[0.00]
Size	0.078	0.089
	(6.17)	[0.00]
Book-to-Market Ratio	-0.056	-0.028
	(-2.03)	[0.12]
Past Returns	0.155	0.274
	(4.48)	[0.00]
Discretionary Accruals	0.572	0.223
	(4.44)	[0.01]
Year Effects	Yes	Yes
Number of Observations	31,214	31,214
Adj. R^2/Likelihood Ratio	0.009	552

Table IV

Recommendation and Earnings Surprise – Portfolio Approach

This table presents means and medians of portfolios formed on recommendation levels. The sample includes all firms with valid recommendations and *EPS* forecasts in IBES over the period 1994 to 2009. *Recommendation Level* is the analyst's outstanding recommendation level three months before the earnings announcement. *(Actual EPS - EPS Forecast)/Price* is the difference between the actual *EPS* and the consensus *EPS* forecast scaled by (lagged) price multiplied by 100. *Earnings Announcement Day Return* is the cumulative market-adjusted return three days around the earnings announcement. *Long-Run Return* is the cumulative six-month DGTW-adjusted return from four months to nine months after earnings announcement. *ΔRecommendation Level* is the difference between the average recommendation before the earnings announcement and the recommendations issued within the first three months after the earnings announcement. *T*-statistics are reported in parentheses.

	Recommendation Level			
Variables	Low	Medium	High	High - Low
Panel A: Earnings Surprise				
Standardized Earnings Surprise	-0.260	-0.133	-0.046	0.213
				(5.65)
Panel B: Earnings Announcement Day Return				
Earnings Announcement Day Return	0.13%	0.27%	0.57%	0.44%
				(2.72)
Panel C: Long-Run Return				
Long-Run Return(t+4, t+9)	-1.10%	-1.86%	-1.87%	-0.77%
				(-1.57)
Panel D: Recommendation Level				
Recommendation Level - before earnings announcement	3.029	3.805	4.548	1.579
ΔRecommendation(t+1, t+3)	0.382	-0.089	-0.592	-0.974
				(-33.08)

Table V

Recommendation and Earnings Surprise – Interaction Terms

This table presents estimates from pooled regressions of the difference between actual *EPS* and consensus *EPS* forecasts on recommendation levels (on a firm/year-level). The sample includes all firms with valid recommendations and *EPS* forecasts in IBES over the period 1994 to 2009. The dependent variable is the difference between the actual *EPS* and the consensus *EPS* forecast scaled by (lagged) price. The independent variables are: *Recommendation Level*, defined to be the analyst's outstanding recommendation level three months before the earnings announcement; *Indicator(Analyst Coverage)*, *Indicator(Return Volatility)* and *Indicator(Firm Size)* equal zero if the respective variable is below the 33^{rd} percentile of its distribution (in a given year), one if it is between the 33^{rd} and 66^{th} percentile, and two, otherwise. Other (untabulated) independent variables include: *Book-to-Market Ratio*, defined to be the logarithm of the firm's book-to-market ratio; *Past Returns*, defined to be the firm's cumulative one-year stock return prior to the earnings announcement; and *Discretionary Accruals*, as defined in Appendix B. All coefficient estimates are multiplied by 100. *T*-statistics account for clustering (by year-month).

	Coefficient (*t*-statistic)			
Variables	(1)	(2)	(3)	(4)
Recommendation Level	0.226 (5.25)	0.029 (0.95)	0.207 (4.68)	0.125 (2.65)
Recommendation Level * I(Analyst Coverage)	-0.117 (-4.16)			-0.101 (-3.02)
Recommendation Level * I(Return Volatility)		0.097 (2.73)		0.085 (2.39)
Recommendation Level * I(Size)			-0.093 (-2.88)	-0.003 (-0.08)
I(Analyst Coverage)	0.511 (4.46)			0.474 (3.48)
I(Return Volatility)		-0.475 (-3.39)		-0.438 (-3.12)
I(Size)			0.503 (3.74)	0.068 (0.42)
Year Effects	Yes	Yes	Yes	Yes
Number of Observations	31,214	31,214	31,214	31,214
Adj. R^2	0.010	0.011	0.010	0.011

Table VI

Recommendation, Past Performance and Earnings Surprise

This table presents estimates from pooled regressions of the difference between actual *EPS* and consensus *EPS* forecasts on recommendation levels conditional on past performance (on a firm/year-level). The sample includes all firms with valid recommendations and *EPS* forecasts in IBES over the period 1994 to 2009. We sort firm-years into terciles based on *Recommendation Level*, defined to be the analyst's outstanding recommendation level three months before the earnings announcement, and *Past Performance*, defined to be the stock's cumulative DGTW-adjusted return from one year to three months prior to the earnings announcement. Firms in the top (bottom) tercile based on *Recommendation Level* are categorized as having a "High (Low) Recommendation Level." A high recommendation-firm's performance is considered to be as predicted if its *Past Performance* is in the top tercile and not as predicted if its *Past Performance* is in the medium or bottom tercile; vice versa, for low recommendation-firm's performance. We estimate the following regression: The dependent variable is the difference between the actual *EPS* and the consensus *EPS* forecast scaled by (lagged) price. The independent variables are: Four indicator variables whether performance is as predicted or not as predicted, *Past Performance Tercile*; *Size*, defined to be the logarithm of the firm's market capitalization (in million$); *Book-to-Market Ratio*, defined to be the logarithm of the firm's book-to-market ratio; *Past Returns*, defined to be the firm's cumulative one-year stock return prior to the earnings announcement; and *Discretionary Accruals*, as defined in Appendix B. *T*-statistics account for clustering (by year-month).

Variables	Coefficient (*t*-statistic)
Low Recommendation Level	
Indicator(Performance not as "predicted"=1)	-0.130
	(-3.14)
Indicator (Performance as "predicted"=1)	-0.070
	(-1.25)
High Recommendation Level	
Indicator (Performance not as "predicted"=1)	0.196
	(2.92)
Indicator (Performance as "predicted"=1)	-0.000
	(-0.01)
Number of Observations	31,214
Adj. R^2	0.010

Table VII

Institutional Ownership and Analyst Strategic Behavior

This table presents estimates from pooled regressions of the difference between actual *EPS* and consensus *EPS* forecasts, and trade imbalance on recommendation levels (on a firm/year-level). In column (1), the sample includes all firms with valid recommendations and *EPS* forecasts in IBES over the period 1994 to 2009. In columns (2) and (3), the sample includes all firms with valid recommendations and *EPS* forecasts in IBES over the period 1994:01 to 2000:07. In column (1), the dependent variable is the difference between the actual *EPS* and the consensus *EPS* forecast scaled by (lagged) price. In column (2), the dependent variable is the dollar proportion of *small* buyer-initiated trades (relative to all *small* trades) three days around the earnings announcement. In column (3), the dependent variable is the dollar proportion of *large* buyer-initiated trades (relative to all *large* trades) three days around the earnings announcement. Trades are categorized as small if their dollar value is less than $5,000, and large if their dollar value is greater than $50,000. Trades are signed using the Lee and Ready algorithm (1991). The independent variables are: *Recommendation Level*, defined to be the analyst's outstanding recommendation level three months before the earnings announcement; *Size*, defined to be the logarithm of the firm's market capitalization (in million$); *Book-to-Market Ratio*, defined to be the logarithm of the firm's book-to-market ratio; *Past Returns*, defined to be the firm's cumulative one-year stock return prior to the earnings announcement; and *Discretionary Accruals*, as defined in Appendix B. The indicator variable is based on institutional holdings and equals zero if the respective variable is below the 33rd percentile of its distribution (in a given year), one if it is between the 33rd and 66th percentile, and two, otherwise. Coefficient estimates in column (1) are multiplied by 100. *T*-statistics account for clustering (by year-month).

	Coefficient (t-statistic)		
Variables	Standardized Earnings Surprise (1)	% Small Buyer-Initiated Trades (2)	% Large Buyer-Initiated Trades (3)
Recommendation Level	0.161	0.029	-0.367
	(3.54)	(5.58)	(-2.34)
Recommendation Level * I(Inst. Hldg.)	-0.054		
	(-1.79)		
I(Inst. Hldg.)	0.263		
	(2.25)		
Size	0.069	0.007	0.725
	(5.88)	(3.94)	(9.16)
Book-to-Market Ratio	-0.033	-0.032	0.200
	(-1.37)	(-5.90)	(2.33)
Past Returns	0.148	0.022	0.543
	(4.48)	(4.23)	(6.46)
Discretionary Accruals	0.544	0.055	0.096
	(4.08)	(2.88)	(0.23)
Year Effects	Yes	Yes	Yes
Number of Observations	29,791	13,561	13,561
Adj. R^2	0.010	0.015	0.016

Table VIII

Robustness Checks

This table presents estimates from pooled regressions of the difference between actual *EPS* and consensus *EPS* forecasts on recommendation levels (on a firm/year-level). The sample includes all firms with valid recommendations and *EPS* forecasts in IBES over the period 1994 to 2009. In columns (1) and (3), the dependent variable is the difference between the actual *EPS* and the consensus *EPS* forecast scaled by (lagged) price. In columns (2) and (4), the dependent variable is an indicator that actual *EPS* is greater than or equal to the consensus *EPS* forecast. The independent variables are: *Recommendation Level*, defined to be the analyst's outstanding recommendation level three months before the earnings announcement. Other (untabulated) independent variables include: *Size*, defined to be the logarithm of the firm's market capitalization (in million$); *Book-to-Market Ratio*, defined to be the logarithm of the firm's book-to-market ratio; *Past Returns*, defined to be the firm's cumulative one-year stock return prior to the earnings announcement; and *Discretionary Accruals*, as defined in Appendix B. In column (1), the coefficient estimates are multiplied by 100. *T*-statistics and *p*-values account for clustering (by year-month).

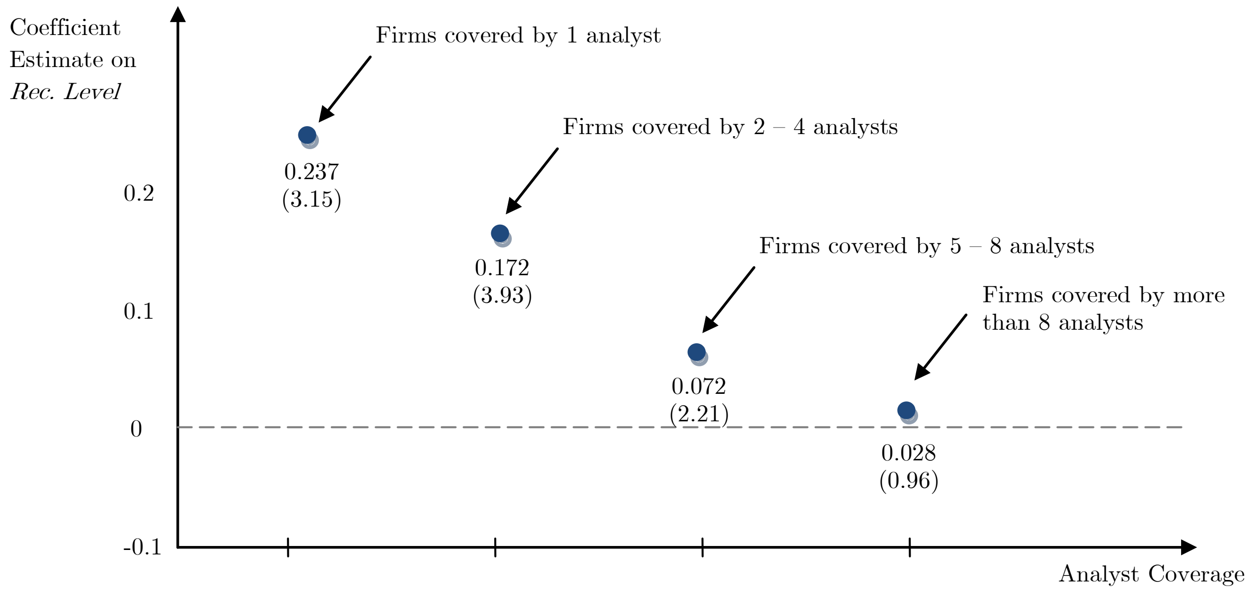
	Coefficient (*t*-statistic),[*p*-value]			
Variables	Standardized Earnings Surprise (1)	Probability (Actual ≥ Forecast) (2)	Standardized Earnings Surprise (3)	Probability (Actual ≥ Forecast) (4)
Panel A: Annual EPS	Mean Forecast		Median Forecast	
Recommendation Level	0.134	0.101	0.133	0.120
	(5.14)	[0.00]	(5.25)	[0.00]
Panel B: Quarterly EPS	Mean Forecast		Median Forecast	
Recommendation Level	0.092	0.130	0.089	0.165
	(7.19)	[0.00]	(6.99)	[0.00]
Panel C: Sample Period	*1994-2001*		*2002-2009*	
Recommendation Level	0.179	0.162	0.121	0.062
	(4.82)	[0.00]	(3.26)	[0.02]

Figure I

Recommendation and Earnings Surprise

This figure presents estimates from pooled regressions of the difference between actual *EPS* and consensus *EPS* forecasts on recommendation levels (on a firm/year-level) for various analyst coverage-subsamples. The sample includes all firms with valid recommendations and *EPS* forecasts in IBES over the period 1994 to 2009. The dependent variable is the difference between the actual *EPS* and the consensus *EPS* forecast scaled by (lagged) price. The independent variables are: *Recommendation Level*, defined to be the analyst's outstanding recommendation level three months before the earnings announcement. Other (untabulated) independent variables include: *Book-to-Market Ratio*, defined to be the logarithm of the firm's book-to-market ratio; *Past Returns*, defined to be the firm's cumulative one-year stock return prior to the earnings announcement; and *Discretionary Accruals*, as defined in Appendix B. A firm is defined to be from the "same locale" if all analysts covering the firm are from the same metropolitan statistical area. All coefficient estimates are multiplied by 100. *T*-statistics account for clustering (by year-month).

Panel A: Analyst Coverage



Panel B: Analyst Coverage and Geography