“Consistent” Earnings Surprises*

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Abstract

We hypothesize that analysts with a bullish stock recommendation have an interest in not being subsequently contradicted by negative firm-specific news. As a result, these analysts report downward-biased earnings forecasts so that the company is less likely to experience a negative earnings surprise. Analogously, analysts with a bearish recommendation report upward biased earnings forecasts so that the firm is less likely to experience a strong positive earnings surprise. Consistent with this notion, we find that stock recommendations significantly and positively predict subsequent earnings surprises, as well as narrow beats versus narrow misses. This predictability is concentrated in situations where the motivation for such behavior is particularly strong. Stock recommendations also predict earnings-announcement-day returns. A long-short portfolio that exploits this predictability earns abnormal returns of 125 basis points per month.

JEL Classification: G12, G14, G23.

Keywords: Stock recommendations, Biased earnings forecasts, Career concerns.

1. Introduction

Professional forecasters play an integral role in financial markets. They collect, process, and transmit information to market participants, who, in turn, use these reports when making their investment decisions (e.g., Stickel 1995; Womack 1996; Barber et al. 2001, 2003; Kothari 2001). While significantly altering market expectations, these reports may not reflect forecasters' true beliefs, however. Researchers find, for example, that sell-side analysts sacrifice forecast accuracy and report biased forecasts in order to stimulate trading (e.g., Hayes 1998), obtain access to management (e.g., Lim 2001), and/or generate investment banking business.[1]

In this study, we propose and test for a different source of bias in earnings forecasts. We propose that analysts have an interest in not having recommendations subsequently contradicted by important firm-specific news. Consider, for example, a sell-side analyst with a bullish stock recommendation, i.e., an analyst who signals to the market that she believes that a firm is currently undervalued. If the firm subsequently misses its consensus earnings forecast and experiences a negative earnings surprise, this could be construed as contradicting the analyst's bullish view on the company and might raise questions about her competency. Similar concerns could arise when a bearish stock recommendation is followed by a strong positive earnings surprise.

We suspect that, to avoid such perceptions, analysts with bullish recommendations report downward biased earnings forecasts, so that the companies are less likely to experience negative earnings surprises. Relatedly, analysts with bearish recommendations report upward biased earnings forecasts, so that the companies are less likely to experience positive earnings surprises. Our idea is related to a large body of literature in economics and psychology suggesting that people avoid disappointment by strategically altering their expectations about desired outcomes (e.g., Bell 1985; Van Dijk et al. 2003).

[1] A related literature suggests that analysts do not process information efficiently, i.e., they either under- or overreact to information, and unintentionally issue "biased" earnings forecasts and recommendations (see Section 2.2 in Daniel et al. (2002) for a review of this literature).

We begin our analysis by assessing the assumption that market participants partially judge an analyst's ability by whether her recommendations are followed by firm-specific news that is consistent or inconsistent with her overall view of the company. In particular, we look at analysts whose recommendations are at variance with subsequent earnings surprises, and we test whether these analysts subsequently experience negative career outcomes. Consistent with this notion, we find that after controlling for earnings-forecast accuracy and stock-return-based measures of recommendation performance, analysts in the bottom quintile with respect to the fraction of "consistent earnings surprises" are 1.6% (p-value<0.00) more likely than other analysts to leave the analyst sample. For comparison, the corresponding impact of being in the bottom quintile with respect to earnings-forecast accuracy is 1.5%. Analysts with a high fraction of inconsistent earnings surprises are also less likely to be named an *Institutional Investors' All-Star* analyst.

Prior literature provides evidence that the effect of forecast accuracy on our measure of analyst career outcomes is highly nonlinear (e.g., Hong et al. 2000, 2003). That is, while being in the 4th or bottom quintile in terms of earnings-forecast accuracy is of great relevance for the analyst's career, being in the 3rd or 4th quintile has no meaningful effect. This nonlinearity suggests that the cost of giving up forecast accuracy is limited in certain situations, providing a justification for why analysts sometimes choose to boost their earnings-surprise consistency by issuing biased earnings forecasts and, essentially, sacrificing forecast accuracy.

To test the central prediction of our proposition, we examine within a regression framework whether recommendations issued prior to a firm's earnings announcement positively predict subsequent earnings surprises, which we define as the difference between the reported earnings-per-share (EPS) and analysts' consensus forecast, scaled by the lagged price. After controlling for variables known to relate to earnings surprises, we find that outstanding recommendations strongly positively predict subsequent earnings surprises. A one-notch increase in outstanding recommendations is associated with a 9.1 basis-point increase in price-scaled earnings surprises (t = 4.04). A long-short calendar-time portfolio that exploits this predictability earns abnormal returns of 125 basis points per month.

When looking at the subsample of earnings announcements where actual earnings narrowly beat or miss the consensus forecast (i.e., where the price-scaled earnings surprise is within +/- 0.2%), we observe that firms with a negative consensus recommendation prior to the earnings announcement, subsequently, experience substantially more narrow misses than firms with a positive consensus recommendation (33.45% vs. 28.42%). Analogously, firms with a positive consensus recommendation prior to the earnings announcement experience substantially more meets/narrow beats than firms with a negative consensus recommendation (71.58% vs. 66.55%). This pattern holds within a multivariate setting.

In further analyses, we exploit potential determinants of the extent to which analysts bias their reported earnings forecasts. First, any intentional bias introduced by a single analyst in his reported earnings forecast has a larger impact on the consensus forecast when analyst coverage is low. Second, given that reporting biased earnings forecasts is congruent with sacrificing forecast accuracy, we expect our proposed mechanism to be stronger for analysts less concerned about being at the bottom with respect to earnings-forecast accuracy. Finally, more experienced analysts may be less incented to report biased earnings forecasts to signal their quality to the market. Consistent with this notion, we find that the association between stock recommendation and subsequent earnings surprise is stronger for firms with lower analyst coverage, among analysts that had high earnings-forecast accuracy in the previous year, and among analysts that have a shorter track-record. In general, our results are robust to the inclusion of a wide set of controls; they also survive a sequence of robustness checks.

Our study speaks to several lines of research. First, our paper relates to the literature on how the market assesses analyst quality. Prior research documents that analysts' career outcomes are closely tied to their earnings-forecast accuracy (Mikhail et al. 1999; Hong et al. 2000, 2003), as well as other "softer" factors, such as analysts' industry knowledge and broker satisfaction (Brown et al. 2013).

Womack (1996), Barber et al. (2001, 2003), and Jegadeesh and Kim (2010) find that investors react strongly to analysts' stock recommendations, and it appears reasonable to entertain the notion that the market (also) evaluates analysts based on the quality of their stock picks. Unlike earnings forecasts, stock recommendations lack an obvious benchmark. Our study complements the accounting and finance literature by proposing and providing evidence that one important benchmark used by the market is whether stock picks are subsequently confirmed or contradicted by firm-specific news, even if analysts can partially manufacture the news themselves.

Our study also relates to the vast literature on analyst forecast bias. The notion that analysts sacrifice forecast accuracy by issuing biased earnings forecasts is not an idea original to our research. There is much evidence that analysts compromise their objectivity and issue biased reports by letting their forecasts be guided and/or by knowingly not fully correcting for earnings management; analysts may do so to stimulate trading and/or to curry favor with firm managers. For instance, Das, Levine, and Sivaramakrishnan (1998) and Lim (2001) suggest that analysts choose to bias their earnings forecasts to gain access to firm management. Lin and McNichols (1998) and Michaely and Womack (1999), among others, suggest that analysts from brokerage houses that have underwriting relations with the firm in question ("affiliated" analysts) tend to issue more optimistic recommendations than their "unaffiliated" peers.

A related literature examines the predictability of earnings surprises and earnings-announcement returns based on analysts' psychological biases. Abarbanell and Bernard (1992) and Zhang (2006), for example, provide evidence that analysts are sluggish and underreact to recent earnings information. In an experimental setting, Hutton and McEwen (1997) find that analysts tend to be overly optimistic due to their cognitive biases. Hilary and Menzly (2006) suggest that analysts who have experienced short-lived success become overconfident in their ability to predict future earnings.

Our study differs conceptually from the aforementioned literature by proposing a novel, seemingly paradoxical behavior: In an attempt to signal their superior quality to the market, analysts sometimes choose to sacrifice forecast accuracy.

In the data, we observe that firms with more pessimistic recommendations are significantly more likely to narrowly miss their consensus forecasts than firms with more optimistic recommendations. This pattern can be explained neither by the aforementioned earnings-management explanation nor by the aforementioned currying-favor explanation. In addition, we obtain management forecast data from *First Call* and focus on the subset where the management's earnings forecast is NOT below analysts' consensus forecast as of the management forecast date (i.e., cases where management does NOT appear to walk down analysts' consensus forecast). We observe that our findings continue to hold within this subset. We conduct a number of additional tests, which, taken together, imply that our proposed mechanism plays an important, incremental role in the data-generating process.

The paper proceeds as follows. Section 2 summarizes our data collection and screening procedures. Section 3 examines the effect of earnings-surprise consistency on analyst career outcomes. Section 4 develops and tests our main prediction. Section 5 discusses alternative explanations and conducts robustness checks. Finally, Section 6 concludes.

2. Data

We obtain information regarding sell-side analyst stock recommendations and annual earnings forecasts 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 all recommendations made by each analyst. Recommendations (ITEXT) include: "Strong Buy," "Buy," "Hold," "Underperform," and "Sell." We assign the following numerical scores: 5 (strong buy), 4 (buy), 3 (hold), 2 (underperform), and 1 (sell). A high value, thus, indicates a more bullish view.

The IBES unadjusted detail history file tracks all historical (i.e., not-split-adjusted), actual EPS and all historical EPS forecasts made by each analyst. Following prior literature (e.g., Teoh et al. 1998a,b), we define the consensus forecast as the average annual EPS forecast across all forecasts issued in the three months prior to the earnings announcement; in robustness tests, we use the *median* earnings forecast as the consensus forecast, and we obtain very similar results. Our earnings surprise variable is the difference between the actual historical annual EPS and the historical annual EPS consensus forecast (both from IBES), scaled by the historical price-per-share from the *Center for Research in Security Prices* (CRSP). The sample period spans from 1993 to 2012 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 CRSP, respectively.[2] In our analysis, we exclude firm observations with the most extreme 1% of standardized earnings surprise (SUE). Less conservative procedures for truncating the sample based on the most extreme 5% or 10% produce results with higher statistical significance than the ones reported in this study. Our final sample comprises 33,757 firm-year observations.

Table 1 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 SUE is significantly negatively skewed, suggesting that firms sometimes choose to take big earnings baths when they are unable to meet the consensus forecast. Stocks of firms that meet or beat their consensus earnings forecast outperform those that miss their consensus forecast by a significant margin in a three-day window around the earnings announcement (1.51% vs. -1.70%).

The average market capitalization is $4.52 billion, and the average market-to-book ratio is 4.18. Compared to the CRSP-sample averages, these figures indicate that firms covered by analysts tend to be larger and more growth-oriented.

3. Building Block: Earnings-Surprise Consistency and Analyst Career Outcomes

Given the crucial information-intermediary role played by sell-side analysts in financial markets, both academics and practitioners have long been interested in understanding how analysts are compensated and motivated. Prior research (e.g., Mikhail et al. 1999; Hong et al. 2000, 2003) documents that analysts' 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 are evaluated: the consistency between an analyst's recommendation and the subsequent earnings surprise ("earnings-surprises consistency").

[2] Ljungqvist et al. (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 purged the data for the most part. As of February 12, 2007, the data on Wharton Research Data Services (WRDS) has been corrected (Glushkov 2007).

The literature shows that investors react strongly to analysts' stock recommendations (e.g., Womack 1996; Barber et al. 2001, 2003; Jegadeesh and Kim 2010). We conjecture that in the absence of a clear rule as to how to evaluate stock recommendation performance, specifically, the horizon over which and the benchmark against which stock performance should be measured, market participants employ "mental shortcuts." One such shortcut is using information regarding whether a recommendation is subsequently confirmed or contradicted by important firm-specific news.

Few firm-specific events draw the level of attention of earnings announcements. Our argument then implies that analysts whose recommendations are subsequently contradicted by earnings surprises are more likely to experience negative career outcomes. Our idea is related to anecdotal accounts, such as that of Merrill-Lynch's Henry Blodget, whose bullish recommendations on various Internet companies were followed by a string of disappointing earnings; Blodget then had to accept a buy-out offer from Merrill Lynch (*Wall Street Journal*, Jan 1st 2001).

3.1 Regression Analysis

To assess whether analysts whose recommendations are subsequently contradicted by earnings surprises are more likely to experience negative career outcomes, we follow prior literature (Mikhail et al. 1999; Hong et al. 2000, 2003) and analyze how earnings-surprise consistency relates to brokerage firms' termination decisions, as these decisions 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 (on an analyst/calendar-year level):

$$\begin{aligned} Termination_{j,t+1} = {} & \alpha + \beta_1 LowConsistency_{j,t} + \beta_2 LowEPSForecastAccuracy_{j,t} \\ & + \beta_3 LowRecommendationPerformance_{j,t} \\ & + \beta_4 LowUpgrade/DowngradePerformance_{j,t} + Controls + \varepsilon_{j,t+1} \qquad (1) \end{aligned}$$

where $Termination_{j,t+1}$ is a dummy variable that equals one if analyst *j* stops producing earnings forecasts in year *t*+1. Since most analysts submit their earnings forecasts to IBES, following Hong et al. (2000), we assume that if an analyst stops producing earnings forecasts in IBES, she has left the profession.

$LowConsistency_{j,t}$ is an indicator variable that equals one if the analyst's fraction of consistent earnings surprises is in the bottom quintile of its distribution in year *t*. An earnings surprise is considered to be consistent if the recommendation is a strong buy or buy recommendation and the firm then meets or beats the EPS consensus forecast, or if the recommendation is a hold, underperform, or sell and the firm then misses the EPS consensus forecast.

$LowEPSForecastAccuracy_{j,t}$ is defined as an indicator that the analyst's average EPS forecast accuracy is in the bottom quintile of its distribution in year *t*, where forecast accuracy is computed as the average absolute difference between the actual 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*.

Similarly, $LowRecommendationPerformance_{j,t}$ is an indicator that the analyst's stock-return-based recommendation performance is in the bottom quintile of its distribution in year *t*. We follow Daniel et al. (1997) and subtract from each stock's return the value-weighted return of a portfolio with similar market capitalization, book-to-market ratio, and one-year stock returns (DGTW-adjusted returns). We then take the difference between the average annualized characteristics-adjusted stock return for the analyst's outstanding strong-buy/buy recommendations and the average annualized characteristics-adjusted stock return for the analyst's outstanding hold/underperform/sell recommendations, with each recommendation being assigned an equal weight.[3] Returns are computed from the day after the recommendation

[3] 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 underperform/sell recommendations, 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 alternative measure of recommendation accuracy. Moreover, we also conduct regression analyses using an alternative 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.

issuance/update to the last trading day of the year, across all recommendations issued/updated by the analyst in year *t*.

As an alternate measure of recommendation performance, we include $LowUpgrade/DowngradePerformance_{i,t}$, which is an indicator that the analyst's stock-return-based upgrade/downgrade performance is in the bottom quintile of its distribution in year *t*. In particular, we take the difference between the average annualized characteristics-adjusted stock return following the analyst's recommendation upgrades and the average annualized characteristics-adjusted stock return following the analyst's recommendation downgrades, with each upgrade/downgrade being given an equal weight. Returns are computed from the day after the upgrade/downgrade to the last trading day of the year, across all recommendations updated by the analyst in year *t*.

We use indicator variables, rather than actual raw performance metrics, in our analysis, because the effect of earnings-surprise consistency, earnings-forecast accuracy, and stock-return-based recommendation performance is likely to be nonlinear (Hong et al. 2000, 2003).

Control variables include *All-Star*, which takes the value of one if the analyst is included in the *Institutional Investor All-Star* team, and zero otherwise; *Brokerage Reputation*, which takes the value of one if the analyst works for a "prestigious brokerage house" (following prior literature (e.g., Ertimur et al. 2011), we define prestigious brokerages as those with a Carter-Manaster rank of 9.1 or higher), and zero otherwise; *Cash Flow Forecast*, which takes the value of one if the analyst issues cash-flow forecasts, and zero otherwise; *Experience*, which is the number of years the analyst has been issuing earnings forecasts in the IBES database; and *S&P 500*, which takes the value of one if the analyst covers at least one S&P 500 firm, and zero otherwise. We also include year-fixed effects to capture time-series variations in market conditions. To facilitate interpretation of the economic significance, all coefficient estimates are converted into marginal probabilities.

The regression results, shown in Table 2, support the idea that earnings-surprise consistency is an important determinant of analyst career outcomes. As reported in column (1), the converted estimate on $LowConsistency_{j,t}$ equals 0.016 (*p*-value<0.01), which implies that being in the bottom quintile of prior-year earnings-surprise consistency increases the probability of termination by 1.6%. For reference, in any given year, 18.9% of analysts leave the IBES sample. Consistent with prior findings, earnings-forecast accuracy is also significantly related to analysts' termination: The converted estimate on $LowEPSForecastAccuracy_{j,t}$ equals 0.015 (p-value<0.01), which implies that being in the bottom quintile of prior-year earnings-forecast accuracy increases the probability of termination by 1.5%.

The converted estimates on $LowRecommendationPerformance_{j,t}$ and $Low\ Upgrade/DowngradePerformance_{i,t}$ are 0.005 (p-value=0.30) and 0.018 (p-value<0.01), respectively, and we make very similar observations when including $LowRecommendationPerformance_{j,t}$ and $Low\ Upgrade/DowngradePerformance_{i,t}$ separately. These estimates imply that being in the bottom quintile of prior-year recommendation performance increases the probability of termination by 0.5% and 1.8%, respectively. The statistical insignificance of the coefficient estimate on $LowRecommendation\text{-}Performance_{j,t}$ may be an artifact of the lack of a well-defined horizon over which recommendation performance should be measured.[4]

Column (2) repeats the analysis but now separates $LowConsistency_{j,t}$ by whether the inconsistency is coming from bullish recommendations preceding negative earnings surprises (*Low Consistency in Strong-Buy/Buy Recommendations*) or from bearish recommendations preceding positive earnings surprises (*Low Consistency in Hold/Underperform/ Sell Recommendations*). The slopes on both *Low Consistency in Strong-Buy/Buy Recommendations* and *Low Consistency in Hold/Underperform/ Sell Recommendations* are positive and strong, implying that the labor market penalizes inconsistency in both bullish recommendations and bearish recommendations.

Together, the results presented in Table 2 support our conjecture that analysts whose recommendations are subsequently contradicted by earnings surprises are more likely to experience negative career outcomes.

[4] This coefficient estimate remains statistically insignificant when using alternative horizons to measure recommendation performance. Specifically, we measure recommendation performance from the day after the recommendation issuance/update to the last trading day of month +6, month +12, and month +24.

3.2 Alternative Interpretations

Two caveats apply to our empirical analysis. The first caveat concerns our use of disappearance from IBES as a proxy for a negative career outcome. As suggested by Wu and Zang (2009), as many as 10% of analysts who disappear from IBES leave as a result of promotions to research executive positions. Thus, in some instances, our analysis may misclassify a disappearance from IBES as a negative career outcome when in fact it is a positive career outcome.

We acknowledge this shortcoming, but we also suspect that if we were to manually sort out disappearances that, in fact, are promotions, this new disappearance variable would only be more strongly associated with poor past performance than our current disappearance variable.

Nevertheless, in an attempt to assess the validity of our conclusion that poor consistency is associated with negative career outcomes, we re-do our regression analysis but replace the dependent variable with a dummy variable that takes the value of one if the analyst is included in the *Institutional Investors' All-Star* list in year t+1. We find that the converted estimate on $LowConsistency_{j,t}$ equals -0.014 (p-value<0.01), which implies that being in the bottom quintile of prior-year earnings-surprise consistency decreases the probability of being including in the *All-Star* list by 1.4%.

A second caveat pertains to an alternative interpretation of our finding. Specifically, one could argue that when observing a company that is currently undervalued by the market, a high-ability analyst would issue a buy recommendation and a high earnings forecast. To the extent that the other, less-able analysts do not follow the high-ability analyst's view and the consensus forecast remains too low, the high-ability analyst's buy recommendation would tend to be followed by a positive earnings surprise. In other words, high ability translates into high consistency. Thus, any relation observed in the data between consistency and career outcome could be due to the analyst's ability rather than the labor market using consistency as a mental shortcut.

In an attempt to address this concern, we focus on cases where high ability does NOT translate into high consistency. Any association observed between consistency and career outcome thus would point towards the labor market using consistency as a mental shortcut.

In particular, we focus on cases where analyst coverage is equal to one, i.e., where the analyst's earnings forecast is the consensus forecast. In these cases, a bullish high-ability analyst would issue a buy recommendation and a high earnings forecast; the high-ability analyst's earnings forecast would, on average, be met by actual earnings (=zero earnings surprise). Similarly, a bearish high-ability analyst would issue a sell recommendation and a low earnings forecast; the low earnings forecast would, on average, be met by actual earnings (=zero earnings surprise). Here, high ability does NOT translate into high consistency between recommendations and earnings surprises, as the earnings surprise averages zero irrespective of the recommendation outstanding.

Yet, in the data, we observe that consistency continues to predict career outcomes even when analyst coverage is equal to one. Specifically, the converted estimate on $LowConsistency_{j,t}$ equals 0.017 (p-value = 0.04), the converted estimate on *Low Consistency in Strong-Buy/Buy Recommendations* equals 0.009 (p-value = 0.09), and *Low Consistency in Hold/Underperform/ Sell* equals 0.015 (p-value = 0.05). This observation is consistent with our "mental-shortcut" view of the data.

4. Biases in Analysts' Earnings Forecasts

In this section, we build on the argument that analysts should avoid situations where the subsequent earnings surprise contradicts the analyst's outstanding recommendation. We develop our main hypothesis, motivate our empirical design, and take our central prediction to the data.

4.1 Hypothesis Development

We propose that to decrease the fraction of inconsistent earnings surprises, analysts with positive (negative) recommendations outstanding report negatively (positively) biased earnings estimates—relative to their true beliefs—so that the firm is less likely to experience a subsequent negative (positive) earnings surprise. Such behavior comes at the cost of sacrificing earnings-forecast accuracy. Given that both earnings-surprise consistency and earnings-forecast accuracy matter for an analyst's career, *ex ante*, it is unclear whether analysts should engage in this kind of behavior.

To study whether it is plausible that analysts sometimes employ our proposed mechanism, we analyze, within a stylized model, how an analyst's utility is affected by her earnings-forecast accuracy and by her earnings-surprise consistency.

Consider analysts maximizing the following objective function:

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

$RANK_{FA}$ and $RANK_{CONS}$ are relative rankings based on forecast accuracy (*FA*) and consistency (*CONS*) in the absence of any strategic reporting behavior, x is the degree of bias in the reported earnings forecast, and $- f(.)$ and $+ k(.)$ are both increasing functions describing the loss in forecast accuracy and the gain in consistency resulting from reporting biased earnings forecasts. $(RANK_{FA} - f(x))$ and $(RANK_{CONS} + k(x))$ thus are the observed relative rankings after analysts issue biased earnings forecasts. g(.) and h(.) capture the effects of forecast-accuracy rank and consistency rank on future career outcomes.

We impose two simple assumptions: (1) We assume that $RANK_{FA}$ and $RANK_{CONS}$ are not perfectly positively correlated. In other words, when an analyst is in the bottom quintile with respect to consistency, the same analyst is not also necessarily in the bottom quintile in terms of forecast accuracy every single time. (2) Our second assumption is that both g(.) and h(.) are increasing and concave. A drop in performance, therefore, negatively impacts analysts' careers, but the effect decreases as we move away from the bottom quintile. Put bluntly, whether an analyst is in the bottom- or fourth quintile is of greater significance than whether an analyst is in the third- or second quintile. This assumption is motivated by prior literature (Hong et al. 2000, 2003).

Without loss of generality, we define $f(x)=\mathrm{a}x$ $(\mathrm{a} > 0, x \geq 0)$, $k(x)=\mathrm{b}x$ $(\mathrm{b} > 0, x \geq 0)$, $g(.) = log(.)$, and $h(.) = log(.)$:

$$U(x) = log(RANK_{FA} - \mathrm{a}x) + log(RANK_{CONS} + \mathrm{b}x). \tag{3}$$

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

$$0 = \mathrm{b}(RANK_{FA} - \mathrm{a}x^*) - \mathrm{a}(RANK_{CONS} + \mathrm{b}x^*). \tag{4}$$

Solving for x^* yields:

$$x^* = \frac{bRANK_{FA} - aRANK_{CONS}}{2ab}, \text{ for } \frac{RANK_{FA}}{RANK_{CONS}} > \frac{a}{b}; \quad (5)$$

$$x^* = 0, \text{ otherwise.}$$

Equation (5) produces the intuitive result that the amount of manipulation, x^*, increases with $RANK_{FA}$ and decreases with $RANK_{CONS}$; that is, the analyst who is in a better position to sacrifice forecast accuracy (high $RANK_{FA}$) and the analyst who is in greater need to boost her earnings-surprise consistency (low $RANK_{CONS}$) is more likely to bias his/her earnings forecasts. Moreover, the higher the cost associated with such behavior (i.e., the larger *a*), and/or the lower the benefit (i.e., the smaller *b*), the less likely analysts are to issue biased earnings forecasts.

Given that $max(RANK_{FA}/RANK_{CONS}) > (a/b)$, the average x^* across all analysts is strictly positive. That is, under the assumptions that earnings-forecast accuracy and earnings-surprise consistency are not perfectly positively correlated and that the performance effect is nonlinear, there must exist some analysts whose true forecast-accuracy rankings are sufficiently high relative to their consistency rankings such that issuing biased earnings forecasts is career-enhancing.

Hypothesis: *Analysts with positive (negative) recommendations outstanding sometimes choose to report negatively (positively) biased earnings estimates—relative to their true beliefs—so that the firm is less likely to subsequently experience a negative (positive) earnings surprise.*

4.2 Regression Analysis

Because analysts' motivation to report biased earnings forecasts stems from their ability to affect the consensus forecast upon which the earnings surprise is calculated, in our main analysis, we aggregate both earnings forecasts and recommendations to the firm level. We then examine whether firms with more optimistic (pessimistic) average recommendations subsequently experience more positive (negative) earnings surprises and announcement day returns.

Besides its intuitive appeal, conducting our analysis at the firm level also has important methodological advantages. This is because aggregating information to the firm level circumvents the problem of us not directly observing analysts' true unbiased earnings forecasts. (See Appendix 1 for a more detailed discussion of this point.)

Our analysis is organized around the following firm-year-level regression specification:

$$e_{i,t+1} - \bar{e}_{i,t+1}^{rep} = \alpha + \beta\, \overline{rec}_{i,t} + Control + \varepsilon_{i,t+1}, \quad (6)$$

where $e_{i,t+1}$ is the actual annual earnings-per-share and $\bar{e}_{i,t+1}^{rep}$ is the consensus earnings forecast (the difference is scaled by price); we consider only the most recent earnings forecasts issued/updated within a three-month window preceding the earnings. Our interest centers on $\overline{rec}_{i,t}$, which is the consensus recommendation prior to the earnings announcement. In our tests, we require that earnings forecasts used to compute the consensus forecast are issued/confirmed following the recommendation issuance/update. We do so to ensure that all information incorporated in the recommendations is available and used when analysts issue their earnings forecasts. We also require recommendations to be issued no more than fifteen months prior to the earnings announcement, to weed out "stale" recommendations. Note that we do not take a stand on when exactly analysts start issuing biased earnings forecasts. Analysts may do so simultaneous to their issuing the recommendations; alternatively, they may wait a few months to (better) evaluate the "need" to report biased earnings forecasts.

The results are presented in Table 3. The coefficient estimate on the firm's average recommendation level is both statistically and economically significant. Specifically, a one-notch upgrade in the consensus recommendation prior to the earnings announcement (e.g., from 3 (hold) to 4 (buy)) is associated with a 9.1-basis-point increase (t = 4.04) in the price-scaled earnings surprise. This result is in line with our main hypothesis that analysts with a positive (negative) recommendation outstanding sometimes choose to report negatively (positively) biased earnings estimates relative to their true beliefs.

The coefficient estimates on the control variables are generally consistent with those reported in prior studies. In particular, the coefficient estimate on *Lag(Earnings Surprise)* is 0.453 (t = 1.70), consistent with the finding of Abarbanell and Bernard (1992) and Zhang (2006) that analysts underreact to recent earnings surprises. The coefficient estimates on *Firm Size* and *Past Returns* are 0.086 (t = 5.13) and 0.125 (t = 2.87), respectively, suggesting that larger firms and firms with more positive past returns are associated with more positive earnings surprises (Matsumoto 2002; So 2013).

We also find that *Discretionary Accruals* and *Total Accruals* are positively correlated with earnings surprises; the computation of *Discretionary Accruals* is detailed in Appendix 2. The coefficient estimate on *Forecast Horizon* is -0.085 (t= 1.97); in other words, forecasts issued more in advance tend to be more optimistic than forecasts issued shortly before the earnings announcement. This finding is consistent with Richardson et al.'s (2004) finding that, on average, forecasts start out the year optimistic and end the year pessimistic.

The coefficient estimates on *Institutional Holdings* and *Loss* are 0.338 (t = 4.27) and -0.522 (t = -9.32), respectively; *Loss* is defined as a dummy variable indicating losses in each of the four most recent quarters. Moreover, the coefficient estimates on *Market-to-Book Ratio*, *Durable Goods*, and *Litigation Risk* are all positive, albeit statistically insignificant; *Durable Goods* and *Litigation Risk* are defined as dummy variables indicating membership in a durable goods industry (three-digit SICs 150-179, 245, 250-259, 283, 301, and 324-399) and membership in a high risk industry (four-digit SICs 2833-2836, 3570-3577, 3600-3674, 7370-7374, and 5200-5961), respectively. These findings are consistent with Matsumoto's (2002) finding that firms with higher institutional ownership, lower value-relevance of earnings, higher growth prospects, greater reliance on implicit claims with stakeholders, and higher ex ante litigation risk are more likely to take actions to avoid negative earnings surprises.

Column 2 of Table 3 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 the consensus earnings forecast. All else equal, a one-notch increase in the average recommendation level is associated with a 1.1% (p-value = 0.05) increase in the likelihood of meeting or beating the consensus forecast, suggesting that our result is not driven by a small number of large negative earnings surprises.

One concern with our current empirical design arises from our reliance on SUE (= actual realized earnings minus analysts' reported consensus forecast, scaled by price). Under the assumption that analysts form rational expectations, we can use the actual realized earnings as a measure of analysts' *true* earnings forecast against which analysts' *reported* earnings forecasts can be compared (see Appendix 1 for more details). If, in contrast, analysts collectively display certain psychological- or agency-issue-related biases (e.g., Abarbanell and Bernard 1992; Francis and Philbrick 1993), the actual realized earnings no longer represent an adequate benchmark for analysts' reported earnings forecasts.

To speak to this concern, we experiment with an alternate measure of analysts' *true* earnings forecasts against which we compare analysts' reported earnings forecasts. In particular, we model the unbiased earnings forecasts, as in So (2013), by using a set of firm characteristics in year t-1 to predict the firm's earnings in year t (see page 622 in So (2013) for details on the methodology). We then take the price-scaled difference between this "firm-characteristic-based forecast" and analysts' reported consensus forecast as our new dependent variable.

The results are reported in Columns 3 and 4 of Table 3. The average recommendation level significantly and positively predicts the degree to which the reported consensus forecast is below the firm-characteristic-based forecast; the coefficient estimate equals 0.018 (t = 3.30). The average recommendation level is also positively related to the likelihood that the firm's consensus forecast is below the characteristic forecast; the point estimate on the recommendation level equals 0.008 (p-value = 0.03).

4.3 Portfolio Analysis

To assess the robustness and economic significance of our findings, we also conduct portfolio analyses. Specifically, in each year, we sort observations into two portfolios based on the average level of recommendation prior to the annual earnings announcement, and we report the average earnings surprise for each portfolio. We assign firms with a buy- or a strong-buy consensus recommendation (i.e., consensus recommendation ≥ 4) to the high recommendation group and firms with a hold-, underperform- or sell-consensus recommendation (i.e., consensus recommendation < 4) to the low recommendation group.

As reported in Table 4, the difference in the price-scaled earnings surprise between the high- and the low-recommendation groups is 26.3 basis points (t = 7.53). Given the long-term average stock price of $35 per share (in the CRSP universe), the difference in price-scaled earnings surprise between the top and bottom portfolios translates into an earnings-surprise difference of 9.2 cents per share. Correspondingly, the fraction of firm-years meeting or beating the analyst consensus forecast is 6.6% higher in the top portfolio than in the bottom portfolio (t = 7.52).

4.4 Narrow Misses and Narrow Beats

Our argument that analysts are concerned about inconsistent earnings surprises, and, as such, report biased earnings forecasts, yields a prediction that is unique to our framework. In particular, if our argument represents an accurate description of the true data-generating process, we should observe relatively more narrow misses, i.e., instances where the actual earnings-per-share is slightly below the consensus earnings forecast, and fewer narrow beats for firms with more pessimistic recommendations compared to firms with more optimistic recommendations. The flip-side of this argument is that we should observe relatively more narrow beats and fewer narrow misses for firms with more optimistic recommendations.

Table 5 takes this prediction to the data. Specifically, we focus on narrow-misses/beats observations (i.e., observations for which the earnings surprise variable is between -0.002 and 0.002). We then sort observations into two portfolios based on the consensus recommendation prior to the earnings announcement (buy/strong buy versus hold/underperform/sell), and we examine the fraction of firms in the high- and low-recommendation groups that report a narrow miss versus a narrow beat. Our results are robust to alternative definitions of narrow misses/beats (e.g., -/+ 0.005, -/+ 0.01, or -/+ 0.02).

As can be seen in Panel A, 33.45% of observations in the portfolio with the more pessimistic recommendations report a narrow miss in the subsequent earnings announcement; this compares to 28.42% narrow misses in the portfolio with the more optimistic recommendations. Similarly, 66.55% of observations in the portfolio with the more pessimistic recommendations report a narrow beat; this contrasts with 71.58% narrow beats in the portfolio with the more optimistic recommendations.

In Panel B, we conduct a logit regression analysis within the subsample of narrow-misses/beats observations. The dependent variable takes the value of one if the earnings surprise is between 0 and 0.002, and zero otherwise. The control variables are the same as those in Table 3. We find that the coefficient estimate on *Recommendation Level* equals 0.021 (p-value = 0.03), indicating that a one-notch increase in *Recommendation Level* translates into a 2.1% greater likelihood of narrowly beating as opposed to narrowly missing the consensus forecast. This finding is consistent with our prediction that there are more narrow beats (as opposed to narrow misses) for firms with more optimistic recommendations compared to firms with more pessimistic recommendations

4.5 Dynamics

Our analysis up to this point has been static, in the sense that we have remained silent on how analysts with bullish (bearish) recommendations arrive at the seemingly downward- (upward-) biased earnings forecasts that lead to more positive (more negative) earnings surprises.

In this subsection, we provide evidence on the dynamics at play. For each year, we sort observations into two portfolios based on the average level of recommendation made prior to the analysts' first earnings forecasts for a given period. If the consensus recommendation is a "strong buy" or "buy," the observation is assigned to the positive-recommendation portfolio. If the consensus recommendation is a "hold," "underperform," or "sell," the observation is assigned to the negative-recommendation portfolio.

The results are reported in Figure 1. First, we observe that when sorting firms based on their consensus recommendation and computing the subsequent realized price-scaled-EPS growth (i.e., $(EPS_{i,t+1}-EPS_{i,t})/P_{i,t}$), firms with a positive consensus recommendation, on average, post a realized EPS growth of 0.75%, whereas firms with a negative consensus recommendation, on average, post a realized EPS growth of -0.79%. These patterns suggest that a drop in realized EPS is considered inconsistent with a buy recommendation. Skilled analysts thus assign "buy" recommendations to firms that are expected to experience positive earnings growth and "sell" recommendations to firms that are expected to experience negative earnings growth.[5]

How do analysts' *forecasts* for $EPS_{i,t+1}$ relate to their recommendation outstanding? For firms with positive recommendations, the price-scaled growth from realized EPS to the initial *forecast* of next year's EPS is 0.83% (i.e., (*initial forecast*($EPS_{i,t+1}$) - $EPS_{i,t}$)/$P_{i,t}$ = 0.83%). Between the time of making the initial forecast and the eventual announcement of $EPS_{i,t+1}$, however, analysts walk down their forecasts such that their final forecast prior to the earnings announcement is (only) 0.35% higher from last year's realized EPS (i.e., (*final forecast*($EPS_{i,t+1}$) - $EPS_{i,t}$)/$P_{i,t}$ = 0.35%). Given that EPS tends to grow by 0.75%, this behavior translates into a positive earnings surprise, on average. In other words, analysts with a positive recommendation post initial forecasts that are very high, but they walk them down to a level that is generally beaten by actual earnings.

The opposite applies to firms with a negative recommendation. The price-scaled growth from realized EPS to the initial forecast of next year's EPS is 0.59% (i.e., (*initial forecast*($EPS_{i,t+1}$) - $EPS_{i,t}$)/$P_{i,t}$ = 0.59%). The initial forecast growth of analysts with a positive recommendation thus is higher than that of analysts with a negative recommendation (0.83% versus 0.59%). At the same time, because firms with a negative recommendation, on average, experience negative earnings growth and because analysts do not walk down their forecasts sufficiently, the consensus forecast reaches a level that is generally not met by actual earnings; firms with negative consensus recommendations thus tend to miss their consensus earnings forecast. Specifically, analysts walk down their forecasts such that their final forecast prior to the earnings announcement is 0.46% lower from last year's realized EPS (i.e., (*final forecast*($EPS_{i,t+1}$) - $EPS_{i,t}$)/$P_{i,t}$ = -0.46%). Because EPS tend to decline by 0.79%, the result is a negative earnings surprise, on average.

[5] To this end, we note that in our analyst-career-outcome regression presented in Section 3, analysts with a high fraction of "inconsistent earnings growth" (≡ earnings growth that is inconsistent with the analyst's recommendation outstanding) are subsequently associated with more negative career outcomes (results are available upon request).

4.6 Moderating Factors

To further assess the validity of our interpretation of the data, we explore potential determinants of the extent to which analysts bias their reported earnings forecasts. First, 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. High analyst coverage, thus, reduces individual analysts' incentives to report biased earnings forecasts. Second, given the nonlinearity in the impact of earnings-surprise consistency and forecast accuracy on analysts' career outcomes, we expect our proposed mechanism to be stronger for firms covered by analysts who are less concerned about being at the bottom with respect to earnings-forecast accuracy. Third, as more experienced analysts are less incented to report biased earnings forecasts to signal their quality to the market, we expect that the predictability from recommendations to subsequent earnings surprises is weaker for firms covered by analysts with a long track record.

To test our predictions, we re-estimate equation (6), but now include interaction terms between the aforementioned firm- and analyst characteristics and the firm's consensus recommendation level prior to the earnings announcement. In particular, we interact the firm's consensus recommendation (a) with the number of analysts covering the firm in question, (b) with the fraction of analysts covering the firm in question whose earnings-forecast accuracy was in the bottom quintile in the previous year, and (c) with the average years of experience of analysts covering the firm in question. We expect the coefficient estimates on all three interaction terms to be negative.

The results are reported in Panel A of Table 6. Consistent with our hypothesis, the association between the average recommendation and subsequent earnings surprise significantly decreases with analyst coverage, analysts' prior forecast inaccuracy, and analysts' experience. The coefficient estimate on the analyst-coverage interaction term is -0.012 (t = -3.11), the estimate on the past forecast inaccuracy interaction term is -0.086 (t = -2.69), and the estimate on the analyst-experience-interaction term is -0.004 (t = -2.90).

While the coefficient estimate on the analyst-coverage-interaction term is consistent with our prediction, an alternative interpretation is that high coverage simply means less biased and more efficient earnings expectations. Both explanations likely play a role.

In an attempt to assess the relative significance of each of these two views, we conduct the following test. We separate stocks into (a) those for which analysts have similar recommendations outstanding (low recommendation dispersion) and (b) those for which analysts have opposing recommendations outstanding (high recommendation dispersion).

It is unclear whether stocks in (a) should be informationally more efficient than those in (b),[6] and whether, as a result, an increase in analyst coverage should lead to more efficient earnings expectations in (a) than in (b).

In contrast, our mechanism has a clear prediction: If all analysts have a buy (sell) recommendation, analysts have a joint interest in lowering (increasing) the consensus forecast. Our mechanism thus should be very evident in the data. If, instead, analysts have conflicting recommendations outstanding, any potential downward-bias of buy-recommendation analysts would be offset by any potential upward-bias of sell-recommendation analysts. Our mechanism thus should be less evident in subset (b) than in subset (a). Consequently, analyst coverage should have less of a moderating effect on the predictability from recommendations to subsequent earnings surprises in subset (b) than in subset (a).

The results are reported in Panel B of Table 6. We subset our observations by whether or not the dispersion in recommendation is above the median of its distribution. Consistent with our mechanism being more evident in the data when analysts have a joint interest in lowering or increasing the consensus forecast, we observe that the coefficient estimate on *Recommendation Level* is stronger in the low-dispersion group than in the high-dispersion group. The coefficient estimate on the interaction term with analyst coverage also is stronger in the low-dispersion group: the estimate equals -0.016 (t = -7.63) in the low-dispersion

[6] On one hand, less information could translate into greater disagreement among analysts. On the other hand, less information could lead to herding and smaller dispersion in forecasts (Hirshleifer and Teoh 2003).

group versus -0.010 (t = -1.63) in the high-dispersion group. These patterns are perhaps easier to understand within the mechanism proposed in this study.

4.7 Earnings-Announcement-Day Returns

As a natural extension, we repeat our analysis in Tables 3 and 4, but now replace the earnings-surprise variable with earnings-announcement-day returns. The basic prediction is as follows: If investors do not fully understand analysts' incentives and take the observed earnings surprise at face value, then the average recommendation prior to an earnings announcement should positively predict earnings-announcement-day returns. If, however, investors are perfectly aware of sell-side analysts' desire to report biased earnings forecasts and respond rationally to the bias component in the earnings surprise, no such return predictability should be observed.

As reported in Panel A of Table 7, recommendation levels and subsequent earnings-announcement-day returns are positively correlated, where earnings-announcement-day returns are DGTW characteristic-adjusted returns in a three-day window around the annual earnings announcement. The coefficient estimate on the consensus recommendation level is 0.160 (t = 2.22). Controlling for known predictors of average returns in the cross section and earnings announcement day returns (Mendenhall (1991), Zhang (2006)) has virtually no impact on our results.

To better assess the economic magnitude of our finding, we employ the following calendar-time portfolio approach: We sort earnings announcements into two groups based on the consensus recommendation prior to the earnings announcement. On any given trading day, we purchase stocks that have a strong buy/buy consensus recommendation and that are announcing earnings in three trading days (i.e., we purchase stocks at time t=-3, where t=0 is the earnings announcement day or the next trading day if earnings are announced on a non-trading day; "long leg"). We short stocks that have a hold/underperform/sell consensus recommendation and that are announcing earnings in three trading days ("short leg"). Each stock is kept in the long/short-portfolio for seven trading days (i.e., until t=+3). If on any given day, there are less than or equal to 10 stocks on either the long or short side, we hold the 3-month Treasury bill instead of the long-short portfolio (this is the case for less than 5% of the trading days).

As can be seen from the first row of Panel B, this simple long-short strategy produces an average monthly DGTW-adjusted return of 1.25% (t = 1.91). We obtain similar results when computing monthly alphas from time-series regressions of long-short portfolio returns on various risk factors that are often used in the asset-pricing literature; for example, the monthly Fama and French (1993) three-factor alpha is 1.59% (t = 2.20) and the monthly Carhart (1997) four-factor alpha is 1.50% (t = 2.05). In the second row, we repeat our portfolio analysis by going long firms in the top tercile with respect to the consensus recommendation, and going short firms in the bottom tercile with respect to the consensus recommendation; the results become stronger.

4.8 Investor-Trading Behavior

Which investor group is more likely to be misled by distortions in analysts' earnings forecasts? Prior studies (Daniel et al. 2002; Schotter 2003; Malmendier and Shanthikumar 2007) suggest that retail investors, who are naïve about incentives, are particularly vulnerable to agents' strategic behavior. We therefore expect that retail investors are more likely to buy (sell) on the part of the positive (negative) earnings surprise that is induced by analysts' strategic behavior.

To test our prediction, we re-estimate equation (2), except that the dependent variable is now the small-trade imbalance (large-trade imbalance) in the three-day window around the earnings announcement, which is defined as $\frac{\text{SmallBuys}-\text{SmallSells}}{\text{SmallBuys}+\text{SmallSells}}\left(\frac{\text{LargeBuys}-\text{LargeSells}}{\text{LargeBuys}+\text{LargeSells}}\right)$. Following Barber et al. (2009), we use "small" orders (i.e., those below $5,000 in value) to gauge retail trading and "large" orders (i.e., those above $50,000 in value) to gauge institutional trading.[7] Trades are classified as buyer-/seller-initiated using the Lee and Ready (1991) algorithm. We limit our analyses to the January 1994-July 2000 period, as the

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

adoption of decimalization by the NYSE in late 2000 renders the identification of retail vs. institutional trading activities using trade-and-quote (TAQ) data impossible.

The results, presented in Table 8, indicate that retail investors submit more buy orders, while institutional investors submit more sell orders around earnings announcements for firms with more optimistic recommendations (relative to firms with more pessimistic recommendations). Specifically, the coefficient estimate on the average recommendation indicator is 0.016 (t = 3.55) for small trade imbalance and -0.200 (t = -2.03) 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.

It is important to note that the results presented in Table 8 do not imply that institutional investors can pinpoint the exact set of analysts reporting biased estimates; instead, the results correspond to "the average." In particular, the equilibrium can be characterized as follows: Analysts, whose future careers are partially dependent on their earnings-surprise consistency, have an incentive to report biased earnings forecasts. Institutional investors, anticipating that some analysts report biased earnings forecasts to ensure consistent earnings surprises, without identifying the exact ones, on average discount realized/observed earnings surprises when incorporating the information into stock prices.

5. Alternative Interpretations and Robustness Checks

5.1 Earnings Management and Forecast Guidance

Firms with more optimistic recommendations have stronger incentives to manage earnings upward, as they are penalized more severely for missing their earnings targets; these firms also have stronger incentives to guide analyst forecasts downward. In contrast, firms with more pessimistic recommendations may be more inclined to take big earnings baths. To the extent that financial analysts do not fully correct for the effect of earnings management and allow their forecasts to be guided, firm management can induce a positive correlation between recommendation level and earnings surprise.

In our regression analyses, we explicitly control for discretionary and total accruals, and we include variables intended to capture earnings-management and earnings-guidance incentives (i.e., firm size, past returns, book-to-market ratio, institutional holdings, loss, durable goods, and litigation risk).

Several additional features of the data lead us to believe that our proposed mechanism also plays a role. The earnings-management story specifically predicts large negative earnings surprises (due to earnings baths) for firms with pessimistic recommendations outstanding. We find, however, that more pessimistic recommendations are associated also with more narrow-misses. This particular finding appears to be consistent with our prediction only.

The forecast-guidance story, in general, has difficulty explaining why more pessimistic recommendations are associated with more negative earnings surprises. In an attempt to further differentiate our mechanism from the forecast-guidance story, we obtain management forecast data from *First Call* and focus on the subset where the management's earnings forecast is NOT below analysts' consensus forecast as of the management forecast date (i.e., cases where management does NOT appear to walk down analysts' consensus forecast). The results are presented in Table 9, and we observe that our main findings continue to hold even within this subset.

5.2 Currying Favor with Firm Managers

Lin and McNichols (1998), Michaely and Womack (1999), Lim (2001), and Richardson et al. (2004), among others, provide evidence that analysts tend to curry favor with management by issuing overly optimistic stock recommendations and beatable earnings forecasts. In particular, Lim (2001) provides evidence that analysts issue biased earnings forecasts to gain access to management for information. Malmendier and Shanthikumar (2009) document that "affiliated" analysts (i.e., analysts whose employer has an underwriting relation with the firm in question) tend to issue both more optimistic recommendations and more beatable earnings forecasts (relative to the consensus forecast); no such association is found for unaffiliated analysts.

The currying-favor interpretation appears to be unable to capture our full set of results. For one, the currying-favor channel has difficulty explaining the more negative earnings surprises associated with more pessimistic recommendations, as no analyst would try to irritate firm managers by issuing both a negative recommendation and an unbeatable earnings forecast.

Also, there is no structural break in our pattern pre- versus post-Global Settlement. In particular, we include an interaction term between *Recommendation Level* and a binary variable that equals one if the corresponding earnings announcement is made after the year 2003, and zero otherwise (*Post2003*). Our choice of 2003 is motivated by the "Global Settlement" reached on April 28, 2003 among the SEC, NASD, NYSE, and ten of the largest investment firms in the US to address conflicts of interest. As can be seen in Table 9, the interaction term between *Recommendation Level* and *Post2003* is both economically and statistically insignificant.

Our results also hold for the subset of analysts working for research firms that have no underwriting business (results are available upon request). Specifically, we search within the subset of IBES firms for which we have the firm name based on the IBES-Broker-Translation file. We then filter out firms that never participate in an equity offering during our sample period, as per the *Securities Data Corporation* (SDC) database. We insert the caveat that only 6% of analysts in our sample work for independent research firms and that, consequently, this subset is small by economic standards.

5.3 Analysts' Sluggish Updating of Earnings Forecasts

Another possible alternative explanation for our findings is that analysts sluggishly update their earnings forecasts. Specifically, analysts with a positive (negative) signal on a firm may issue a high (low) recommendation, yet only partially update their earnings forecasts, resulting in a subsequent true positive (negative) earnings surprise.

To assess the explanatory power of this alternative story, we exploit the feature that analysts generally issue earnings forecasts for up to five years ahead. We compute price-scaled changes in forecasts for earnings in year t+1 right after earnings in year t are announced and examine whether these forecast changes depend on analysts' recommendations. If analysts with optimistic (pessimistic) recommendations truly are sluggish, then as these analysts subsequently are truly positively (negatively) surprised by year t's earnings announcement, we may expect subsequent earnings forecast revisions to be more positive for analysts with optimistic recommendations than for those with pessimistic recommendations.

To illustrate by example, an analyst, in her report, would not only issue forecasts for earnings pertaining to fiscal year 2014 (FY2014), but also for earnings pertaining to fiscal years 2015-2018. If analysts that have a buy recommendation prior to the announcement of FY2014 are sluggish, they would only partially update their earnings forecast and be genuinely positively surprised by FY2014-earnings. These analysts should then subsequently upward-revise their earnings forecasts for fiscal years 2015-2018. Similarly, if analysts have a sell recommendation and are genuinely negatively surprised by FY2014-earnings, they should downward-revise their earnings forecasts for fiscal years 2015-2018.

In our analysis, we sort observations into two portfolios based on the average level of recommendation prior to the annual earnings announcement t. If the consensus recommendation is a "strong buy" or "buy," the observation is assigned to the positive-recommendation portfolio. If the consensus recommendation is a "hold," "underperform," or "sell," the observation is assigned to the negative-recommendation portfolio.

As before, we observe that observations in the positive-recommendation portfolio experience more positive earnings surprises (for the annual earnings announcement t) than those in the negative-recommendation portfolio. More importantly in the context of this subsection, we compare, for each observation, (a) the consensus EPS_{t+1}-forecast issued *before* the annual earnings announcement t with (b) the updated consensus EPS_{t+1}-forecast issued in the month *after* the annual earnings announcement t, and we compute the price-scaled difference.

We observe that positive-recommendation observations do NOT experience more positive forecast revisions for EPS_{t+1} than negative-recommendation observations. The difference in price-scaled forecast revisions between positive-recommendation observations and negative-recommendation observations is -0.006 (t=-0.64). The results are very similar when computing revisions for two or three months after the annual earnings announcement t.

In sum, our goal in this paper is not to reject the aforementioned channels. Rather, we hope to introduce a novel mechanism through which analysts—in an attempt to appear consistent—in fact give up earnings-forecast accuracy. Although it is difficult to pin down this channel conclusively, all of the results presented in this study are consistent with this view of analyst behavior. Moreover, while all of the aforementioned mechanisms likely play a role in explaining parts of our findings, none can explain the full set of results by itself, making our interpretation the most parsimonious.

5.4 Robustness Checks

Before concluding, we perform a couple of additional robustness checks. First, we test whether our results hold for an alternative definition of analysts' consensus earnings forecast. 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. The results shown in Table 9 reveal that taking the median rather than the mean has little impact on our results: The coefficient estimate on *Recommendation Level* equals 0.091 (t = 4.04) when taking the mean and 0.077 (t = 3.61) when taking the median.

We also analyze whether analysts distort their forecasts for quarterly earnings reports. Panel D of Table 9 shows that our findings strengthen notably at the quarterly level. In particular, we observe a coefficient estimate of 0.050 (t = 6.02) when the consensus forecast is defined as the mean forecast and an estimate of 0.045 (t = 5.52) when the consensus forecast is defined as the median forecast.

6. Conclusion

We conjecture that analysts issue biased earnings forecasts in a direction that helps avoid earnings surprises that "contradict" their outstanding stock recommendations. In particular, we hypothesize that analysts with an optimistic (pessimistic) outstanding recommendation are concerned that their firm might subsequently experience a negative (positive) earnings surprise; to hedge against such risk, analysts introduce a negative (positive) bias into their reported forecasts.

The results presented in this study are consistent with our hypothesis. We start by providing evidence that the consistency between recommendations and subsequent earnings surprises importantly determines an analyst's future career. Next, we show that firms with more optimistic recommendations prior to earnings announcements later experience more positive earnings surprises (in particular, narrow beats versus narrow misses) and earnings-announcement-day returns. Further, our documented effect is significantly stronger among firms with low analyst coverage, for analysts with high past forecast accuracy, and among analysts with shorter track records. Altogether, our paper provides novel evidence on the incentives of financial forecasters.

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Appendix 1: Analyst- vs. Firm-Level Analysis

Conducting our main analysis at the firm level has important methodological advantages. To see this, we decompose an analyst's earnings forecast error into a forecast-bias component, a true forecast-deviation component, and a true earnings surprise component:

$$
\begin{aligned}
e_{i,t+1} - \hat{e}^{rep}_{j,i,t+1} &= e_{i,t+1} - \hat{e}_{j,i,t+1} + \hat{e}_{j,i,t+1} - \hat{e}^{rep}_{j,i,t+1} \\
&= e_{i,t+1} - \bar{e}_{i,t+1} + \hat{e}_{j,i,t+1} - \hat{e}^{rep}_{j,i,t+1} + \bar{e}_{i,t+1} - \hat{e}_{j,i,t+1} \qquad \text{(A1)} \\
&= (\hat{e}_{j,i,t+1} - \hat{e}^{rep}_{j,i,t+1}) + (\bar{e}_{i,t+1} - \hat{e}_{j,i,t+1}) + (e_{i,t+1} - \bar{e}_{i,t+1}),
\end{aligned}
$$

where $e_{i,t+1}$ and $\hat{e}^{rep}_{j,i,t+1}$ are firm i's earnings per share and analyst j's reported earnings forecast, respectively. The above equation is derived by simultaneously adding and subtracting $\hat{e}_{j,i,t+1}$ and $\bar{e}_{i,t+1}$, where $\hat{e}_{j,i,t+1}$ is analyst j's true earnings forecast and $\bar{e}_{i,t+1}$ is the true consensus forecast.

The first term in the decomposition captures the forecast bias, which is the focus of our analysis. The second term in the decomposition measures the deviation of an analyst's unbiased earnings forecast from that of the other analysts covering the same stock, labeled *True Deviation*. The third term, *True Surprise*, captures the difference between the actual EPS and the true consensus forecast, which, under the assumption that analysts form rational beliefs, equals zero in expectations.

Thus, any observed correlation between earnings forecast error and recommendation level reflects both the effect of recommendation level on forecast bias (*Forecast Bias*) and the effect on the analyst's true deviation from the consensus belief (*True Deviation*). We conjecture that the latter is negative because analysts with more positive recommendations likely also have more optimistic true beliefs about future earnings than their less positive counterparts. The coefficient on recommendation in an analyst level regression, which captures the joint effect of recommendation on *Forecast Bias* and *True Deviation*, is thus biased downward. That is, while an analyst with a "strong buy" recommendation may report a negatively biased forecast relative to his true belief, because his true belief is higher than that of his peer with a "hold" recommendation on the same stock, the "strong buy" analyst's reported forecast may still be higher than that of the "hold" analyst even in the presence of strategically distorted forecasts.

The advantage of our firm-level regression is that, in aggregating earnings forecast errors to the firm level, we eliminate the *True Deviation* term as

$$\frac{1}{J}\sum_j(\bar{e}_{i,t+1} - \hat{e}_{j,i,t+1}) \rightarrow 0. \tag{A2}$$

That is, the positive association between analysts' recommendations and their relative views on subsequent earnings of any particular firm washes out at the firm level. The firm-level equation, therefore, allows for a cleaner test of the hypothesis that we propose in this study.

Appendix 2: Discretionary Accruals

We begin with total accruals, calculated as the difference between net income and net cash flow.[29] 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:

$$ACCR_{i,j,t}/TA_{i,j,t-1} = \alpha_{0j,t} + \alpha_{j,t}\left[1/TA_{i,j,t-1}\right] + \beta_{j,t}\left[\Delta REV_{i,j,t}/TA_{i,j,t-1}\right] + \gamma_{j,t}\left[PPE_{i,j,t}/TA_{i,j,t-1}\right] + \varepsilon_{i,j,t}\,, \quad \text{(A3)}$$

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:

$$NDACCR_{i,j,t} = \hat{\alpha}_{0j,t} + \hat{\alpha}_{j,t}\left[1/TA_{i,j,t-1}\right] + \hat{\beta}_{j,t}\left[\left(\Delta REV_{i,j,t} - \Delta AR_{i,j,t}\right)/TA_{i,j,t-1}\right] + \hat{\gamma}_{j,t}\left[PPE_{i,j,t}/TA_{i,j,t-1}\right]. \quad \text{(A4)}$$

Our estimate for the discretionary component in accruals is the difference between total accruals and the non-discretionary accruals component:

$$DACCR_{i,j,t} = ACCR_{i,j,t}/TA_{i,j,t-1} - NDACCR_{i,j,t}\,. \quad \text{(A5)}$$

Other studies following this approach include Teoh et al. (1998a; 1998b) and Xie (2001).

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

Figure 1
Initial Forecast-, Final Forecast-, and Actual Earnings Growth

This figure plots the *Initial Forecast-*, *Final Forecast-*, and *Actual Earnings Growth*. The sample period is 1993-2012. *Initial Forecast Growth* is the growth from realized earnings to the initial consensus forecast of next year's earnings (=(initial forecast($EPS_{i,t+1}$)-$EPS_{i,t}$)/$P_{i,t}$). *Final Forecast Growth* is the growth from realized earnings to the final consensus forecast of next year's earnings (=(final forecast($EPS_{i,t+1}$)-$EPS_{i,t}$)/$P_{i,t}$). *Actual Earnings Growth* is the realized, actual earnings growth (=($EPS_{i,t+1}$-$EPS_{i,t}$)/$P_{i,t}$). Each year, firms are sorted into the positive-recommendation portfolio if their consensus recommendations are a "Strong Buy" or "Buy", and into the negative-recommendation portfolio if their consensus recommendations are a "Hold", "Underperform" or "Sell". We compute and plot, for both portfolios, the average *Initial Forecast-*, *Final Forecast-*, and *Actual Earnings Growth*.

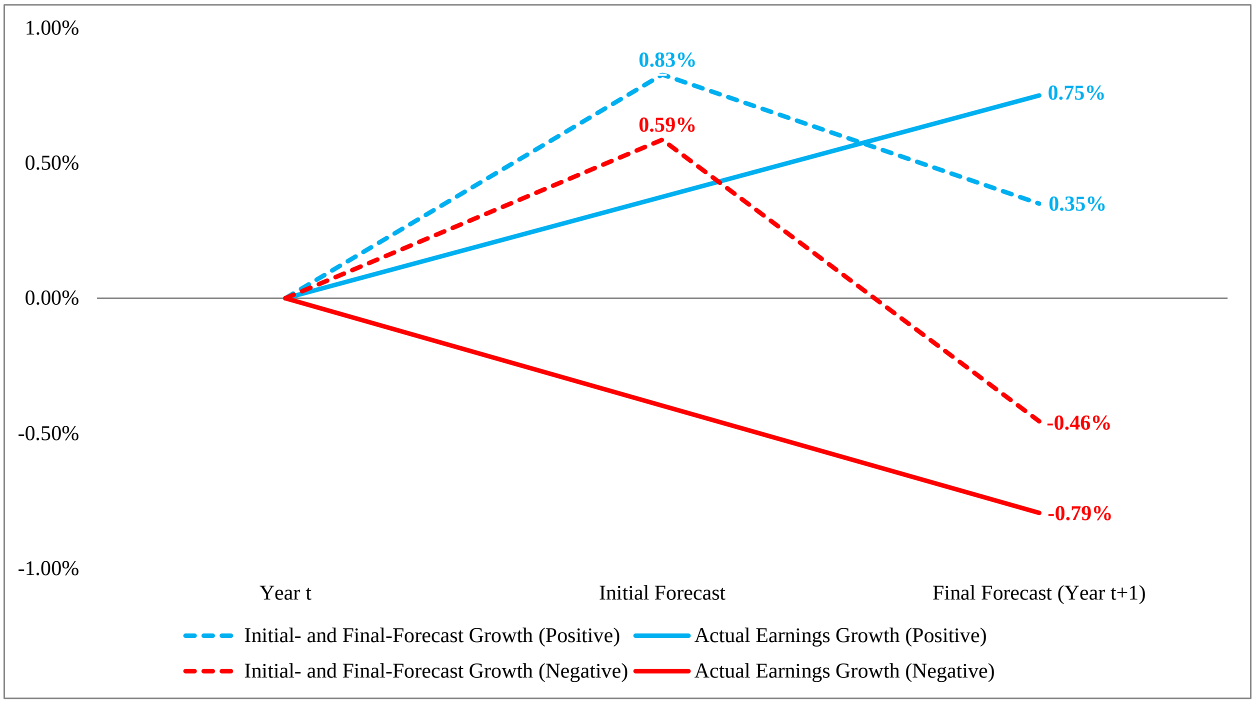

Table 1
Summary Statistics

This table presents summary statistics on variables used in this study. The sample includes all firms with valid recommendations and *EPS* forecasts in IBES over the period of 1993 to 2012. *(Actual EPS - Consensus)/Price* is the difference between the actual *EPS* and the consensus *EPS* forecast scaled by (lagged) price. *Earnings Announcement Returns* is the cumulative DGTW-adjusted return seven days around the earnings announcement [-3,+3]. *Recommendation Level* is the consensus recommendation prior to the earnings announcement. *Firm Size* is the firm's market capitalization (in million$). *Market-to-Book Ratio* is the firm's market-to-book ratio. *Past Returns* is the firm's cumulative one-year stock return prior to the earnings announcement. *Discretionary Accruals* is the firm's discretionary accruals. *Total Accruals* is the firm's change in current assets plus the change in current liabilities minus the change in cash and short-term investments and minus the change in current liabilities. *Forecast Horizon* is the average number of days between the analyst's most recent forecast report date and the earnings announcement date. *Forecast Revision* is the average difference between analysts' last *EPS* forecast and second-to-last-*EPS* forecast scaled by (lagged) price prior to the earnings announcement. *Institutional Holdings* is the firm's institutional holdings in the month prior to the earnings announcement. *Durable Goods* is a dummy variable indicating membership in a durable goods industry (three-digit SICs 150-179, 245, 250-259, 283, 301, and 324-399). *Loss* is a dummy variable indicating losses in each of the four most recent quarters. *Litigation Risk* is a dummy variable indicating membership in a high risk industry (four-digit SICs 2833-2836, 3570-3577, 3600-3674, 7370-7374, and 5200-5961).

Variables	N	Mean	Median	Std Dev
(Actual EPS - Consensus)/Price	33,757	-0.002	0.000	0.021
Earnings Announcement Returns	29,128	0.31%	0.11%	9.48%
Earnings Announcement Returns, when Actual EPS>Consensus	18,223	1.51%	1.00%	9.25%
Earnings Announcement Returns, when Actual EPS<Consensus	10,905	-1.70%	-1.40%	9.51%
Recommendation Level	33,757	3.832	3.900	0.665
Firm Size ($MM)	33,757	4,515	785	17,562
Market-to-Book Ratio	33,757	4.175	2.344	37.121
Past Returns	33,757	0.239	0.101	0.873
Discretionary Accruals	33,757	0.007	0.009	0.097
Total Accruals	33,757	-0.035	-0.040	0.129
Forecast Horizon	33,757	4.600	4.619	0.451
Forecast Revision	33,757	-0.222	-0.022	1.388
Institutional Holdings	33,757	0.658	0.683	0.267
Durable Goods	33,757	0.360	0.000	0.48
Loss	33,757	0.383	0.000	0.486
Litigation Risk	33,757	0.293	0.000	0.455

Table 2
Consistency and Career Outcomes

This table presents estimates from pooled regressions of measures of analyst career outcomes on measures of earnings-forecast accuracy, recommendation performance, and earnings-surprise consistency (on an analyst/year-level). The dependent variable is an indicator that the analyst stopped producing earnings forecasts in year *t*+1. The sample includes all analysts with valid recommendations and EPS forecasts in IBES over the period 1993 to 2012. The independent variables are: (1) *Low Consistency*, which is defined to be an indicator that the analyst's fraction of consistent earnings surprises is in the bottom quintile of its distribution (in year *t*). An earnings surprise is considered to be consistent if it is a strong buy or buy recommendation and the firm subsequently meets or beats the EPS consensus forecast OR if it is a hold, underperform or sell recommendation and the firm subsequently misses the EPS consensus forecast. In column (2), we separate *Low Consistency* into whether the fraction of consistent earnings surprises associated with strong buy/buy recommendations is in the bottom quintile of its distribution (in year *t*) and/or whether the fraction of consistent earnings surprises associated with hold/underperform/sell recommendations is in the bottom quintile of its distribution (in year *t*). (2) *Low EPS Forecast Accuracy*, which 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*. (3) *Low Recommendation Performance*, which is defined to be an indicator that the analyst's recommendation performance is in the bottom quintile of its distribution (in year *t*). Recommendation performance is computed as the difference in DGTW-adjusted returns of firms recommended be bought and firms recommended be held/sold by the analyst in question. (4) *Low Upgrade/Downgrade Performance*, which is defined to be an indicator that the analyst's upgrade/downgrade performance is in the bottom quintile of its distribution (in year *t*). Upgrade/downgrade performance is computed as the difference in DGTW-adjusted returns of firms upgraded and firms downgraded by the analyst in question. (5) *All-Star* takes the value of one if the analyst is included in the *Institutional Investor All-Star* team, and zero otherwise. (6) *Brokerage Reputation* takes the value of one if the analyst works for a prestigious brokerage house. We define prestigious brokerages as those with a Carter-Manaster rank of 9.1, and zero otherwise. (7) *Cash Flow Forecast* takes the value of one if the analyst issues cash flow forecast, and zero otherwise. (8) *Experience* is the number of years since the analyst's first earnings forecast in the I/B/E/S database. (9) *S&P 500* takes the value of one if the analyst covers at least one S&P 500 firm, and zero otherwise. Coefficient estimates are converted into marginal probabilities. We do not report the intercept. *P*-values account for clustering (at the analyst-level). *, **, *** denote significant values of $p<0.1$, $p<0.05$, and $p<0.01$, respectively.

Table 2. Continued.

Variables	Coefficient [*p*-value] (1)	(2)
Low Consistency	0.016*** [0.00]	
Low Consistency in Strong-Buy/Buy Recommendations		0.012** [0.02]
Low Consistency in Hold/Underperform/ Sell Recommendations		0.019*** [0.00]
Low EPS Forecast Accuracy	0.015*** [0.00]	0.015*** [0.00]
Low Recommendation Performance	0.005 [0.27]	0.005 [0.30]
Low Upgrade/Downgrade Performance	0.018*** [0.01]	0.018*** [0.01]
All-Star	-0.035*** [0.00]	-0.034*** [0.00]
Brokerage Reputation	-0.005 [0.35]	-0.005 [0.34]
Cashflow Forecast	-0.010** [0.03]	-0.010** [0.03]
Experience	-0.002*** [0.00]	-0.002*** [0.00]
S&P 500	-0.014 [0.44]	-0.014 [0.46]
Year Effects	Yes	Yes
Pseudo R-square	0.032	0.033
Observations	15,121	15,121

Table 3

Recommendation and Earnings Surprise – Regression Approach

This table presents estimates from pooled regressions of earnings surprises on recommendation levels (on a firm/year-level). The sample includes all firms with valid recommendations and *EPS* forecasts in IBES over the period 1993 to 2012, and for which the stock price is greater than $5. In column (1), the dependent variable is the difference between actual *EPS* and the consensus *EPS* forecast scaled by (lagged) price. In column (2), the dependent variable is an indicator that actual *EPS* is greater than or equal to the consensus *EPS* forecast. In column (3), the dependent variable is the difference between a "firm-characteristic-based *EPS* forecast" (see So 2013) and the consensus *EPS* forecast scaled by (lagged) price. In column (4), the dependent variable is an indicator that the "firm-characteristic-based *EPS* forecast" (see So (2013)) is greater than or equal to the consensus *EPS* forecast. The independent variables are: *Recommendation Level*, defined to be the firm's consensus recommendation level; lagged dependent variable; *Firm Size*, defined to be the logarithm of the firm's market capitalization as of the corresponding earnings' fiscal year end (in million$); *Market-to-Book Ratio*, defined to be the logarithm of the firm's market-to-book ratio as of the corresponding earning's fiscal year end; *Past Returns*, defined to be the firm's cumulative one-year stock return prior to the earnings announcement; *Discretionary Accruals*, defined to be the firm's discretionary accruals; *Total Accruals*, defined to be the firm's total accruals; *Forecast Horizon*, defined to be the logarithm of the average number of days between analysts' most recent forecast report date and the earnings announcement date; *Institutional Holdings*, which is the firm's institutional holdings in the month prior to the earnings announcement; *Durable Goods*, which is a dummy variable indicating membership in a durable goods industry (three-digit SICs 150-179, 245, 250-259, 283, 301, and 324-399); *Loss*, which is a dummy variable indicating losses in each of the four most recent quarters; and *Litigation Risk*, which is a dummy variable indicating membership in a high risk industry (four-digit SICs 2833-2836, 3570-3577, 3600-3674, 7370-7374, and 5200-5961). We do not report the intercept. The coefficient estimates are multiplied by 100. *T*-statistics and *p*-values account for heteroskedasticity and clustering (by year). *, **, *** denote significance at the 10%, 5%, and 1% level, respectively.

Table 3. Continued.

	Coefficient (*t*-statistic)/[*p*-value]			
	Actual EPS *versus* Consensus EPS Forecast		Characteristics-based EPS Forecast *versus* Consensus EPS Forecast	
	OLS	Logit	OLS	Logit
Variables	(1)	(2)	(3)	(4)
Recommendation Level	0.091***	0.011**	0.018***	0.008**
	(4.04)	[0.05]	(3.30)	[0.03]
Lag(Dependent Variable)	0.453*	0.023	0.001	-0.001**
	(1.70)	[0.16]	(1.58)	[0.05]
Firm Size	0.086***	0.021***	0.006***	0.032***
	(5.13)	[0.00]	(2.94)	[0.00]
Market-to-Book Ratio	0.027	0.023***	0.026***	0.048***
	(1.01)	[0.00]	(5.34)	[0.00]
Past Returns	0.125***	0.073***	-0.006	-0.008**
	(2.87)	[0.00]	(-1.65)	[0.03]
Discretionary Accruals	0.900***	-0.060	-0.118*	0.016
	(4.24)	[0.18]	(-1.82)	[0.58]
Total Accruals	0.284**	0.078**	-0.061	0.198***
	(2.07)	[0.03]	(-1.50)	[0.00]
Forecast Horizon	-0.085**	0.020	0.014*	0.013**
	(-1.97)	[0.13]	(1.87)	[0.02]
Institutional Holdings	0.338***	0.134***	-0.050***	0.038***
	(4.27)	[0.00]	(-3.42)	[0.00]
Durable Goods	0.024	0.008	0.010	-0.043***
	(1.01)	[0.36]	(1.66)	[0.00]
Loss	-0.522***	-0.164***	-0.066***	-0.248***
	(-9.32)	[0.00]	(-6.76)	[0.00]
Litigation Risk	0.005	0.080***	-0.003	-0.002
	(0.11)	[0.00]	(-0.44)	[0.64]
Year Effects	Yes	Yes	Yes	Yes
Number of Observations	29,916	29,916	27,718	27,718
Adj./Pseudo R-square	0.05	0.07	0.01	0.01

Table 4
Recommendation and Earnings Surprise – Portfolio Approach

This table presents means of portfolios formed on recommendation levels. The sample includes all firms with valid recommendations and *EPS* forecasts in IBES over the period 1993 to 2012, and for which the stock price is greater than $5. *Recommendation Level* is the firm's consensus recommendation level prior to the annual earnings announcement. We sort observations into two portfolios based on whether the consensus recommendation is a *Buy*/*Strong Buy* or a *Hold*/*Underperform*/*Sell*. *Standardized Earnings Surprise (*100)* is the difference between the actual *EPS* and the consensus *EPS* forecast scaled by (lagged) price multiplied by 100. *Indicator (Actual ≥ Forecast)* is an indicator that actual *EPS* is greater than or equal to the consensus *EPS* forecast. *T*-statistics, reported in parentheses, account for heteroskedasticity and clustering (by year). *, **, *** denote significance at the 10%, 5%, and 1% level, respectively.

	Recommendation Level		
Variables	Hold/Sell	Buy	Buy minus Hold/Sell
Recommendation Level	2.855	4.372	
*Standardized Earnings Surprise (*100)*	-0.493	-0.230	0.263*** (7.53)
Indicator (Actual ≥ Forecast)	0.555	0.621	0.066*** (7.52)

Table 5
Recommendation and Narrow Beats versus Narrow Misses

This table presents the fraction of observations by recommendation levels and the degree to which the earnings consensus forecasts are missed versus beaten. The sample includes all firms with valid recommendations and *EPS* forecasts in IBES over the period 1993 to 2012, and for which the stock price is greater than $5. *Recommendation Level* is the firm's consensus recommendation level prior to the annual earnings announcement. We sort observations into two portfolios based on whether the consensus recommendation is a *Buy*/*Strong Buy* or a *Hold*/*Underperform*/*Sell*. We report the fraction of observations for which the *Standardized Earnings Surprise* is between -0.2% and 0%, but not equal to 0% (*Narrow Miss*) and between 0% and +0.2% (*Narrow Beat*). *Standardized Earnings Surprise* is the difference between the actual *EPS* and the consensus *EPS* forecast scaled by (lagged) price. *Z*-statistics of tests on the equality of proportions are reported in parentheses. *, **, *** denote significance at the 10%, 5%, and 1% level, respectively. Panel B presents estimates from a pooled regression where the dependent variable is an indicator that actual *EPS* is greater than or equal to the consensus *EPS* forecast. The sample includes firms where the difference between actual *EPS* and the consensus *EPS* forecast is between -0.2% and 0.2% (*Narrow Miss* and *Narrow Beat*). The independent variables are: *Recommendation Level*; lagged dependent variable; *Firm Size*; *Market-to-Book Ratio*; *Past Returns*; *Discretionary Accruals*; *Total Accruals*; *Forecast Horizon*; *Institutional Holdings*; *Durable Goods*; *Loss*; and *Litigation Risk*. The independent variables are as described in Table 1. Coefficient estimates are converted into marginal probabilities. *P*-values are reported in parentheses and account for heteroskedasticity and clustering (by year). *, **, *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: Portfolio Approach

	Recommendation Level		
Variables	Hold/Sell	Buy	Buy minus Hold/Sell
Narrow Miss	33.45%	28.42%	-5.03%*** (-4.95)
Narrow Beat	66.55%	71.58%	5.04%*** (4.95)
Narrow Beat vs. Narrow Miss	33.10%	43.16%	10.06%*** (11.85)

Table 5. Continued.

Panel B: Multivariate Logit Model

Variables	Coefficients [p-value]
Recommendation Level	0.021** [0.03]
Lag(Dependent Variable)	0.369* [0.08]
Firm Size	0.028*** [0.00]
Market-to-Book Ratio	0.035*** [0.00]
Past Returns	0.068*** [0.00]
Discretionary Accruals	-0.187*** [0.00]
Total Accruals	0.046 [0.43]
Forecast Horizon	-0.008 [0.63]
Institutional Holdings	0.190*** [0.00]
Durable Goods	0.015 [0.22]
Loss	-0.139*** [0.00]
Litigation Risk	0.029** [0.02]
Year Effects	Yes
Number of Observations	16,766
Pseudo R-square	0.04

Table 6
Recommendation and Earnings Surprise – Determinants

This table presents estimates from pooled regressions of the difference between actual EPS and consensus EPS forecasts on recommendation levels (on a firm/annual-earnings-announcement-level). The sample includes all firms with valid recommendations and EPS forecasts in IBES over the period 1993 to 2012, and for which the stock price is greater than $5. The dependent variable is the difference between the actual EPS and the consensus EPS forecast, scaled by (lagged) price. In Panel A, the tabulated independent variables are: (1) *Recommendation Level*, defined to be the firm's consensus recommendation level. (2) An interaction term between *Recommendation Level* and *Coverage*, where *Coverage* is the number of analysts covering the firm in question. (3) An interaction term between *Recommendation Level* and *Low Past EPS Forecast Accuracy*, where *Low Past EPS Forecast Accuracy* is the fraction of analysts covering the firm in question whose average EPS forecast error was in the top quintile of its distribution in the previous year. (4) An interaction term between *Recommendation Level* and *Experience*, where *Experience* is the average number of years that analysts covering the firm in question have been producing earnings forecasts. Untabulated independent variables include: lagged dependent variable; *Coverage*; *Low Past EPS Forecast Accuracy*; *Experience*; *Firm Size*; *Market-to-Book Ratio*; *Past Returns*; *Discretionary Accruals*; *Total Accruals*; *Institutional Holdings*; *Durable Goods*; *Loss*; and *Litigation Risk*. In Panel B, we subset our sample by whether *Dispersion* is above or below the median of its distribution. *Dispersion* is defined as the standard deviation of recommendations across analysts covering the firm in question. The tabulated independent variable are: (1) *Recommendation Level*. (2) An interaction term between *Recommendation Level* and *Coverage*. Untabulated independent variables include: lagged dependent variable; *Coverage*; *Firm Size*; *Market-to-Book Ratio*; *Past Returns*; *Discretionary Accruals*; *Total Accruals*; *Institutional Holdings*; *Durable Goods*; *Loss*; and *Litigation Risk*. We do not report the intercept. All coefficient estimates are multiplied by 100. *T*-statistics, reported in parentheses, account for heteroskedasticity and clustering (by year). *, **, *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: Analyst Coverage, Past Forecast Accuracy, and Experience

	Coefficient (*t*-statistic)			
Variables	(1)	(2)	(3)	(4)
Recommendation Level	0.021**	0.136***	0.130***	0.030*
	(2.14)	(5.34)	(4.02)	(1.84)
*Recommendation Level *Coverage*	-0.012***			-0.004**
	(-3.11)			(-2.14)
*Recommendation Level *Low Past EPS Forecast Accuracy*		-0.086**		-0.083**
		(-2.69)		(-2.62)
*Recommendation Level *Experience*			-0.004***	-0.007
			(-2.90)	(-1.23)
Year Effects	Yes	Yes	Yes	Yes
Number of Observations	29,916	29,916	29,916	29,916
Adj. R^2	0.05	0.05	0.03	0.03

Table 6. Continued.

Panel B:Analyst Coverage and Recommendation Dispersion

Variables	Coefficient (*t*-statistic) (1) Dispersion Low	 (2) Dispersion High
Recommendation Level	0.203*** (4.71)	0.101*** (2.95)
*Recommendation Level *Coverage*	-0.016*** (-7.63)	-0.010 (-1.63)
Year Effects	Yes	Yes
Number of Observations	15,029	14,867
Adj. R^2	0.05	0.05

Table 7
Recommendation and Earnings-Announcement-Day returns

This table analyzes how annual earnings-announcement-day returns relate to recommendation levels. The sample includes all firms with valid recommendations and *EPS* forecasts in IBES over the period 1993 to 2012. Panel A presents estimates from pooled regressions (on a firm/annual-earnings-announcement-level). The dependent variable is the DGTW-adjusted return around [-3,+3]. The independent variables are as described in Table 1. We do not report the intercept. All coefficient estimates are multiplied by 100. In Panel B, we sort earnings announcements into two groups based on the consensus recommendation prior to the earnings announcement. In Row 1, we sort observations into two portfolios based on whether the consensus recommendation is a *Buy*/*Strong Buy* or a *Hold*/*Underperform*/*Sell*. In Row 2, we sort observations into tercile portfolios based on *Recommendation Level*. An observation is categorized as having a high (low) recommendation level if it is in the top (bottom) tercile of its distribution. On any given trading day, we purchase stocks that are categorized as having a high recommendation level and that are announcing earnings in three trading days (i.e, we purchase stocks at t=-3, where t=0 is the earnings announcement day or the next trading day if earnings are announced on a non-trading day; "long leg"). We short stocks that are categorized as having a low recommendation level and that are announcing earnings in three trading days ("short leg"). Each stock is kept in the long/short-portfolio (L/S-Portf) for seven trading days (i.e., until t=+3). We report monthly alphas from time-series regressions of the long-short portfolio return on excess market returns (1-Factor Alpha); excess market returns, the Small-minus-Big factor and the High-minus-Low factor (3-Factor Alpha); excess market returns, the Small-minus-Big factor, the High-minus-Low factor and the Winner-minus-Loser factor (4-Factor Alpha); as well as DGTW-adjusted returns. *T*-statistics, reported in parentheses, account for heteroskedasticity and clustering (by year in Panel A and by year-month in Panel B). *, **, *** denote significance at the 10%, 5%, and 1% level, respectively

Table 7. Continued.

Panel A: Regression Approach

Variables	Coefficient (*t*-statistic) (1)	(2)
Recommendation Level	0.160**	0.159***
	(2.22)	(2.15)
Lag(Dependent Variable)		0.525
		(0.86)
Firm Size	-0.072*	-0.120***
	(-1.84)	(-2.90)
Market-to-Book Ratio	-0.147	-0.054
	(-1.69)	(-0.53)
Past Returns	-0.048	-0.140
	(-0.60)	(-1.36)
Discretionary Accruals	-1.427**	-1.892***
	(-2.41)	(-3.08)
Total Accruals	-0.546	-0.805
	(-0.70)	(-1.00)
Forecast Horizon	-0.265	-0.303
	(-1.54)	(-1.52)
Forecast Revision	0.103***	0.096***
	(3.72)	(3.19)
Institutional Holdings	1.762***	1.663***
	(7.43)	(6.13)
Durable Goods	-0.064	-0.078
	(-0.77)	(-0.77)
Loss	-1.459***	-1.471***
	(-8.58)	(-7.94)
Litigation Risk	0.382**	0.444***
	(2.47)	(2.48)
Year Effects	Yes	Yes
Number of Observations	27,694	23,547
Adj. R^2	0.01	0.01

Table 7. Continued.

Panel B: Calendar-Time Portfolio Approach

Categorization	1-Factor Alpha of L/S-Portf.	3-Factor Alpha of L/S-Portf.	4-Factor Alpha of L/S-Portf.	DGTW-Adjusted Returns of L/S-Portf.
High Recommendation Stocks = *Strong Buy/Buy*	1.50%**	1.59%**	1.50%**	1.25%*
Low Recommendation Stocks = *Hold/Underperf/Sell*	(2.15)	(2.20)	(2.05)	(1.91)
High Recommendation Stocks = Top Tercile,	1.65%**	1.63%**	1.56%**	1.57%**
Low Recommendation Stocks = Bottom Tercile	(2.53)	(2.46)	(2.29)	(2.46)

Table 8
Recommendation and Trading around Earnings Announcements

This table presents estimates from pooled regressions of trade imbalances on recommendation levels (on a firm/annual-earnings-announcement-level). The sample includes all firms with valid recommendations and *EPS* forecasts in IBES over the period 1993:01 to 2000:07. In column (1), the dependent variable is the dollar proportion of *small* buyer-initiated trades vs. *small* seller-initiated trades three days around the annual earnings announcement scaled by (lagged) trading volume. In column (2), the dependent variable is the dollar proportion of *large* buyer-initiated trades vs. *large* seller-initiated trades three days around the earnings announcement scaled by (lagged) trading volume. 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 as described in Table 1. We do not report the intercept. *T*-statistics, reported in parentheses, account for heteroskedasticity and clustering (by year). *, **, *** denote significance at the 10%, 5%, and 1% level, respectively.

	Coefficient (*t*-statistic)	
Variables	% Small Buyer-Initiated Trades (1)	% Large Buyer-Initiated Trades (2)
Recommendation Level	0.016***	-0.200**
	(3.55)	(-2.03)
Firm Size	0.022***	0.384***
	(9.10)	(8.22)
Market-to-Book Ratio	0.021***	-0.014
	(6.12)	(-0.10)
Past Returns	0.022***	0.151***
	(5.45)	(3.20)
Discretionary Accruals	0.026**	-0.115
	(2.05)	(-0.51)
Total Accruals	0.015	-0.012
	(1.37)	(-0.67)
Forecast Horizon	0.005	0.001
	(0.48)	(0.56)
Forecast Revision	0.009**	0.012**
	(2.11)	(2.33)
Institutional Holdings	-0.032***	0.056***
	(-5.12)	(6.33)
Durable Goods	0.005*	0.008
	(1.88)	(0.82)
Loss	-0.001	-0.005
	(-0.98)	(-1.24)
Litigation Risk	-0.008	-0.009
	(-1.19)	(-0.81)
Year Effects	Yes	Yes
Number of Observations	9,846	9,912
Adj. R^2	0.05	0.02

Table 9
Robustness Checks

This table presents estimates from pooled regressions of the difference between actual *EPS* and consensus *EPS* forecasts on recommendation levels. The sample includes all firms with valid recommendations and *EPS* forecasts in IBES over the period 1993 to 2012, and for which the stock price is greater than $5. The dependent variable is the difference between the actual *EPS* and the consensus *EPS* forecast, scaled by (lagged) price. The independent variables are as described in Table 3. The coefficient estimates are multiplied by 100. *T*-statistics, reported in parentheses, account for heteroskedasticity and clustering (by year). *, **, *** denote significance at the 10%, 5%, and 1% level, respectively.

	Coefficient (*t*-statistic)	
Variables	(1) Mean Forecast	(2) Median Forecast
Panel A: Annual EPS		
Recommendation Level	0.091*** (4.04)	0.077*** (3.61)
Panel B: Annual EPS – Subsample for which Mgmt Forecast>Consensus Forecast		
Recommendation Level	0.108*** (4.16)	0.090*** (3.77)
Panel C: Annual EPS - Global Settlement		
Recommendation Level	0.105*** (2.75)	0.098*** (2.72)
*Recommendation Level * Post2003*	-0.029 (-0.63)	-0.039 (-0.95)
Panel D: Quarterly EPS		
Recommendation Level	0.050*** (6.02)	0.045*** (5.52)