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Do Sell-Side Stock Analysts Exhibit Escalation of Commitment?

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Abstract

This paper presents evidence that when an analyst makes an out-of-consensus forecast of a company's quarterly earnings that turns out to be incorrect, she escalates her commitment to maintaining an out-of-consensus view on the company. Relative to an analyst who was close to the consensus, the out-of-consensus analyst adjusts her forecasts for the current fiscal year's earnings less in the direction of the quarterly earnings surprise. On average, this type of updating behavior reduces forecasting accuracy, so it does not seem to reflect superior private information. Further empirical results suggest that analysts do not have financial incentives to stand by extreme stock calls in the face of contradictory evidence. Managerial and financial market implications are discussed.

Keywords

escalation of commitment, stock market, updating, behavioral economics

Disciplines

Behavioral Economics | Finance and Financial Management | Marketing | Other Social and Behavioral Sciences

Do Sell-Side Stock Analysts Exhibit Escalation of Commitment?

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This paper presents evidence that when an analyst makes an out-of-consensus forecast of a company's quarterly earnings that turns out to be incorrect, she escalates her commitment to maintaining an out-of-consensus view on the company. Relative to an analyst who was close to the consensus, the out-of-consensus analyst adjusts her forecasts for the current fiscal year's earnings less in the direction of the quarterly earnings surprise. On average, this type of updating behavior reduces forecasting accuracy, so it does not seem to reflect superior private information. Further empirical results suggest that analysts do not have financial incentives to stand by extreme stock calls in the face of contradictory evidence.

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[1] The authors contributed equally to this paper.

I. Introduction

By synthesizing and interpreting data on publicly traded firms, sell-side stock analysts act as information conduits in financial markets. Their opinions influence stock prices (Brown, Foster, and Noreen (1985)) and may be viewed as "a natural upper bound to the quality of the earnings forecasts of less sophisticated agents" (De Bondt and Thaler (1990)). Observing analysts can provide some insight into the processes by which financial market participants form their beliefs about the future prices of securities. To better understand the factors that may lead to systematic errors in investors' forecasts of asset returns, a task that is particularly important in light of the recent financial crisis, it is natural to study systematic biases in analysts' decision-making. Previous research has demonstrated that sell-side stock analysts display overconfidence (Hilary and Menzly (2006); Friesen and Weller (2006)) as well as a tendency to make upwardly biased forecasts (DeBondt and Thaler (1990)), to exhibit cognitive dissonance (Friesen and Weller (2006)), and to overreact to positive information but underreact to negative information (Easterwood and Nutt (1999)). In this paper we explore the possibility that analysts are widely susceptible to another behavioral bias: the tendency to irrationally escalate commitment to a previously selected course of action.

The psychology literature on "escalation bias" suggests that people often become irrationally overcommitted to a previously selected course of action when they feel the need to justify past decisions that have had bad outcomes (Staw (1976)) or when they feel that they have already made large investments in past decisions (Arkes and Blumer (1985)). We argue that if an analyst's views on a firm differ dramatically from those of her peers, she may feel pressure to invest more time and energy than usual supporting her opinion. Once an analyst has invested in such an opinion, escalation bias may make her particularly reluctant to back down from that position, even in the presence of contradictory information.

This paper presents evidence that analysts can indeed become committed to their out-of-consensus views in a way that decreases their responsiveness to firms' financial disclosures. We document this pattern of stubbornness among extreme forecasters using Institutional Brokers' Estimate System (I/B/E/S) data from January 1990 to March 2008. We find that when a company announces a quarterly earnings surprise relative to the consensus (median) forecast, analysts whose forecasts differed meaningfully from consensus in the wrong direction update their forecasts for subsequent quarters less in the direction of the earnings surprise than analysts whose forecasts were closer to consensus, controlling for analyst-firm fixed effects.

To illustrate this finding with an example, consider two analysts, A and B, covering company XYZ. Imagine that analyst A has estimated that this company will achieve earnings per share (EPS) of \$1.10 for the first quarter of its fiscal year and \$4.40 for the entire year, while analyst B has estimated that the same company will achieve EPS of \$1.00 for fiscal quarter one and \$4.00 for the entire year.[2] Analysts other than A and B cover company XYZ, and the median EPS estimate for the company's first fiscal quarter is \$1.00. Now imagine that XYZ's earnings announcement for the quarter reveals

[2] For ease of exposition, this example discusses earnings in units of dollars per share. However, throughout our analysis, we scale all EPS variables by the firm's stock price per share as of the end of the prior fiscal year.

that its actual first quarter EPS was $0.90, proving that the estimate of analyst A was off in the wrong direction relative to consensus. On average, we find that the extreme analyst (analyst A) adjusts her EPS estimate for the remaining quarters less in the direction of the earnings surprise than the analyst with a forecast matching the consensus (analyst B). For instance, analyst A might update her EPS estimate for the fiscal year to $4.19 from $4.40, a change of just $0.01 to her forecast for the remaining quarters in the direction of the earnings surprise after accounting for the mechanical incorporation of her $0.20 miss of Q1 EPS, while analyst B might update her EPS estimate for the fiscal year to $3.84 from $4.00, a change of $0.06 to her forecast for the remaining quarters in the direction of the surprise after accounting for the mechanical incorporation of her $0.10 miss of Q1 EPS. See Figure 1 for a pictorial representation of this example.

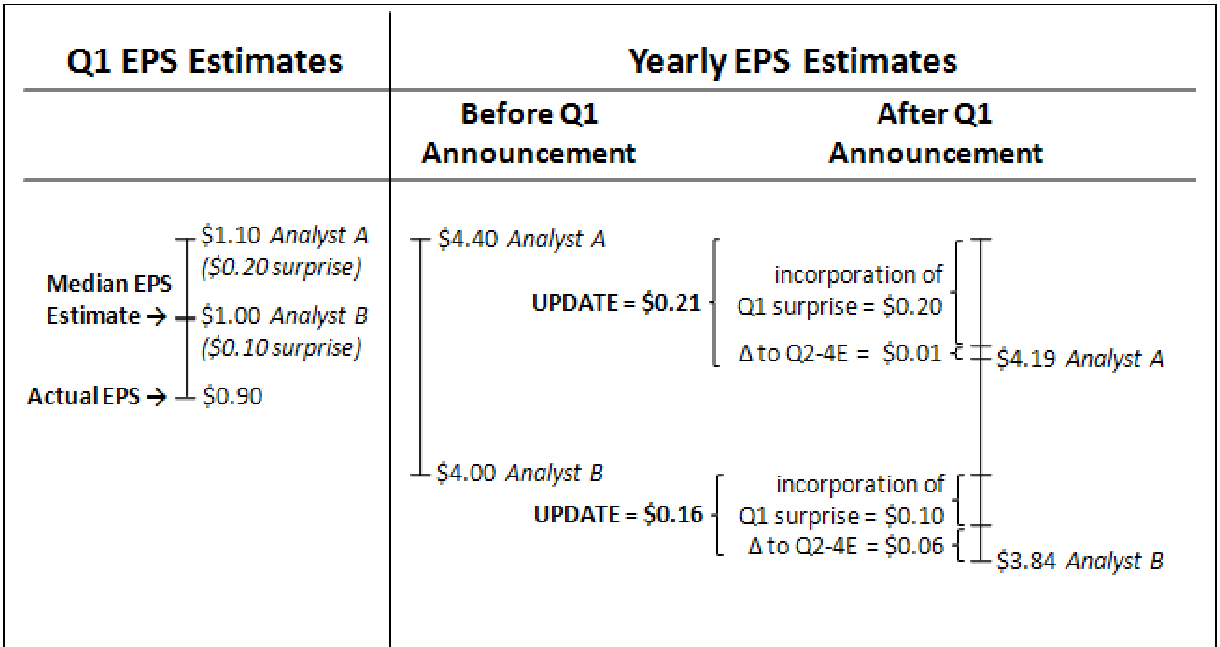

Figure 1. Pictorial Representation of Illustrative Example.[2]
Analysts other than A and B are not shown.

Two further features of the example are noteworthy. First, analyst A differs from analyst B both in that analyst A is out of consensus and in that analyst A has a larger forecast error for the first quarter. In our econometric analysis, however, we control for differences in the sizes of quarterly forecast errors, allowing us to focus on how the updating behavior of out-of-consensus analysts differs from that of analysts at consensus. Second, as illustrated in the example, our predictions and results concern analysts whose quarterly earnings forecasts deviate from the median quarterly forecast in the direction *opposite* from announced quarterly earnings. We refer to analysts in this situation as "incorrect out-of-consensus analysts" and refer to their forecasts as "incorrect out-of-consensus forecasts." We do not focus on analysts whose quarterly earnings forecasts deviate from the median quarterly forecast in the *same* direction as announced quarterly earnings, since analysts in this situation have a strong rationale for stubbornly maintaining their views on a company.

An analyst who issues an incorrect out-of-consensus quarterly EPS forecast for a firm but who subsequently persists in maintaining her extreme view of the company may appear to have high-quality information that her peers do not have. However, we find that the type of escalation or stubbornness described above reduces the accuracy of analysts' forecasts, suggesting that our results are not driven by superior private information. We document this reduction in forecast accuracy associated with stubborn incorrect extremism by showing that analysts' actual yearly EPS forecasts are less accurate, on average, than hypothetical yearly EPS forecasts we construct. These hypothetical forecasts are the forecasts that incorrect extreme analysts would produce if they updated their yearly earnings estimates in response to an earnings surprise like analysts whose estimates matched the consensus. Indeed, we find evidence that incorrect extreme analysts would be even more accurate if their forecast updates were *more* responsive to earnings surprises than the forecast updates of analysts with consensus estimates.

Of course, even in the face of contradictory evidence, an incorrect out-of-consensus analyst may rationally choose to maintain her view on a company if there are rewards associated with doing so. This is a potential explanation for analyst escalation. Because analyst payoffs are not purely a function of forecast accuracy, incorrect out-of-consensus analysts may persist in maintaining their views in order to demonstrate their conviction and/or consistency. An analyst who frequently changes her mind about a company she covers may be perceived as lacking an understanding of the company. On the other hand, an analyst who sticks to an out-of-consensus view may receive attention from investors because of her unique perspective and may also be more credible the next time she makes an out-of-consensus forecast. McKenzie and Amin (2002) find experimental support for the possibility that forecasters who make extreme predictions may be deemed more competent, even when they turn out to be incorrect. An analyst who is considered more competent is probably better able to generate trading commissions for her brokerage house and, in turn, increase her own compensation (Cowen, Groysberg, and Healy (2006)). Alternatively, if the rewards for making out-of-consensus forecasts that turn out to be correct are sufficiently large relative to the costs of making out-of-consensus forecasts that turn out to be incorrect, it may be in the best interest of an analyst to "swing for the fences" by maintaining an out-of-consensus forecast even in the face of contradictory evidence.

In this paper, we empirically explore the roles that the two broad explanations described above – biases and incentives – may play in generating stubbornness. To do this, we link our data on analyst forecasts to the list of analysts who were recognized as members of *Institutional Investor* magazine's "All-America Research Team" from 1998 to 2007. Groysberg, Healy, and Maber (2008) show that receipt of an "All-America" designation, which is determined by a survey of analysts' clients, is a good predictor of analyst compensation, so we use the designation as a measure of analyst rewards. Controlling for factors such as past "All-America" designations, we find that earning a higher level of *Institutional Investor* recognition is negatively correlated with a variable we construct to capture an analyst's tendency to stubbornly stick to incorrect extreme EPS forecasts. This suggests that incentives created by analysts' clients punish the type of escalation behavior we detect, and this is the case even after controlling for the average accuracy of an analyst's forecasts.

Our findings shed light on a source of systematic error in financial market participants' estimates of the future performance of publicly traded firms. In particular, we document a pattern whereby market participants maintain inaccurate beliefs even in the face of contradictory evidence. Thus, our work provides support for the underpinnings of models that rely on disagreement among investors to explain asset pricing anomalies.[3] To the extent that our findings regarding incomplete updating by out-of-consensus forecasters are indicative of a more general bias in investors' updating decisions, this research also suggests a mechanism by which asset prices may deviate from fundamental values in a persistent fashion.

This paper proceeds as follows. Section II reviews the relevant literature on escalation bias and analyst forecast updates. In Section III, we describe the construction of our data set, and in Section IV, we present analyses that measure analyst stubbornness as well as the impact of this stubbornness on analysts' forecasting accuracy. Section V discusses the factors that may drive analyst stubbornness, and Section VI concludes.

[3] See Hong and Stein (2007) for a brief overview of this literature.

II. Relevant Literature

A. Escalation Bias

This paper builds on a large prior literature examining escalation bias. Escalation bias was first identified in a laboratory study by Barry Staw (1976) in which participants were found to invest significantly more in an initiative that had performed poorly in the past when they were responsible for starting the initiative than when someone else was responsible for it. This differential was not present for initiatives with strong past performance. Staw concluded that self-justification leads people to escalate commitment to unsuccessful past decisions. In other words, individuals often find it easier to ignore the negative results of their past choices than to admit their mistakes and move on.

Following up on Staw's findings, Caldwell and O'Reilly (1982) determined that after choosing a course of action, people will selectively filter future information both for themselves and for others in a way that makes their chosen course appear wiser than alternatives, a pattern that can lead to escalation of commitment. Arkes and Blumer (1985) identified what they called the "sunk cost effect," a term that describes people's tendency to increase their probability of continuing an endeavor the more time, money, or effort they have invested in that endeavor in the past. According to this line of work, escalation bias is a manifestation of the sunk cost effect: after investing in a course of action, people will irrationally escalate their commitment to that course of action because they focus on sunk costs.

In addition to the research mentioned above and many other laboratory experiments, several studies of escalation bias have been conducted in field settings. In a paper published in 1988, F. David Schoorman found evidence of escalation bias among supervisors in a large, public sector organization. He observed that supervisors who are involved in a decision to hire or promote an employee and support that decision have a tendency to evaluate the subsequent performance of the employee in question more positively than others. Similarly, when supervisors participate in a hiring or promotion decision and disagree with the eventual decision, they tend to evaluate the subsequent performance of the employee in question more negatively than others.

In another field study of this phenomenon, Barry Staw and Ha Hoang (1995) found evidence that National Basketball Association (NBA) teams suffer from escalation bias. The authors observed that NBA teams escalate their commitment to players who were higher draft picks. According to Staw and Hoang, after controlling for the performance, injuries, trade status, and position of a given basketball player, the player's draft order still has a strong effect on his career length in the NBA, his playing time, and the time before his team trades him.

Staw, Barsade and Koput (1997) found further evidence of escalation bias in the field when they conducted a longitudinal study of bank executives and problematic loans during the 1980s. In a sample of 132 California banks over a 9-year period, the authors found that bank executive turnover predicted both provision for loan losses and the write-off of bad loans but not vice versa.

This paper extends previous field studies of escalation bias by demonstrating that this bias is persistent even among a group of individuals who are subjected to frequent feedback and strong incentives discouraging irrational behavior. To the best of our knowledge, this paper also provides the first evidence that escalation bias may affect the judgment of financial market participants, a group of decision-makers who are of particular interest because of their collective ability, as demonstrated in the recent financial crisis, to generate massive economic dislocation through erroneous forecasts of future asset performance.

B. Analyst Updating

In addition to extending previous research on escalation bias, this paper builds upon prior studies of how analysts update their earnings forecasts. Mendenhall (1991), Abarbanell and Bernard (1992), Zitzewitz (2001), and Friesen and Weller (2006) find that analysts generally fail to fully update their forecasts in response to earnings announcements. Our contribution is to demonstrate that the tendency to underweight the information contained in earnings announcements is particularly strong among incorrect out-of-consensus stock analysts, who exhibit more stubbornness than others when it comes to updating their predictions.

Zitzewitz (2001) and Bernhardt, Campello, and Kutsoati (2006) also find that the best predictor of future extremism in analyst forecasts is past extremism. We extend these results by showing that extremism persists when out-of-consensus analysts learn that they have made an incorrect earnings forecast, and that this pattern is detrimental to analysts' accuracy and probability of receiving awards.

Our findings are also related to past research on analysts' career concerns. Theoretical work on "herding" has pointed out that decision-makers may rationally disregard their own private information and imitate the decisions of others in order to protect their reputations in the labor market (Scharfstein and Stein (1990)).[4] Consistent with the theory, empirical evidence indicates that analysts do indeed herd, both in their forecasts and in their investment recommendations (De Bondt and Forbes (1999); Graham (1999); Hong, Kubik, and Solomon (2000); Welch (2000)).[5] Because analysts tend to herd, an analyst who deviates from the herd with an out-of-consensus prediction may be acting on a strong private signal. Clement and Tse (2005) find that out-of-consensus forecasts are in fact more accurate than other forecasts, and Jegadeesh and Kim (2008) find that out-of-consensus recommendations receive stronger stock price reactions. Like these authors, we examine the earnings estimates made by out-of-consensus analysts, but we focus in particular on the estimates of *incorrect* out-of-consensus forecasters. We address a question related to those investigated by Clement and Tse and by Jegadeesh and Kim: when an analyst makes an out-of-consensus prediction that initially proves incorrect (as judged by quarterly forecast accuracy), how does she react? We document that analysts in this position update their subsequent forecasts stubbornly and that this stubbornness reduces forecast accuracy.

Evidence has also been presented (Chen and Jiang (2005)) that analysts generally overweight private information when updating their forecasts and that they do so more when they are issuing favorable estimates relative to the consensus and less when they are issuing unfavorable estimates relative to the consensus. Furthermore, these patterns

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[4] Trueman (1994) presents a model of herding that applies directly to the context of analyst forecasts. See Graham (1999) as well. Herding is also a feature of models of informational cascades (Banerjee (1992); Bikhchandani, Hirshleifer, and Welch (1992)).

[5] For related results, see Stickel (1990). Cote and Sanders (1997) provide experimental evidence of herding in earnings forecasts. Research on herding in other contexts can be found in, for example, Chevalier and Ellison (1999).

are consistent with analyst rewards (Chen and Jiang (2005)). We demonstrate that analyst escalation occurs when extreme analysts issue optimistic or pessimistic estimates relative to consensus, and we find evidence that the type of stubbornness we detect is inconsistent with analyst rewards.

III. Data

The data we use to conduct our analyses were obtained from the Institutional Brokers' Estimate System (I/B/E/S). I/B/E/S tracks the quarterly and yearly earnings per share (EPS) forecasts for publicly traded companies that are published by thousands of sell-side stock analysts around the world. In the analyses presented in this paper, we rely on data from the I/B/E/S Detail Earnings Estimate History File for the period January 1990 to March 2008. We merge this data with stock price data from the Center for Research in Security Prices (CRSP) in order to scale all of the EPS variables in the I/B/E/S data set by the inverse of their stock price as of the previous fiscal year's end. We drop all observations of "penny stocks" (stocks with prices of less than $1.00). In addition, to obtain a meaningful measure of consensus, we require that a stock be covered by at least three analysts in a given quarter to be included in our data set.[6] Our final data set includes estimates made by 6,202 analysts who cover a total of 3,513 unique firms and work for 432 different brokerage houses. An average analyst in our data set publishes 5.16 earnings forecast updates per year (standard deviation = 5.36) and remains in our sample for 4.07 years (standard deviation = 3.38 years).

[6] Note that 79% of observations in our data set involve stocks covered by more than three analysts.

The I/B/E/S data allow us to track the forecasts made by a given analyst about a given firm over time. We are interested in examining analysts' last quarterly and yearly EPS forecasts before a firm's first, second, or third quarter earnings are announced, as well as their first new, updated yearly EPS forecasts after each of those quarterly earnings announcements. In total, we observe 130,499 paired sets of EPS estimates made by the same analyst for the same firm before and after a first, second, or third quarter earnings announcement.

We construct several variables to employ in our analyses of analyst stubbornness (Appendix A provides a list of all variables discussed in this paper with mathematical definitions and brief descriptions). First, we create the variable *UPDATE* to measure how much an analyst updates her yearly EPS forecast in response to a firm's announcement of its actual earnings for the first, second or third quarter of that fiscal year. Because our analyses examine both positive and negative earnings surprises relative to the consensus earnings estimate (which we define as the median EPS estimate across analysts covering a given stock), we define this variable in such a way that its value is increasing as an analyst updates her estimate more in the direction of an earnings surprise. Thus, when a quarter's actual earnings exceed the consensus estimate, *UPDATE* is the new yearly EPS estimate minus the old, and an increase to an analyst's yearly EPS estimate to accommodate a positive earnings shock is recorded as a positive update. However, when a quarter's actual earnings are less than or equal to the consensus estimate, *UPDATE* is negative one times the new yearly EPS estimate minus the old, so a reduction in an analyst's yearly EPS estimate to accommodate a negative earnings shock is recorded as a positive update.[7] Returning to the example in Figure 1, *UPDATE* for analyst A would be equal to \$0.21 divided by the firm's per-share stock price, and *UPDATE* for analyst B would be equal to \$0.16 divided by the firm's per-share stock price.

We next construct a variable to measure how far off an analyst's EPS estimate is from a company's actual, reported EPS for a given quarter: *EPS_SURPRISE*. *EPS_SURPRISE* is defined to correspond to the sign convention adopted for *UPDATE,* so it is the difference between a company's actual EPS and an analyst's quarterly EPS forecast when actual earnings exceed the consensus estimate, and it is negative one times this difference otherwise. This signing convention ensures that if *EPS_SURPRISE* and *UPDATE* are both positive, an analyst updated her forecast of the fiscal year's EPS in the same direction as the earnings surprise relative to her own pre-announcement EPS forecast for the quarter in question. Again returning to the example in Figure 1, *EPS_SURPRISE* for analyst A would be equal to \$0.20 divided by the firm's per-share stock price, and *EPS_SURPRISE* for analyst B would be equal to \$0.10 divided by the firm's per-share stock price.

To measure the degree of an analyst's extremism, we construct two variables. The first, *INCORRECT_DEV,* measures an analyst's degree of incorrect extremism, which we define as the maximum of zero and the number of standard deviations

[7] We acknowledge it is somewhat arbitrary that we group observations for which actual quarterly earnings equal the consensus with observations for which actual quarterly earnings are less than the consensus when defining *UPDATE*. However, we perform our analyses on a subsample of estimates for which actual quarterly earnings are strictly greater than consensus and a subsample for which actual quarterly earnings are strictly less than consensus, and our results are not driven by this aspect of the definition (see Tables III and IV).

separating the analyst's estimate from consensus if the analyst's estimate is off from consensus in the wrong direction relative to the earnings surprise. The second, *CORRECT_DEV,* measures an analyst's degree of correct extremism, which we define as the maximum of zero and the number of standard deviations separating the analyst's estimate from consensus if the analyst's estimate is off from consensus in the right direction relative to an earnings surprise. In the example in Figure 1, analyst A's Q1 estimate deviates from the median Q1 estimate by $0.10 in the opposite direction from reported Q1 earnings, so *INCORRECT_DEV* would be $0.10 divided by the standard deviation of analysts' Q1 estimates for firm XYZ, while *CORRECT_DEV* would be zero. Because analyst B's Q1 estimate exactly matches the median Q1 estimate, both *INCORRECT_DEV* and *CORRECT_DEV* would be zero for analyst B. Note that some previous research has quantified analyst extremism by calculating the absolute deviation separating an analyst's estimate from the consensus without standardizing this distance (see, for example, Hilary and Menzly (2006) and Hong, Kubik, and Solomon (2000)). The findings we present are robust to this alternative definition of analyst extremism, but we believe our measure of analyst extremism is superior for our purposes, as it captures how extreme a given analyst's estimates are relative to the general dispersion of estimates for a given stock.

To measure the accuracy of an analyst's adjusted yearly EPS estimate, we create a variable called *ERROR*. *ERROR* is defined as the absolute value of the difference between an analyst's new (stock-price-normalized) yearly EPS estimate following a first, second, or third quarter earnings announcement and the actual (stock-price-normalized) yearly EPS announced by the company. For analyst A in the Figure 1 example, *ERROR* would be equal to the absolute difference between the analyst's adjusted yearly forecast of $4.19 and the firm's actual yearly EPS, divided by the firm's per-share stock price as of the end of the previous fiscal year. For analyst B, *ERROR* would be equal to the absolute difference between $3.84 and the firm's actual yearly EPS, divided by the firm's per-share stock price as of the end of the previous fiscal year.

These are the primary variables of interest in our analysis. If a variable that takes on positive and negative values falls below the 1^{st} or above the 99^{th} percentile of its distribution, we drop that observation from our data set. Similarly, if a variable that takes on only non-negative values falls above the 99^{th} percentile of its distribution, we drop that observation from our data set. This trimming of the data set helps ensure that outliers do not exert too much influence on our results. Summary statistics provided earlier in this section were reported after the trimming of these outliers, and Table I presents additional summary statistics from the trimmed data set. Note that typical earnings surprises and earnings estimate updates are quite small.

Table I

Summary Statistics

Summary statistics for the stock-price adjusted variables created from our I/B/E/S data set, after outliers were removed (earnings variables are reported in units of dollars of earnings per dollar of stock price).

	All Surprises					**Positive Surprises**					**Negative Surprises**				
Variable	**Mean**	**Median**	**Std. dev.**	**Q3**	**Q1**	**Mean**	**Median**	**Std. dev.**	**Q3**	**Q1**	**Mean**	**Median**	**Std. dev.**	**Q3**	**Q1**
UPDATE	0.00226	0.00087	0.00576	0.00300	0.00004	0.00123	0.00067	0.00395	0.00214	0.00003	0.00387	0.00154	0.00745	0.00498	0.00023
EPS_SURPRISE	0.00193	0.00068	0.00469	0.00224	0.00010	0.00144	0.00069	0.00369	0.00187	0.00020	0.00301	0.00114	0.00583	0.00364	0.00021
INCORRECT_DEV	0.27834	0.00000	0.51819	0.34314	0.00000	0.29644	0.00000	0.52923	0.40976	0.00000	0.32453	0.00000	0.54672	0.49536	0.00000
CORRECT_DEV	0.29031	0.00000	0.52522	0.38633	0.00000	0.31539	0.00000	0.54683	0.46980	0.00000	0.33034	0.00000	0.53958	0.52223	0.00000
ERROR	0.00642	0.00166	0.02305	0.00523	0.00049	0.00469	0.00142	0.01379	0.00428	0.00043	0.00901	0.00224	0.03178	0.00727	0.00065
	(N=130,499)					**(N=67,166)**					**(N=50,481)**				

IV. Are Analysts Stubborn to the Detriment of Their Accuracy?

Now that we have measures of how much analysts adjust their yearly earnings forecasts in response to a quarterly earnings announcement, the extent to which analysts' quarterly earnings estimates are incorrect, and the extent to which analysts are extremists, we evaluate whether analysts who have made extreme, incorrect forecasts exhibit stubbornness when they receive new information in the form of an earnings announcement. We also evaluate how the updating behavior of analysts who have made incorrect extreme forecasts affects their forecasting accuracy.

In our analyses, we explore whether our results hold for the periods before and after the SEC's 2002-2003 investigation of conflicts of interest in equity research, which found that analysts were inappropriately influenced by the investment banking branches of their firms. Because "Chinese walls" have since been erected within firms to prevent analysts from communicating with investment bankers and to prevent analysts from receiving compensation based on investment banking fees, the nature of analysts' incentives has almost certainly changed, and we conduct separate analyses to make sure that our results are not driven solely by one incentive regime or the other.

A. Evidence of Analyst Stubbornness

In this section, we ask whether analysts who have made incorrect extreme forecasts relative to their peers covering the same firm update more or less than others in response to an earnings surprise. To capture the relationship between an analyst's adjustment to her yearly earnings forecast and the surprise she receives in the form of an earnings announcement for a given quarter, we rely on the following ordinary least squares (OLS) regression specification:

$$\begin{aligned} UPDATE_{aft} = \; & \beta_1 EPS\_SURPRISE_{aft} + \beta_2 INCORRECT\_DEV_{aft} \\ & + \beta_3 CORRECT\_DEV_{aft} + \beta_4 INCORRECT\_DEV_{aft} * EPS\_SURPRISE_{aft} \\ & + \beta_5 CORRECT\_DEV_{aft} * EPS\_SURPRISE_{aft} + \beta_6 Q1_t + \beta_7 Q2_t + \alpha_{af} + \varepsilon_{aft} \end{aligned}$$

where a indexes analysts, f indexes firms, and t indexes the time period in question and α_{af} is an analyst-firm fixed effect.

To be included in these analyses, an analyst must have updated her estimate of a firm's quarterly EPS at some point in the year prior to the firm's quarterly EPS announcement, and an analyst must have updated her estimates of a firm's future quarterly earnings at some point during the quarter following the firm's EPS announcement.

Table II presents estimates from the OLS regression described above. Column (1) presents these results when the full analyst-estimate data set is analyzed, while columns (2) and (3) present the results using subsets of the data including only estimates made, respectively, before and after the SEC's 2002-2003 investigation into analyst conflicts of interest. The coefficients presented in column (1) of Table II indicate that for every additional ten basis points of the stock price separating an analyst's EPS estimate for a given company in a given quarter from that quarter's actual EPS, an analyst updates her earnings forecast for the company's fiscal year by 5.7 more basis points of the stock price in the direction of the earnings surprise. As predicted, we also find that the extent to which an analyst adjusts her fiscal year earnings estimate in the direction of an earnings surprise is decreased by the degree to which that analyst made an extreme estimate on the wrong side of the estimate distribution relative to announced earnings. Specifically, if an analyst's quarterly estimate differs from the consensus by one standard deviation in the opposite direction from reported earnings, when she experiences an additional ten basis points of earnings surprise she will update her forecast of the company's yearly earnings in the direction of that surprise by 3.8 more basis points of the stock price.[8] This represents a reduction in responsiveness of approximately 33% relative to the 5.7 basis point response of an analyst whose quarterly forecast was at consensus. Figure 2 illustrates this effect.

Table II
The Effect of Earnings Surprises on Extreme Earnings Forecasts

The adjustments that security analysts make to their forecasts of a company's earnings in a given fiscal year in response to quarterly earnings surprises are tracked to examine whether extremists react less than others to a given surprise. Standard errors are in parentheses; they are clustered by analyst-firm pair. All data are included in the regression presented in column (1), while the regression presented in column (2) includes only pre-Chinese Wall data and the regression in column (3) includes only post-Chinese Wall data. (*Significant at 10 percent level. **Significant at 5 percent level. *** Significant at 1 percent level.)

	All Data	Pre-SEC Investigation	Post-SEC Investigation
	(1)	(2)	(3)
EPS_SURPRISE	0.573***	0.627***	0.540***
	(0.032)	(0.047)	(0.057)
***INCORRECT_DEV* x 10^{-3}**	0.328***	0.370***	0.353**
	(0.071)	(0.101)	(0.142)
***CORRECT_DEV* x 10^{-3}**	0.297***	0.272***	0.304***
	(0.050)	(0.069)	(0.096)
EPS_SURPRISE* x *INCORRECT_DEV	-0.194***	-0.203***	-0.200***
	(0.026)	(0.039)	(0.049)
EPS_SURPRISE* x *CORRECT_DEV	-0.063	-0.082	0.014
	(0.040)	(0.053)	(0.076)
Quarter Effects	Yes	Yes	Yes
Analyst-Firm Fixed Effects	Yes	Yes	Yes
Observations	130,499	80,811	37,572
Analyst-Firm Pairs	46,841	28,978	18,415
R^2	0.556	0.567	0.667

[8] From column (1) of Table II, (0.57)*(10 basis points) + (-0.19)*(1 std. dev.)*(10 basis points) = 3.8 basis points.

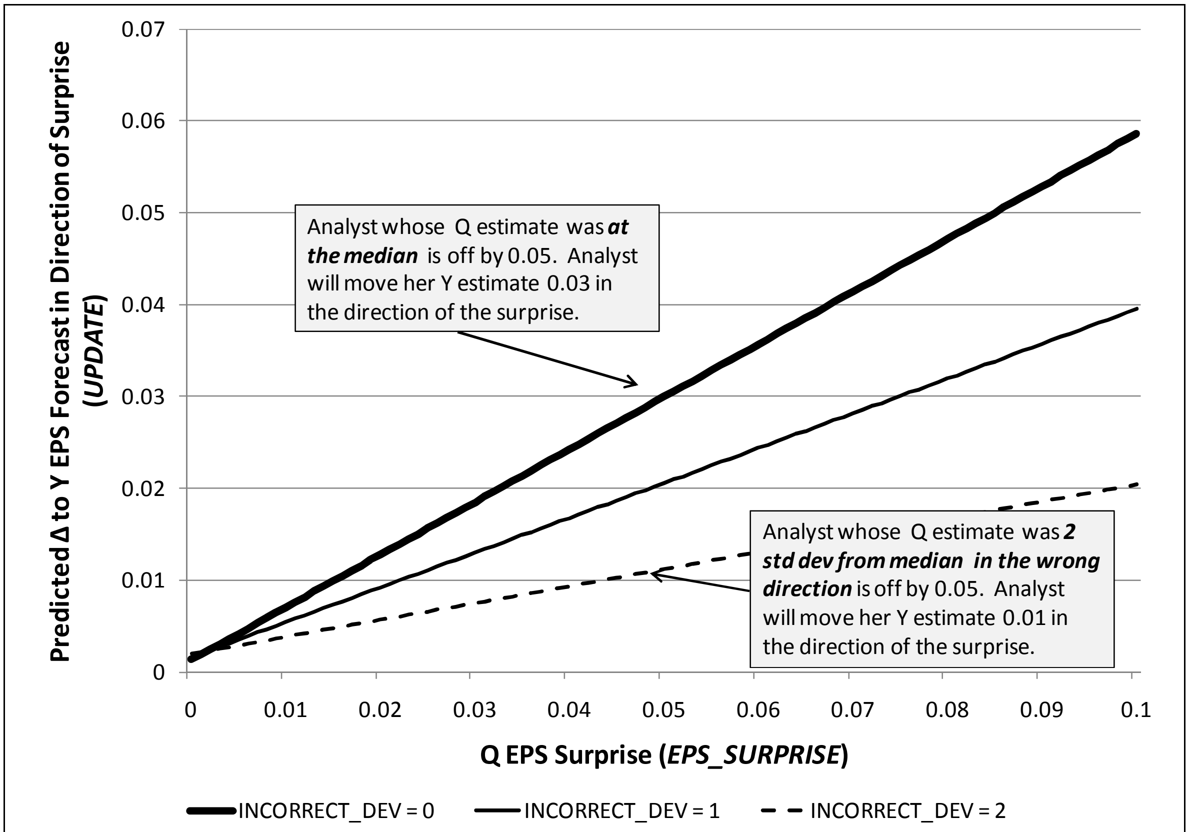

Figure 2. Pictorial Representation of Regression (1) Results

The significant negative coefficient on the interaction between the variables *INCORRECT_DEV* and *EPS_SURPRISE* confirms our prediction that analysts who have made more extreme incorrect earnings forecasts relative to their peers dig in their heels and update less in the direction of an earnings surprise than analysts who have made less extreme incorrect earnings forecasts. The regressions presented in columns (2) and (3) demonstrate that our results are essentially the same if we restrict our analyses to the periods before or after the SEC's investigation into inappropriate relationships between the investment banking and equity research divisions of finance firms.

Tables III and IV present the results of the same set of regressions as Table II but include only the subset of observations that correspond to positive and negative earnings surprises relative to the consensus (median) estimate, respectively. The OLS coefficient estimates presented in these tables reveal that our main results from Table II hold whether we look at positive or negative earnings surprises. Interestingly, the estimated coefficient magnitudes for the interaction between *INCORRECT_DEV* and *EPS_SURPRISE* suggest that the effect of incorrect extremism on stubbornness may be slightly larger in situations where an analyst's estimate is lower than consensus and a company announces a positive earnings surprise than in situations where an analyst's estimate is higher than consensus and a company announces a negative earnings surprise. However, it is important to note that the estimated coefficients on *EPS_SURPRISE* (not interacted) are larger in the regressions analyzing positive earnings surprises than in the regressions analyzing negative earnings surprises. In proportion to these estimated coefficients on *EPS_SURPRISE*, the impact of incorrect extremism on stubbornness is roughly comparable for positive and negative surprises.[9]

[9] The coefficient on the interaction of *EPS_SURPRISE* and *CORRECT_DEV* is negative for the regressions using the sample of positive earnings surprises (Table III), while the coefficient is positive for the regressions using the sample of negative earnings surprises (Table IV). However, these results are difficult to interpret because quarterly EPS forecasts with a nonzero value for *CORRECT_DEV* may be higher or lower than reported quarterly EPS, making the sign of *EPS_SURPRISE* and therefore the sign of the interaction term ambiguous.

Table III

The Effect of Positive Earnings Surprises on Extreme Earnings Forecasts

The adjustments that security analysts make to their forecasts of a company's earnings in a given fiscal year in response to positive quarterly earnings surprises are tracked to examine whether extremists react less than others to a given surprise. Standard errors are in parentheses; they are clustered by analyst-firm pair. Standard errors are in parentheses; they are clustered by analyst-firm pair. All data on positive surprises are included in the regression presented in column (4), while the regression presented in column (5) includes only pre-Chinese Wall data and the regression in column (6) includes only post-Chinese Wall data. (*Significant at 10 percent level. **Significant at 5 percent level. *** Significant at 1 percent level.)

	All Data	Pre-SEC Investigation	Post-SEC Investigation
	(4)	(5)	(6)
EPS_SURPRISE	0.818***	0.874***	0.696***
	(0.039)	(0.055)	(0.078)
***INCORRECT_DEV* x 10^{-3}**	0.347***	0.355***	0.342**
	(0.063)	(0.069)	(0.167)
***CORRECT_DEV* x 10^{-3}**	0.377***	0.324***	0.330***
	(0.053)	(0.071)	(0.118)
EPS_SURPRISE* x *INCORRECT_DEV	-0.292***	-0.286***	-0.266***
	(0.031)	(0.041)	(0.068)
EPS_SURPRISE* x *CORRECT_DEV	-0.320***	-0.377***	-0.077
	(0.052)	(0.069)	(0.088)
Quarter Effects	Yes	Yes	Yes
Analyst-Firm Fixed Effects	Yes	Yes	Yes
Observations	67,166	39,216	21,704
Analyst-Firm Pairs	31,777	18,738	12,861
R^2	0.646	0.648	0.751

Table IV

The Effect of Negative Earnings Surprises on Extreme Earnings Forecasts

The adjustments that security analysts make to their forecasts of a company's earnings in a given fiscal year in response to negative quarterly earnings surprises are tracked to examine whether extremists react less than others to a given surprise. Standard errors are in parentheses; they are clustered by analyst-firm pair. Standard errors are in parentheses; they are clustered by analyst-firm pair. All data on negative surprises are included in the regression presented in column (7), while the regression presented in column (8) includes only pre-Chinese Wall data and the regression in column (9) includes only post-Chinese Wall data. (*Significant at 10 percent level. **Significant at 5 percent level. *** Significant at 1 percent

	All Data (7)	Pre-SEC Investigation (8)	Post-SEC Investigation (9)
EPS_SURPRISE	0.522***	0.572***	0.437***
	(0.042)	(0.051)	(0.129)
INCORRECT_DEV **x 10^{-3}**	0.465***	0.568***	-0.231
	(0.165)	(0.204)	(0.456)
CORRECT_DEV **x 10^{-3}**	0.412***	0.392***	0.148
	(0.127)	(0.148)	(0.382)
EPS_SURPRISE **x** ***INCORRECT_DEV***	-0.204***	-0.219***	-0.110
	(0.037)	(0.046)	(0.102)
EPS_SURPRISE **x** ***CORRECT_DEV***	0.072	0.044	0.055
	(0.071)	(0.088)	(0.203)
Quarter Effects	Yes	Yes	Yes
Analyst-Firm Fixed Effects	Yes	Yes	Yes
Observations	50,481	34,132	11,888
Analyst-Firm Pairs	27,508	17,745	8,762
R^2	0.696	0.695	0.823

If we run the analyses discussed above without including analyst-firm fixed effects or without multiplying our EPS variables by the inverse of a firm's stock price, our results remain essentially the same in magnitude, and their statistical significance does not change. Dropping observations in our data set involving quarterly forecasts that were not revised within 90, 30 or 15 days of the end date of the quarter in question also does not change any of our results meaningfully. Nor do our primary results change meaningfully if we re-run our analyses separately for first quarter, second quarter, and third quarter earnings surprises. Finally, an analysis of the impact of an analyst's experience on escalation suggests that there is no significant relationship between an analyst's years of experience forecasting and her tendency to exhibit the type of stubbornness uncovered in this paper.[10]

B. Evidence that Stubbornness Harms Accuracy

The next question we investigate is whether the type of stubbornness we detect among analysts who have made extreme EPS forecasts is harmful or helpful to their forecasting accuracy. It seems plausible that analysts who make more extreme estimates and update less in response to earnings announcements could have some private information that leads updating their forecasts in this way to improve their accuracy. In order to investigate this possibility, we compare the effectiveness of analysts' actual updating strategies with the effectiveness of a hypothetical updating strategy in which we eliminate the degree of stubbornness observed in our above regression analyses. For these analyses, we rely on the variable *ERROR* (described in Section III), which measures the distance between an analyst's updated yearly forecast following a quarterly earnings announcement and the actual yearly earnings a company reported. We also create a hypothetical measure of an analyst's accuracy in a world without stubbornness: *HYP_ERROR* (see Appendix A). To generate this hypothetical accuracy value, we calculate the product of an analyst's degree of incorrect extremeness (*INCORRECT_DEV*) and his EPS surprise (*EPS_SURPRISE*) for a given quarter and multiply this product by the coefficient on the interaction term between these variables in column (1) of Table II (β_4 from our regression equation). This "average stubbornness" quantity is then removed from an analyst's actual yearly forecast by subtracting the

[10] The full results from all robustness tests reported are available upon request from the authors.

quantity from the yearly forecast when reported quarterly EPS is above the consensus estimate and adding the quantity to the yearly forecast otherwise (to conform to the sign conventions for *UPDATE*).

For all of the observations of EPS estimate updates included in the regression presented in column (1) of Table II, we then conduct a paired t-test to examine whether the mean accuracy of analysts' actual forecasts or hypothetical forecasts is higher. We find that hypothetical forecasts from which analysts' stubbornness has been excised would be significantly more accurate than analysts' actual EPS forecasts (two sample paired t-test, p-value $< .001$). Thus, it appears that analysts who have made incorrect extreme earnings forecasts about a given company exhibit stubbornness in updating their opinions that is harmful to their forecasting accuracy.

When constructing hypothetical forecasts to demonstrate that analysts exhibiting no stubbornness would be more accurate on average than actual analysts, our calculations started with analysts' actual forecasts and adjusted them such that β_4, the coefficient on the interaction of *INCORRECT_DEV* and *EPS_SURPRISE*, was zero instead of the estimated -0.19 from column (1) of Table II. Using the same framework, we can also ask what value of β_4 would maximize accuracy (or minimize *ERROR*), on average, among analysts in our sample. In other words, holding all other components of our regression model fixed, we can answer the question: how should incorrect, out-of-consensus analysts respond to an earnings surprise in order to optimize their average accuracy? In the sample used in column (1) of Table II, a β_4 value of 0.03 (standard error 0.01)[11] would produce the largest reduction in mean error over actual forecasts, where error is measured as the absolute difference between forecasted and reported earnings (see Figure 2). This result suggests that analysts with incorrect extreme forecasts could improve their accuracy if they were more instead of less responsive to earnings surprises than analysts with forecasts closer to consensus.

[11] The standard error is calculated as follows. We construct one thousand bootstrap samples by randomly drawing 10% subsamples with replacement from the sample of analysts used in column (1) of Table II. For each of these bootstrap samples, we determine the value of β_4 that gives the largest improvement in mean accuracy. The standard error is the standard deviation of these β_4 coefficients across bootstrap samples, multiplied by the square root of 0.1 to adjust for the size of the bootstrap samples relative to the full sample.

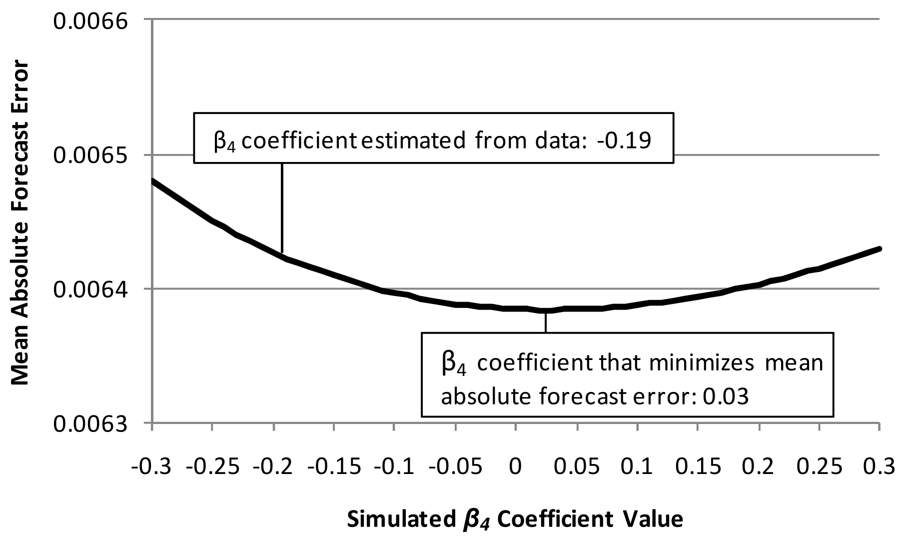

Figure 2. The Effect of Simulated Changes in the Degree of Stubbornness on Average Forecast Error

Plot of yearly forecast error against hypothetical coefficient values for the interaction of *INCORRECT_DEV* and *EPS_SURPRISE*. Adopting the sample and coefficient estimates from column (1) of Table II, we use the regression equation presented in Section IV.A to simulate yearly forecast updates by holding all components of this equation fixed except for β_4, which we vary from -0.3 to 0.3. The mean absolute yearly forecast error implied by these simulated updates is plotted against the coefficient β_4.

V. Discussion

The analyses presented above indicate that out-of-consensus analysts who have made incorrect forecasts update less than others in response to equivalent earnings surprises and that this behavior is harmful to their accuracy. As discussed previously, there are a number of potential explanations for these findings. One potential reason for the stubbornness we detect in analysts is that they are suboptimal decision makers who are prone to systematic error. Analysts may, for example, become overcommitted to their previously published out-of-consensus opinions and fail to update appropriately in response to new, contradictory information - a pattern of behavior that has been detected in previous research on escalation bias (Staw (1976); Arkes and Blumer (1985)). Or, analysts may become so focused on their private information regarding a firm that they overweight it relative to public information, making them reluctant to update their forecasts in response to earnings surprises. Incorrect out-of-consensus analysts might also anchor too strongly on their previous earnings estimates (Tversky and Kahneman (1974)), leading them to be less responsive to the information contained in new earnings announcements. Alternatively, they may underweight the value of attending carefully to earnings updates.

Another potential explanation for our findings about analysts' updating behavior is that analysts are rewarded for sticking doggedly with their incorrect estimates. Because analysts are paid not only based on the accuracy of their forecasts but also based on the ratings they receive from clients and the trading commissions they generate for their employers (Cowen, Groysberg, and Healy (2006); Groysberg, Healy, and Maber (2008)), they may have an incentive to demonstrate the conviction of their views even when this is harmful to their accuracy. Previous theoretical work has suggested that it may be a wise strategy for low ability analysts to issue extreme earnings forecasts and under-update in response to new information in order to imitate high ability analysts (Prendergast and Stole (1996); Ehrbeck and Waldmann (1996)).

In order to explore which of the above explanations is most plausible, we examine whether analysts seem to be rewarded or punished by clients for stubbornly maintaining incorrect extreme earnings forecasts. To investigate this question, we gather data on the approximately 380 analysts who were named "All-Americans" each year by *Institutional Investor* (*II*) magazine, an honor that has been associated with increased pay (Cowen, Groysberg, and Healy (2008)) and that is based on client reviews rather than analysts' accuracy. We merge our I/B/E/S estimates data with a list of the analysts who were named first team, second team, third team or runner-up *II* "All-Americans" each year between 1998 and 2007. We then construct an analyst-year data set including variables that capture an analyst's average degree of incorrect extremism, average degree of correct extremism, average degree of incorrect stubbornness, and average degree of correct stubbornness during the twelve months leading up to the announcement of the "All-America" analyst team. For details on the creation of this data set, see Appendix B.[12,13]

To examine the factors that contribute to an analyst's likelihood of receiving different levels of *II* "All-America" recognition, we perform ordered logit regressions where the award received by an analyst in a given year is the outcome variable (4 = first team, 3 = second team, 2 = third team, 1 = runner-up, 0 = no award). Our primary explanatory variable, *%INCORRECT_STUB*, captures the degree of stubbornness

[12] Note that before 2007, it was possible to obtain an I/B/E/S translation file from Thomson (the owner of the data) to de-anonymize brokerage house and analyst ID's. However, Thomson no longer makes this file available and actually requested that those previously in possession of the file destroy it. For a period, Thomson would grant individual researchers access to the translation file, but they have stopped granting such requests, which is why we were required to find an alternate way to translate the data (see Appendix B). Our translation method did not allow us to identify all analysts in our data set, and those analysts who could not be identified were, by necessity, dropped from the analyses in this section.

[13] Our procedure for linking I/B/E/S data to information on *II* "All-American" status only produced matches for a subset of brokerage houses. When we perform the analyses presented in Section IV on this subsample, our results do not change meaningfully.

exhibited by an analyst when she was incorrect during the year leading up to the awards' announcement. It is defined as the fraction of quarterly earnings forecasts issued by the analyst during the year that satisfy two criteria: (i) the quarterly forecast differed from the consensus forecast in the direction opposite from reported earnings per share; and (ii) the analyst adjusted her forecast for the remaining quarters of the fiscal year by less in the direction of the earnings surprise than a hypothetical benchmark. The benchmark is constructed as follows. We perform the regression presented in column (1) of Table II using the subset of analysts who are included in the data set that merges information from I/B/E/S and *II* "All-America" lists. We use the coefficient estimates from this regression to predict the value of the variable *UPDATE* according to the regression equation presented in Section IV.A, except we set the coefficients on the two interaction terms (β_4 and β_5) to zero. These adjusted predicted values serve as the benchmark, and they are intended to capture the way a typical analyst at consensus (with no need to stubbornly stick by an incorrect out-of-consensus forecast) would update her yearly forecast in response to a quarterly earnings surprise. If an analyst updates a forecast by less in the direction of the earnings surprise than this hypothetical benchmark, we deem the analyst to be acting stubbornly. For symmetry, we also construct a second stubbornness variable, *%CORRECT_STUB*. This variable is defined as the fraction of quarterly earnings forecasts issued by the analyst during the year that satisfy two criteria: (i) the quarterly forecast differed from the consensus forecast in the same direction as reported earnings per share; and (ii) the analyst adjusted her forecast for the remaining quarters of the fiscal year by less in the direction of the earnings surprise than the hypothetical benchmark explained above (see Appendix B for summary statistics for these variables).

In Table V, column (10) reports the results of an ordered logit regression predicting the level of "All-American" honor an analyst receives in a given year with *%INCORRECT_STUB* and *%CORRECT_STUB* on the right-hand side.[14] In addition, the right-hand side of regression (10) includes dummy variables indicating which "All-American" designation an analyst received the previous year.[15] This information on past honors helps us control for an analyst's reputation. The positive coefficient on *%CORRECT_STUB* is not surprising. If an analyst's quarterly forecast deviates from the consensus in the direction that turns out to be correct, it seems logical for her to update her forecasts less than her peers, and her clients may reward her for presenting and maintaining an accurate out-of-consensus view of the firm. The negative and statistically significant coefficient on *%INCORRECT_STUB*, on the other hand, suggests that analysts are punished for sticking to views that initially prove to be incorrect. According to these regression results, an analyst who had not received an "All-American" designation previously and who had values of *%INCORRECT_STUB* and *%CORRECT_STUB* at their sample means would have a predicted probability of 4.0% of being recognized as an

[14] Because *%INCORRECT_STUB* and *%CORRECT_STUB* are constructed using estimated parameters, the standard errors reported in Table V are calculated as follows. We create one thousand bootstrap samples by randomly drawing 20% subsamples with replacement from the sample of analysts used in Table V. For each of these bootstrap samples, we conduct the regression procedure for obtaining hypothetical benchmarks, recalculate the variables that rely on these benchmarks, perform the ordered logit regressions in Table V, and collect the coefficient estimates from those regressions. The standard error for a given coefficient is the standard deviation of that coefficient across bootstrap samples, multiplied by the square root of 0.2 to adjust for the size of the bootstrap samples relative to the full sample.

[15] When information on whether the analyst received an "All-American" designation was unavailable for the prior year, we used the next most recent year for which information was available.

“All-American” runner-up or better, and an increase in the *%INCORRECT_STUB* variable of one standard deviation would decrease that probability by 0.3 percentage points. Thus, it does not seem that incorrect out-of-consensus analysts are rewarded for the type of stubbornness we detect in Section IV.

Table V

The Effect of Stubbornness on an Analyst's Probability of Winning an *Institutional Investor* Award

The analysts who receive *Institutional Investor* "All-American" status in a given year are tracked to examine whether extremists who are proven incorrect in their estimates by an earnings surpise and who react stubbornly to that surprise are more or less likely to receive such an honor. Below are the results of ordered logit regression analyses where the outcome categories are "no award," "runner up," "third team," "second team," and "first team." Bootstrapped standard errors, calculated using the method described in the text, are in parentheses. (*Significant at 10 percent level. **Significant at 5 percent level. *** Significant at 1 percent level.)

	(10)	(11)	(12)
%INCORRECT_STUB	-0.323**	-0.796***	
	(0.146)	(0.218)	
%CORRECT_STUB	0.331**	0.352*	0.352*
	(0.145)	(0.187)	(0.187)
%INCORRECT_DEV		0.583***	0.583***
		(0.180)	(0.180)
%CORRECT_DEV		0.084	0.084
		(0.144)	(0.144)
AVG_ERROR		-8.664*	-8.672*
		(5.122)	(5.132)
%INCORRECT_STUB_SUC			-0.801***
			(0.257)
%INCORRECT_STUB_FAIL			-0.792***
			(0.248)
Indicator Variables for Ranking Achieved in Previous Year	Yes	Yes	Yes
Observations	13,064	13,064	13,064
Log-Pseudolikelihood	-4831.37	-4825.29	-4825.29

While the empirical pattern demonstrated in column (10) of Table V offers support for the hypothesis that analysts are punished for sticking to their incorrect out-of-consensus views, it is interesting to ask whether these punishments still arise when an analyst’s out-of-consensus views are initially incorrect but are eventually revealed to be correct at a later point in time. Although the stubbornness we have documented reduces forecasting accuracy on average, there are certainly occasions when an analyst makes an out-of-consensus forecast, stubbornly maintains her view on a firm despite initial indications that her view was incorrect, and gains ultimate vindication because her view turns out to be correct in the long run. As discussed previously, if the rewards on these occasions are sufficiently large (and if the punishment for sticking with a view that ultimately proves incorrect is relatively small), analysts may sometimes "swing for the fences" with their predictions, maintaining views that have only a small probability of being correct. To explore this possibility, the regression presented in column (11) of Table V adds the explanatory variable *AVG_ERROR*, which is the mean of *ERROR* (defined in Section III) over all observations for a given analyst in a given year (see Appendix B for summary statistics). The variable *AVG_ERROR* captures the accuracy of the long-horizon (yearly) forecasts that the analyst publishes after learning about the accuracy of her short-horizon (quarterly) forecasts. In addition, we add two other control variables. Because the variable *%INCORRECT_STUB* simultaneously captures both whether or not an analyst updates her forecasts stubbornly when her quarterly estimate is incorrect and the number of instances in which her quarterly estimate is incorrect, we construct a control variable to measure the average extent to which an analyst's quarterly estimates are incorrect. The variable *%INCORRECT_DEV* is defined as the percentage of the time that an analyst's quarterly forecast differs from the consensus forecast in the wrong direction relative to an earnings surprise. For the sake of symmetry, we also define a variable – *%CORRECT_DEV* – as the percentage of the time that an analyst's quarterly forecast differs from the consensus forecast in the right direction relative to an earnings surprise. As reported in column (11) of Table V, the coefficient on

AVG_ERROR indicates that analysts with greater long-horizon accuracy are indeed more likely to receive greater recognition from *Institutional Investor*. In addition, the coefficients on *%INCORRECT_DEV* and *%CORRECT_DEV* are both positive and significant, suggesting that being an extremist can be rewarding. However, the coefficient on *%INCORRECT_STUB* remains negative.

To further explore the possibility that analysts have an incentive to "swing for the fences," we break out the variable *%INCORRECT_STUB* into two pieces: *%INCORRECT_STUB_SUC* and *%INCORRECT_STUB_FAIL*. The variable *%INCORRECT_STUB_SUC* is defined as the fraction of quarterly earnings forecasts issued by a given analyst during a given year that satisfy three criteria: (i) the quarterly forecast differed from the consensus forecast in the direction opposite from reported earnings per share; (ii) the analyst adjusted her forecast for the remaining quarters of the fiscal year by less in the direction of the earnings surprise than the hypothetical benchmark used in the definition of *%INCORRECT_STUB*; and (iii) the analyst's forecast for the remaining quarters of the fiscal year was more accurate than the forecast implied by the hypothetical benchmark update. The variable *%INCORRECT_STUB_FAIL* is defined similarly, except criterion (iii) is that the analyst's forecast for the remaining quarters of the fiscal year was less accurate than the forecast implied by the hypothetical benchmark update. Note that these two new variables sum to *%INCORRECT_STUB*. As shown in column (12) of Table V, when we replace *%INCORRECT_STUB* with these two variables, the point estimate for the coefficient on *%INCORRECT_STUB_SUC* is essentially the same as the point estimate for the coefficient on *%INCORRECT_STUB_FAIL*, suggesting that "swinging for the fences" is punished even when doing so improves accuracy.

Overall, the empirical evidence suggests that analysts are punished for stubbornly updating their subsequent earnings forecasts when their out-of-consensus quarterly forecasts prove incorrect. These results cast doubt on the possibility that the stubbornness documented in Section IV is a response to compensation-related or career-related incentives. Of course, the analyses we have presented here are primarily exploratory in nature.

VI. Conclusion

We find that when a stock analyst makes an extreme earnings forecast that a future earnings announcement reveals was incorrect, she sticks stubbornly to her opinion rather than updating as much as analysts whose estimates were closer to consensus. Furthermore, this type of behavior is harmful to analysts' forecasting accuracy on average. We explore potential explanations for this behavior, and the available evidence indicates that analysts are punished for digging in their heels when they make incorrect extreme earnings forecasts, suggesting that this behavior is not a response to compensation-related or career-related incentives.

These results deepen our understanding of the factors that contribute to market participants' errors in predicting the future performance of assets. Insofar as the pattern of escalation we detect is indicative of a broader pattern of stubbornness in the updating behavior of investors, our findings suggest a channel through which securities may be mispriced relative to fundamentals for extended periods of time. Of course, one limitation of our analysis is that it does not directly assess the implications of our results for asset prices, so an investigation of the degree to which escalation affects market prices would be an interesting direction for future research. It may also be productive to extend this line of inquiry from equity markets to credit markets, as recent macroeconomic events have revealed forecasting mistakes in the latter context to be particularly disruptive to economic activity.

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Appendix A. Variable Definitions

Primary Analyses

- Variable Used in Definitions: $YepsE_{aft}^{pre}$

  Description: The EPS estimate issued by analyst *a* for firm *f* that applies to the fiscal year containing quarter *t* and that was published immediately preceding the announcement of earnings for quarter *t*, divided by the per-share price of company *f* stock at the end of the prior fiscal year.

- Variable Used in Definitions: $YepsE_{aft}^{post}$

  Description: The EPS estimate issued by analyst *a* for firm *f* that applies to the fiscal year containing quarter *t* and that was published immediately following the announcement of earnings for quarter *t*, divided by the per-share price of company *f* stock at the end of the prior fiscal year.

- Variable Used in Definitions: $YepsA_{ft}$

  Description: The actual earnings per share reported by firm *f* for the fiscal year including quarter *t*, divided by the per-share price of company *f* stock at the end of the prior fiscal year.

- Variable Used in Definitions: $QepsE_{aft}^{pre}$

  Description: The EPS estimate issued by analyst *a* for firm *f* that applies to quarter *t* and that was published immediately preceding the announcement of earnings for quarter *t*, divided by the per-share price of company *f* stock at the end of the prior fiscal year.

- Variable Used in Definitions: $QepsA_{ft}$

  Description: The actual earnings per share reported by firm *f* for quarter *t*, divided by the per-share price of company *f* stock at the end of the prior fiscal year.

- Variable Used in Definitions: $median\_QepsE_{ft}^{pre}$

  Description: The median of the price-per-share adjusted EPS estimates issued by all analysts covering firm *f* that applied to quarter *t* and that were published immediately preceding the announcement of earnings for quarter *t*.

- Variable Used in Definitions: $stddev\_QepsE_{ft}^{pre}$

  Description: The standard deviation of the price-per-share adjusted EPS estimates issued by all analysts covering firm *f* that applied to quarter *t* and that were published immediately preceding the announcement of earnings for quarter *t*.

- Variable Used in Analyses: $UPDATE_{aft}$
  Description: The magnitude of an analyst's update to her forecast of EPS for the fiscal year in response to a quarterly earnings announcement. Specifically, this variable captures the size of an analyst *a*'s adjustment to her EPS estimate for a firm *f*'s fiscal year containing quarter *t* in response to the announcement of firm *f*'s actual earnings for quarter *t*. This variable's value is increasing as an analyst updates her estimate more in the direction of the quarterly earnings surprise, where the quarterly earnings surprise is measured relative to the median analyst estimate.
  Definition: $$\begin{cases} (YepsE_{aft}^{post} - YepsE_{aft}^{pre}) & if \quad QepsA_{ft} > median\_QepsE_{ft}^{pre} \\ (YepsE_{aft}^{pre} - YepsE_{aft}^{post}) & otherwise \end{cases}$$

- Variable Used in Analyses: $EPS\_SURPRISE_{aft}$
  Description: The amount by which an analyst misforecasted a firm's quarterly EPS. Specifically, this variable measures how far off analyst *a*'s EPS estimate is from firm *f*'s actual EPS for quarter *t*. This variable's value is increasing as an analyst's quarterly EPS estimate differs from actual EPS by a larger amount in the same direction that the median analyst EPS estimate differs from actual EPS.
  Definition: $$\begin{cases} (QepsA_{ft} - QepsE_{aft}^{pre}) & if \quad QepsA_{ft} > median\_QepsE_{ft}^{pre} \\ (QepsE_{aft}^{pre} - QepsA_{ft}) & otherwise \end{cases}$$

- Variable Used in Analyses: $INCORRECT\_DEV_{aft}$
  Description: The magnitude of an analyst's incorrect extremism. Specifically, this variable is the maximum of zero and the number of standard deviations separating an analyst's quarterly EPS estimate from the median quarterly EPS estimate if the analyst's estimate is off from the median estimate in the wrong direction relative to the earnings surprise.
  Definition: $$\begin{cases} \max\left(0, \dfrac{median\_QepsE_{ft}^{pre} - QepsE_{aft}^{pre}}{stddev\_QepsE_{ft}^{pre}}\right) & if \quad QepsA_{ft} > median\_QepsE_{ft}^{pre} \\ \max\left(0, \dfrac{QepsE_{aft}^{pre} - median\_QepsE_{ft}^{pre}}{stddev\_QepsE_{ft}^{pre}}\right) & otherwise \end{cases}$$

- Variable Used in Analyses: $CORRECT\_DEV_{aft}$
  Description: The magnitude of an analyst's correct extremism. Specifically, this variable is the maximum of zero and the number of standard deviations separating an analyst's quarterly EPS estimate from the median quarterly EPS estimate if the analyst's estimate is off from the median estimate in the right direction relative to the earnings surprise.
  Definition: $$\begin{cases} \max\left(0, \dfrac{QepsE_{aft}^{pre} - median\_QepsE_{ft}^{pre}}{stddev\_QepsE_{ft}^{pre}}\right) & if \quad QepsA_{ft} > median\_QepsE_{ft}^{pre} \\ \max\left(0, \dfrac{median\_QepsE_{ft}^{pre} - QepsE_{aft}^{pre}}{stddev\_QepsE_{ft}^{pre}}\right) & otherwise \end{cases}$$

- Variable Used in Analyses: $ERROR_{aft}$
  Description: The error in an analyst's adjusted yearly EPS estimate, which is the absolute difference between analyst *a*'s new stock-price-normalized yearly EPS estimate following firm *f*'s quarter *t* earnings announcement and the actual stock-price-normalized yearly EPS announced by firm *f*.
  Definition: $\left| YepsA_{ft} - YepsE_{aft}^{post} \right|$

- Variable Used in Analyses: HYP_ERROR_{aft}
  Description: The error in an analyst's hypothetical adjusted yearly EPS estimate in a world without stubbornness. We calculate the product of analyst *a*'s degree of incorrect extremism and her EPS surprise for firm *f* and quarter *t*, and we multiply this product by the coefficient on the appropriate interaction term in column (1) of Table II. Then, this "average stubbornness" quantity is removed from an analyst's actual forecast. Finally, we calculate the absolute difference between this hypothetical forecast and the actual stock-price-normalized yearly EPS announced by firm *f*.
  Definition:

$$\begin{cases} \left| YepsA_{ft} - (YepsE_{aft}^{post} - \hat{\beta}_4 * INCORRECT\_DEV_{aft} * EPS\_SURPRISE_{aft}) \right| & if \quad QepsA_{ft} > median\_QepsE_{ft}^{pre} \\ \left| YepsA_{ft} - (YepsE_{aft}^{post} + \hat{\beta}_4 * INCORRECT\_DEV_{aft} * EPS\_SURPRISE_{aft}) \right| & otherwise \end{cases}$$

Analyses Presented in Discussion

- Variable Used in Definitions: $benchmark\_update_{aft}$
  Description: A hypothetical benchmark update that is intended to capture what typical forecast updates would look like if all analysts responded to earnings surprises in the same way as analysts with quarterly estimates at the consensus. We perform the regression presented in column (1) of Table II using the subset of analysts who are included in our *II* data set. We use the coefficient estimates from this regression to predict the value of the variable *UPDATE* according to the regression equation presented in Section IV.A, except we set the coefficients on the two interaction terms (β_4 and β_5) to zero.
  Definition:

$$\hat{\beta}_1 EPS\_SURPRISE_{aft} + \hat{\beta}_2 INCORRECT\_DEV_{aft} + \hat{\beta}_3 CORRECT\_DEV_{aft} + \hat{\beta}_6 Q1\_dummy_t + \hat{\beta}_7 Q2\_dummy_t + \hat{\alpha}_{af}$$

- Variable Used in Definitions: $benchmark\_YepsE_{aft}^{post}$
  Description: A hypothetical benchmark forecast that is intended to capture what an analyst's updated forecast would look like if all analysts responded to earnings surprises with a benchmark update as described in the previous definition.
  Definition:

$$\begin{cases} (YepsE_{aft}^{pre} + benchmark\_update_{aft}) & if \quad QepsA_{ft} > median\_QepsE_{ft}^{pre} \\ (YepsE_{aft}^{pre} - benchmark\_update_{aft}) & otherwise \end{cases}$$

- Variable Used in Analyses: $award\_level_{ay}$
  Description: A variable that takes on integer values ranging from 0 to 4 indicating the level of "All-American" recognition analyst *a* achieved from *Institutional Investor* magazine in year *y*. If an analyst was named a first team All-American, this variable takes on a value of 4; if an analyst was named a second team All-American, it takes on a value of 3; if an analyst was named a third team All-American, it takes on a value of 2; if an analyst was named a runner-up All-American, it takes on a value of 1; and if an analyst received no award, it takes on a value of 0.

- Variable Used in Analyses: $\%INCORRECT\_DEV_{ay}$
  Description: A measure of how often an analyst exhibited incorrect extremism. This variable is equal to the percentage of analyst *a*'s quarterly EPS forecasts in year *y* that differ from the median forecast in the wrong direction relative to an earnings surprise.
  Definition[16]: $\dfrac{\sum_f \sum_{t \in S(y)} I[INCORRECT\_DEV_{aft} > 0])}{\sum_f \sum_{t \in S(y)} 1}$

- Variable Used in Analyses: $\%CORRECT\_DEV_{ay}$
  Description: A measure of how often an analyst exhibited correct extremism. This variable is equal to the percentage of analyst *a*'s quarterly EPS forecasts in year *y* that differ from the median forecast in the right direction relative to an earnings surprise.
  Definition: $\dfrac{\sum_f \sum_{t \in S(y)} I[CORRECT\_DEV_{aft} > 0])}{\sum_f \sum_{t \in S(y)} 1}$

- Variable Used in Analyses: $\%INCORRECT\_STUB_{ay}$
  Description: A measure of how often an analyst exhibited stubbornness in updating when her estimate deviated from the median estimate in the wrong direction relative to the earnings surprise. This variable is equal to the proportion of analyst *a*'s updates in response to an earnings announcement during year *y* that involved less adjustment in the direction of the earnings surprise than the hypothetical benchmark defined above and that involved a situation where the analyst's estimate of quarterly earnings deviated from the median estimate in the opposite direction as announced earnings.
  Definition: $\dfrac{\sum_f \sum_{t \in S(y)} I[INCORRECT\_DEV_{aft} > 0\ \&\ benchmark\_update_{aft} > UPDATE_{aft}]}{\sum_f \sum_{t \in S(y)} 1}$

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[16] *S(y)* is the set of all time periods *t* with end dates that fall within the year-long (July 1 to June 30) period *y*.

- Variable Used in Analyses: $\%CORRECT\_STUB_{ay}$
  Description: A measure of how often an analyst exhibited stubbornness in updating when her estimate deviated from the median estimate in the right direction relative to the earnings surprise. This variable is equal to the proportion of analyst *a*'s updates in response to an earnings announcement during year *y* that involved less adjustment in the direction of the earnings surprise than the hypothetical benchmark defined above and that involved a situation where the analyst's estimate of quarterly earnings deviated from the median estimate in the same direction as announced earnings.
  Definition: $\dfrac{\sum_f \sum_{t\in S(y)} I[CORRECT\_DEV_{aft} > 0 \,\&\, benchmark\_update_{aft} > UPDATE_{aft}]}{\sum_f \sum_{t\in S(y)} 1}$

- Variable Used in Analyses: AVG_ERROR_{ay}
  Description: A measure of an analyst's average forecasting error. This variable is equal to the average absolute difference between an analyst's updated stock-price-normalized forecast for a firm's fiscal year EPS following a quarterly earnings announcement and the firm's actual stock-price-normalized yearly EPS.
  Definition: $\dfrac{\sum_f \sum_{t\in S(y)} ERROR_{aft}}{\sum_f \sum_{t\in S(y)} 1}$

- Variable Used in Analyses: $\%INCORRECT\_STUB\_SUC_{ay}$
  Description: A measure of how often an analyst exhibited stubbornness in updating that eventually proved correct when her estimate deviated from the median estimate in the wrong direction relative to the earnings surprise. This variable is equal to the proportion of an analyst's yearly estimates that were more accurate than the benchmark estimate described above and for which the analyst's quarterly earnings estimate deviated from the median estimate in the opposite direction from the earnings surprise and the analyst updated less in the direction of this surprise than the benchmark update defined above.
  Definition: $\dfrac{\sum_f \sum_{t\in S(y)} I\begin{bmatrix} INCORRECT\_DEV_{aft} > 0 \,\&\, benchmark\_update_{aft} > UPDATE_{aft} \,\& \\ ERROR_{aft} < \left|YepsA_{ft} - benchmark\_YepsE_{aft}^{post}\right| \end{bmatrix}}{\sum_f \sum_{t\in S(y)} 1}$

- Variable Used in Analyses: *%INCORRECT_STUB_FAIL*$_{ay}$
  Description: A measure of how often an analyst exhibited stubbornness in updating that eventually proved incorrect when her estimate deviated from the median estimate in the wrong direction relative to the earnings surprise. This variable is equal to the proportion of an analyst's yearly estimates that were less accurate than the benchmark estimate described above and for which the analyst's quarterly earnings estimate deviated from the median estimate in the opposite direction from the earnings surprise and the analyst updated less in the direction of this surprise than the benchmark update defined above.
  Definition: $$\frac{\sum_f \sum_{t \in S(y)} I\left[\begin{array}{l} INCORRECT\_DEV_{aft} > 0 \,\&\, benchmark\_update_{aft} > UPDATE_{aft} \,\& \\ ERROR_{aft} > \left| YepsA_{ft} - benchmark\_YepsE_{aft}^{post} \right| \end{array}\right]}{\sum_f \sum_{t \in S(y)} 1}$$

Appendix B. The Construction of Our Analyst Rewards Data Set

The data we use to measure analyst rewards come from *Institutional Investor* (*II*) magazine. Each year, *Institutional Investor* magazine names an All-American Research Team. For each of the 75 market sectors identified by *Institutional Investor* (e.g., Airlines, Beverages, Computer Services, etc.), the magazine annually names a first place, second place, and third place analyst as well as one or more runner-up analysts. The *II* rankings are based on the results of a survey that the magazine conducts each year of "the directors of research and chief investment officers of major money management firms".[17]

We gather data on the *Institutional Investor* All-American Research Team rankings published between 1998 and 2007, which are made available on the magazine's website. This data set includes rankings of 3,774 analysts, 3,415 of whom cover stocks rather than making forecasts about macroeconomic conditions. Because the EPS forecasting data provided by I/B/E/S only identify analysts and their brokerage houses with unique, anonymous ID's, we create an algorithm to match the names of *II* winners with I/B/E/S analyst ID's. In the first stage of our matching algorithm, we rely on FirstCall analyst estimate data to de-anonymize the brokerage houses in our I/B/E/S data set. FirstCall lists the names of brokerage houses along with analysts' EPS forecasts.[18] We identify the brokerage house that corresponds to a broker ID in I/B/E/S by looking at the number of times an EPS estimate for a given company on a given date in the FirstCall database matches an EPS estimate for the same company on the same date in the I/B/E/S database. When at least 90% of such matches for a given FirstCall brokerage house correspond to a given broker ID in I/B/E/S and we have more than 100 observations of estimates

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[17] See www.iimagazine.com (accessed April 23, 2008).
[18] We rely on I/B/E/S and not FirstCall as the source of our EPS estimates data because fewer analysts are included in the FirstCall data set than in the I/B/E/S data set. This more limited sample would give us a less accurate measure of consensus estimates about a stock.

by analysts from that brokerage house in our FirstCall data, we assume we have identified the brokerage house in question in our I/B/E/S data set. This method allows us to identify the name of the brokerage house associated with 204 of the 432 broker ID's in our I/B/E/S data. We restrict our analyses of analyst rewards to include only analysts working for this subset of brokerage houses, which reduces the number of *II* award winners in our data set to 1,678. Note that when we use only the subset of data from the 204 brokerage houses we are able to identify and re-run our primary analyses to investigate whether analysts who have made incorrect extreme EPS forecasts are more stubborn than others and whether this is harmful to analysts' accuracy, our results do not change meaningfully.

The next stage of our algorithm designed to match I/B/E/S analyst ID's with *II* award winners is as follows. We begin by collecting I/B/E/S Recommendations data, which include data on the first initials and last names of analysts along with the stocks they cover at a given point in time. We then match the first initial and last name of each *II* winner with the first initial and last name of an analyst in the I/B/E/S Recommendations data to find the list of stocks that a given *II* winner covers. For the small number of *Institutional Investor* winners whose names do not appear in the I/B/E/S Recommendations data, we find the names of one to three stocks the analyst covers manually using the internet. We then match the names of analysts who won *II* awards with Analyst ID's in our I/B/E/S EPS data set based on the stocks they cover and the brokerage houses they work for.[19] This algorithm allows us to identify an analyst in our I/B/E/S EPS data set who we believe corresponds to an *II* award winner for 99% of the *II* award winners at the 204 brokerage houses we are able to identify between 1998 and 2007.

[19] For a more detailed explanation of this matching methodology, see Appendix C.

Having constructed a dataset containing information about which analysts received which *II* awards in a given year, we create a number of variables to use in our analysis, as described in Section V. We define a year leading up to an announcement of the *Institutional Investor* awards, which are published in *II* magazine's September issue, as the twelve-month period ending on July 1st of the year the *II* rankings in question are published. Because our ordered logit regressions presented in Table V control for four dummy variables indicating whether an analyst was ranked first, second, third, or runner-up in the previous year's *II* ranking list, we exclude observations from all years prior to 1999 from our final data set. In the end, our analyst-year data set includes 13,064 observations of the behavior and performance of 4,212 analysts over 9 years. Table B.I presents summary statistics for the variables.

Table B.I

Summary statistics from our analyst-year *Institutional Investor* data set.

	Mean	Std. Dev.
award_level	0.28575	0.85540
%INCORRECT_STUB	0.21974	0.27816
%CORRECT_STUB	0.13765	0.22038
%INCORRECT_DEV	0.30841	0.30753
%CORRECT_DEV	0.31748	0.30924
AVG_ERROR	0.00488	0.00731
%INCORRECT_STUB_SUC	0.10699	0.20581
%INCORRECT_STUB_FAIL	0.11275	0.21546
ranked_1st_previous_year$_{ay}$	0.02549	0.15761
ranked_2nd_previous_year$_{ay}$	0.02449	0.15459
ranked_3rd_previous_year$_{ay}$	0.02411	0.15340
runner-up_previous_year$_{ay}$	0.04876	0.21537
	(N =13,064)	

Appendix C. Method for Matching Analyst ID's in I/B/E/S Estimates Data with Analyst Names in List of *Institutional Investor* Award Winners

Step 1: In the I/B/E/S Estimates data and list of *Institutional Investor* award winners, drop all analysts who work for brokerage houses that we were not able to identify using FirstCall. In the list of *II* award winners, drop all analysts who forecast macroeconomic conditions instead of covering individual stocks.

Step 2: Match names in the list of *Institutional Investor* award winners to names in the I/B/E/S Recommendations data. This gives us a list of stocks covered by a given analyst in the *II* list during a given year. For each analyst in the *II* list who cannot be matched to the I/B/E/S Recommendations data, find 1-3 stocks covered by the analyst manually.

Step 3: For each *Institutional Investor* winner in each year, find the observations in the I/B/E/S Estimates data that match the winner's brokerage house (identified using FirstCall data, as described in Appendix B), the year, and one of the stocks covered by the winner (identified in Step 2). Each of these observations is associated with an I/B/E/S Analyst ID. Define an Analyst ID's "ratio" as the proportion of observations matched to the *II* winner in that year that are associated with that Analyst ID. If there are multiple Analyst ID's that could be assigned to the same *II* winner in a given year, choose the one with the highest value for "ratio."

Step 4: If the same analyst is assigned different I/B/E/S Analyst ID's in different years, sort the data set by analyst and year, and for each analyst apply the following rules in order:

a. If
   i. Analyst ID for year 'y' does not match Analyst ID for year 'y-1'
   ii. Analyst ID for year 'y' does not match Analyst ID for year 'y+1'
   iii. Analyst ID for year 'y-1' matches Analyst ID for year 'y+1'
   iv. Analyst ID for year 'y-1' has a ratio greater than 0.8 and at least 10 matched observations and
   v. Analyst ID for year 'y+1' has a ratio greater than 0.8 and at least 10 matched observations

   Then replace Analyst ID for year 'y' with Analyst ID for year 'y-1'/year 'y+1' [Note: 'y-1' and 'y+1' can be interpreted as 'y-2' and 'y+2']

b. If
   i. The analyst switches firms
   ii. Analyst ID for the last year at the old firm does not match Analyst ID for any prior years at the old firm
   iii. Analyst ID matches for all prior years at the old firm
   iv. Analyst ID for the last year at the old firm has a ratio lower than 0.8 or a number of matched observations less than 10 and
   v. Analyst ID for at least one prior year at the old firm has a ratio greater than 0.8 and at least 10 matched observations

Then replace Analyst ID for the last year at the old firm with Analyst ID for prior years at the old firm

c. If
    i. The analyst switches firms
    ii. Analyst ID for the first year at the new firm does not match Analyst ID for any subsequent years at the new firm
    iii. Analyst ID matches for all subsequent years at the new firm
    iv. Analyst ID for the first year at the new firm has a ratio lower than 0.8 or a number of matched observations less than 10 and
    v. Analyst ID for at least one subsequent year at the new firm has a ratio greater than 0.8 and at least 10 matched observations

    Then replace Analyst ID for the first year at the new firm with Analyst ID for subsequent years at the new firm

d. If
    i. Analyst ID in the first year the analyst appears in *II* does not match Analyst ID for any subsequent years the analyst appears in *II*
    ii. Analyst ID matches for all subsequent years the analyst appears in *II*
    iii. Analyst ID in the first year the analyst appears in *II* has a ratio lower than 0.8 or a number of matched observations less than 10 and
    iv. Analyst ID for at least one subsequent year the analyst appears in *II* has a ratio greater than 0.8 and at least 10 matched observations

    Then replace Analyst ID in the first year with Analyst ID in subsequent years

e. If
    i. Analyst ID in the last year the analyst appears in *II* does not match Analyst ID for any prior years the analyst appears in *II*
    ii. Analyst ID matches for all prior years the analyst appears in *II*
    iii. Analyst ID in the last year the analyst appears in *II* has a ratio lower than 0.8 or a number of matched observations less than 10 and
    iv. Analyst ID for at least one prior year the analyst appears in *II* has a ratio greater than 0.8 and at least 10 matched observations

    Then replace Analyst ID in the last year with Analyst ID in prior years

f. If
    i. Analyst ID in all years up to and including ‘y’ where the analyst appears in *II* matches
    ii. Analyst ID in all years from ‘y+1’ forward where the analyst appears in *II* matches
    iii. Analyst ID in at least one of the years up to and including ‘y’ where the analyst appears in *II* has a ratio greater than 0.8 and at least 10 matched observations and
    iv. Analyst ID in at least one of the years from ‘y+1’ forward where the analyst appears in *II* has a ratio greater than 0.8 and at least 10 matched observations

    Then the analyst is deemed to have had a change in Analyst ID

g. If
    i. One Analyst ID has a ratio greater than 0.8 and at least 10 matched observations and
    ii. No other Analyst ID has this property

    Then the Analyst ID with a ratio greater than 0.8 and at least 10 matched observations applies to all years that the analyst appears in *II*

h. If more than one Analyst ID or no Analyst ID has a ratio greater than 0.8 and at least 10 matched observations
    Then the Analyst ID with the highest cumulative number of matched observations applies to all years that the analyst appears in *II*

Step 5: If there is an analyst and year for which no Analyst ID is assigned, use the Analyst ID that applies to that analyst in other years, provided that the analyst does not switch firms.