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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.

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1. 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 et al., 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 (Friesen and Weller, 2006; Hilary and Menzly, 2006; see also Deaves et al., 2010) as well as a tendency to make upwardly biased forecasts (De Bondt 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 exhibit another pattern of bias in their decisions: the tendency to irrationally escalate commitment to a previously selected course of action.

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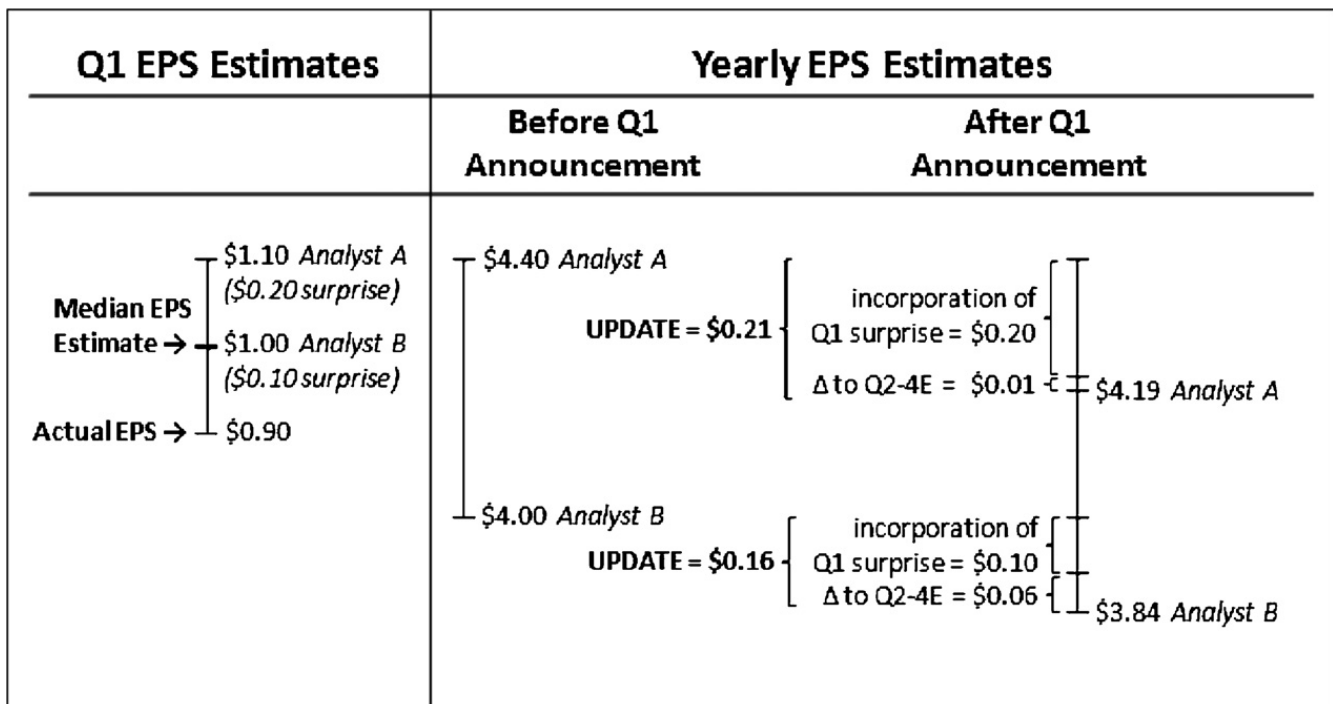


Fig. 1. Pictorial representation of illustrative example. Analysts other than A and B are not shown.

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). Such escalation can have important managerial implications. For example, a manager who escalates commitment to hand-picked investment projects or employees who continually underperform may be misallocating resources. An awareness of this bias might offset such errors.

We study the possibility that stock analysts exhibit escalation bias. 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. 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 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 Fig. 1 for a pictorial representation of this example.

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 described above reduces the accuracy of analysts’ forecasts, suggesting that our results are not driven by superior private information. Documenting the reduction in forecast accuracy associated with stubborn incorrect extremism requires constructing counterfactual forecasts that would have been made in the absence of stubbornness. 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. We show that analysts’ actual yearly EPS forecasts are less accurate, on average, than these hypothetical yearly EPS forecasts. 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 et al., 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 et al. (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 It is important to note that our results on stubbornness in updating incorrect out-of-consensus forecasts may be driven by multiple psychological biases that are closely related to escalation, such as overconfidence and cognitive dissonance. Nonetheless, to the extent that our findings regarding incomplete updating by out-of-consensus forecasters are indicative of a general pattern of bias in investors’ updating decisions, this research suggests a mechanism by which asset prices may deviate from fundamental values in a persistent fashion.

This paper proceeds as follows. Section 2 reviews the relevant literature on escalation bias and analyst forecast updates. In Section 3, we describe the construction of our data set, and in Section 4, we present analyses that measure analyst stubbornness as well as the impact of this stubbornness on analysts’ forecasting accuracy. Section 5 discusses the factors that may drive analyst stubbornness, and Section 6 concludes.

2. Relevant literature

2.1. Escalation bias

This paper builds on a large prior literature examining escalation bias. Escalation bias was first identified in a laboratory study by 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

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

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 our empirical application, analysts' sunk costs could be interpreted as their investments in incorrect out-of-consensus stock forecasts.

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 (Schoorman, 1988). 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, Staw and 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 et al. (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.

2.2. 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 et al. (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 et al., 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 (2010) 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?

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 et al., 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).

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 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.

3. 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 these 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) because such stocks are thinly traded, making data on their prices potentially unreliable.⁶ 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.⁷ Our final data set includes estimates made by 6202 analysts who cover a total of 3513 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).

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.⁸ Returning to the example in Fig. 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 *EPS_SURPRISE*, which is a measure of how far off an analyst's EPS estimate is from a company's actual, reported EPS for a given quarter. *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 Fig. 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 number of standard deviations 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 (otherwise the variable takes a value of zero). The second, *CORRECT_DEV*, measures an analyst's degree of correct

⁶ Our results are robust to retaining these observations.

⁷ Note that 79% of observations in our data set involve stocks covered by more than three analysts.

⁸ 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 3 and 4).

Table 1

Summary statistics.

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

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). See [Appendix A](#) for variable definitions.

extremism, which we define as 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 (otherwise the variable takes a value of zero). In the example in [Fig. 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](#); [Hong et al., 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 [Fig. 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 1st or above the 99th 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 99th 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 1](#) presents additional summary statistics from the trimmed data set. Note that typical earnings surprises and earnings estimate updates are quite small.

4. Are analysts stubborn to the detriment of their accuracy?

In this section, 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

Table 2

The effect of earnings surprises on extreme earnings forecasts.

	All data	Pre-SEC investigation	Post-SEC investigation
	(1)	(2)	(3)
<i>EPS_SURPRISE</i>	0.573*** (0.032)	0.627*** (0.047)	0.540*** (0.057)
<i>INCORRECT_DEV</i> × 10 ⁻³	0.328*** (0.071)	0.370*** (0.101)	0.353** (0.142)
<i>CORRECT_DEV</i> × 10 ⁻³	0.297*** (0.050)	0.272*** (0.069)	0.304*** (0.096)
<i>EPS_SURPRISE</i> × <i>INCORRECT_DEV</i>	-0.194*** (0.026)	-0.203*** (0.039)	-0.200*** (0.049)
<i>EPS_SURPRISE</i> × <i>CORRECT_DEV</i>	-0.063 (0.040)	-0.082 (0.053)	0.014 (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

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 5 percent level.

*** Significant at 1 percent level.

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.

4.1. 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:

$$UPDATE_{aft} = \beta_1 EPS_SURPRISE_{aft} + \beta_2 INCORRECT_DEV_{aft} + \beta_3 CORRECT_DEV_{aft} + \beta_4 INCORRECT_DEV_{aft} * EPS_SURPRISE_{aft} + \beta_5 CORRECT_DEV_{aft} * EPS_SURPRISE_{aft} + \beta_6 Q1_t + \beta_7 Q2_t + \alpha_{af} + \varepsilon_{aft}$$

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 2 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 2 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.⁹ 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. Fig. 2 illustrates this effect.

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. Because our regression specification includes analyst–firm fixed effects, this result is not driven by differences in analyst ability at covering a particular stock. 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 3 and 4 present the results of the same set of regressions as Table 2 but include only the subset of observations that correspond to positive and negative earnings surprises relative to the consensus (median) estimate, respectively. The OLS

⁹ From column (1) of Table 2, $(0.57) \times (10 \text{ basis points}) + (-0.19) \times (1 \text{ std. dev.}) \times (10 \text{ basis points}) = 3.8 \text{ basis points}$.

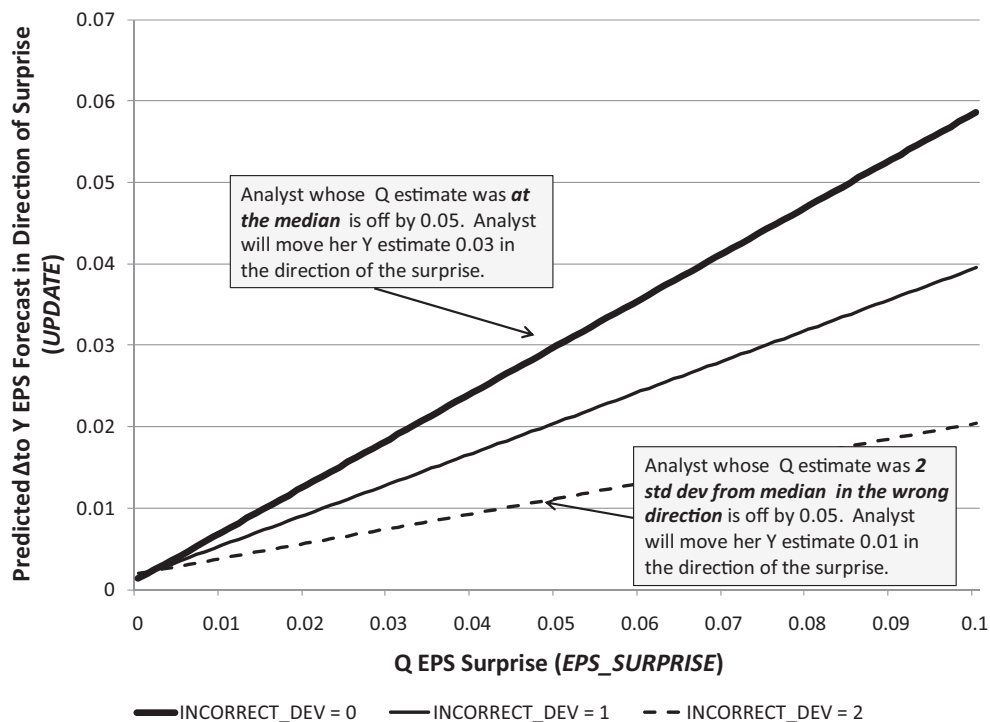


Fig. 2. Pictorial representation of regression (1) results.

Table 3

The effect of positive earnings surprises on extreme earnings forecasts.

	All data (4)	Pre-SEC investigation (5)	Post-SEC investigation (6)
<i>EPS_SURPRISE</i>	0.818*** (0.039)	0.874*** (0.055)	0.696*** (0.078)
<i>INCORRECT_DEV</i> × 10 ⁻³	0.347*** (0.063)	0.355*** (0.069)	0.342** (0.167)
<i>CORRECT_DEV</i> × 10 ⁻³	0.377*** (0.053)	0.324*** (0.071)	0.330*** (0.118)
<i>EPS_SURPRISE</i> × <i>INCORRECT_DEV</i>	-0.292*** (0.031)	-0.286*** (0.041)	-0.266*** (0.068)
<i>EPS_SURPRISE</i> × <i>CORRECT_DEV</i>	-0.320*** (0.052)	-0.377*** (0.069)	-0.077 (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

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. 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 5 percent level.

*** Significant at 1 percent level.

coefficient estimates presented in these tables reveal that our main results from Table 2 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.¹⁰

¹⁰ The coefficient on the interaction of *EPS_SURPRISE* and *CORRECT_DEV* is negative for the regressions using the sample of positive earnings surprises (Table 3), while the coefficient is positive for the regressions using the sample of negative earnings surprises (Table 4). 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 4

The effect of negative earnings surprises on extreme earnings forecasts.

	All data (7)	Pre-SEC investigation (8)	Post-SEC investigation (9)
<i>EPS_SURPRISE</i>	0.522*** (0.042)	0.572*** (0.051)	0.437*** (0.129)
<i>INCORRECT_DEV</i> × 10 ⁻³	0.465*** (0.165)	0.568*** (0.204)	-0.231 (0.456)
<i>CORRECT_DEV</i> × 10 ⁻³	0.412*** (0.127)	0.392*** (0.148)	0.148 (0.382)
<i>EPS_SURPRISE</i> × <i>INCORRECT_DEV</i>	-0.204*** (0.037)	-0.219*** (0.046)	-0.110 (0.102)
<i>EPS_SURPRISE</i> × <i>CORRECT_DEV</i>	0.072 (0.071)	0.044 (0.088)	0.055 (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

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. 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 1 percent level.

If we run the analyses discussed above including only analyst fixed effects (instead of analyst–firm fixed effects), without including any 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.¹¹

4.2. 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 3), 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 2 (β_4 from our regression equation). This “average stubbornness” quantity is then removed from an analyst's actual yearly forecast by subtracting the 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 2, 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.

This result provides some insight into possible interpretations of our findings on analyst stubbornness. The findings on analyst stubbornness alone might suggest, for example, that analysts with incorrect extreme forecasts are acting on more precise prior beliefs than other analysts. These precise priors could lead the analysts both to issue their initial extreme forecasts and to update their forecasts less in the direction of the earnings surprises that reveal the initial forecasts to be incorrect. However, this hypothesis postulating simple Bayesian updating with prior beliefs that differ in their levels of precision is not consistent with the result that the hypothetical forecasts we construct are more accurate on average than analysts' actual forecasts. We demonstrate that there is information contained in the size of an earnings surprise and in

¹¹ The full results from all robustness tests reported are available upon request from the authors.

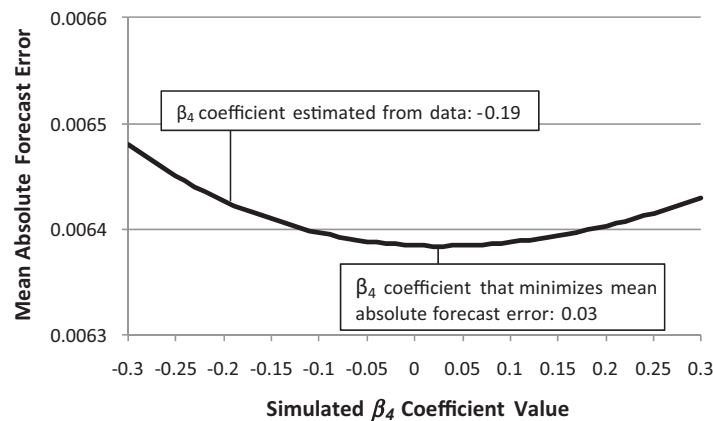


Fig. 3. The effect of simulated changes in the degree of stubbornness on average forecast error. Plot of yearly forecast error against hypothetical coefficient values for the interaction of *INCORRECT_DEV* and *EPS_SURPRISE*. Adopting the sample and coefficient estimates from column (1) of Table 2, we use the regression equation presented in Section 4.1 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 .

analysts' initial forecasts that incorrect out-of-consensus analysts could use to improve their forecast updates. Therefore, a model of Bayesian updating would have to be somewhat convoluted relative to the "precise priors" argument outlined above in order to explain the data.

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 2. 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 2, a β_4 value of 0.03 (standard error 0.01)¹² 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 Fig. 3). 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.

5. Possible explanations for analyst stubbornness

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 (Arkes and Blumer, 1985; Staw, 1976). 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 et al., 2006; Groysberg et al., 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 (Ehrbeck and Waldmann, 1996; Prendergast and Stole, 1996).

¹² 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 2. 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.

Table 5The effect of stubbornness on an analyst's probability of winning an *Institutional Investor* award.

	(10)	(11)	(12)
%INCORRECT_STUB	−0.323** (0.146)	−0.796*** (0.218)	
%CORRECT_STUB	0.331** (0.145)	0.352* (0.187)	0.352* (0.187)
%INCORRECT_DEV		0.583*** (0.180)	0.583*** (0.180)
%CORRECT_DEV		0.084 (0.144)	0.084 (0.144)
AVG.ERROR		−8.664* (5.122)	−8.672* (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

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 surprise and who react stubbornly to that surprise are more or less likely to receive such an honor. This table presents 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.

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 et al., 2006) 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.13,14

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 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 2 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 4.1, 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 5, 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.¹⁵ In addition,

¹³ 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.

¹⁴ 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 4 on this subsample, our results do not change meaningfully.

¹⁵ Because %INCORRECT_STUB and %CORRECT_STUB are constructed using estimated parameters, the standard errors reported in Table 5 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 5.

the right-hand side of regression (10) includes dummy variables indicating which “All-American” designation an analyst received the previous year.¹⁶ 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 “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 4.

While the empirical pattern demonstrated in column (10) of Table 5 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 5 adds the explanatory variable AVG_ERROR, which is the mean of ERROR (defined in Section 3) 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 5, 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 5, 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 4 is a response to compensation-related or career-related incentives.

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 5, 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.

¹⁶ 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.

6. 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 stubbornness when they make incorrect extreme earnings forecasts, suggesting that this behavior is not a response to compensation-related or career-related incentives. It seems likely that the behavior is instead a result of escalation and related psychological biases, such as overconfidence.

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 stubbornness 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.

Future research could explore the implications of our results for asset prices. For example, if analysts are especially stubborn when updating their forecasts about the future performance of a particular stock, that stock's returns might exhibit heightened autocorrelation. 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. Supplementary data

Supplementary data associated with this article can be found, in the online version, at [doi:10.1016/j.jebo.2010.11.003](https://doi.org/10.1016/j.jebo.2010.11.003).

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