STANDING OUT FROM THE CROWD: THE OUTLIER'S EFFECT ON CORPORATE GOVERNANCE*

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Abstract

This paper examines the real effects of outliers in the context of extreme analyst optimism and corporate governance. Using earnings forecasts issued by sell-side analysts between 1991 and 2011, we construct a proxy to capture two essential traits of an outlier's opinion—being markedly distinct from the others and coming from an individual instead of a cohort of agents. We show that when an analyst issues extremely optimistic forecasts that drastically deviate from peer consensus, there is a greater tendency on the part of firms to manage earnings. When exploring possible underlying mechanisms through which extreme analyst optimism imposes pressure on managers to meet short-term targets, we find that the arrival of an outlier forecast gives rise to the optimism of peer analysts and generates stronger reactions from investors. Further analyses reveal that private information and conflicts of interest cannot explain the effect of an outlier's opinion on earnings management. Instead, an analyst's self-motivated incentives are likely at play.

Keywords: Outliers; extreme optimism; earnings management; financial analyst; corporate governance

JEL: G34; M41; G24

Outlier: "A statistical observation that is markedly different in value from the others of the sample"

Merriam-Webster Dictionary

1. INTRODUCTION

Outliers are vexing to economists. To draw correct economic inferences, researchers focus on the average effects and employ various econometric treatments to mitigate the influence of outliers. Presumably, except for biasing the true interpretation of an empirical analysis, the presence of outliers themselves is economically negligible.

Anecdotes in the real world often suggest otherwise. The most vocal and extreme opinion is common in many social dimensions. For instance, during political election campaigns, only the most extreme views occupy the attention of the mass media and the general public for a considerable period of time (Hirano, Synder, and Ting 2009). Whether such opinions are reflective of private information or are oblivious to it, they may still exert their influence upon others (Demarzo, Vayanos, and Zwiebel 2003).

What largely remains unanswered, therefore, is whether outliers are indeed a noise undesirable for econometricians, and if not, whether they can impose a real, long-lasting effect. This is because it is empirically challenging to systematically compare among economic agents' tendency to exert an extreme behavior and to directly assess the economic consequences of such a behavior. In this paper we take on this challenge and examine the real effect of outliers in the context of corporate governance and analysts' extreme optimism. Specifically, we study whether analysts' outlier forecasts affect managers' incentive to manipulate earnings. Furthermore, we explore to what extent an outlier's opinion shapes the opinion of the group, and how an outlier's view influences other market participants.

Using a sample of earnings forecasts issued by sell-side analysts between 1991 and 2011, we construct a proxy to capture the two essential characteristics of an outlier's opinion—being markedly distinct from the others and coming from an individual instead of a cohort of agents. For a firm in each year, we identify the most optimistic forecast as the outlier forecast. The difference between the most optimistic forecast and the consensus from peer analysts, thus captures to what extent an outlier's opinion deviates from the group consensus and serves as a proxy for the extremism of an outlier forecast.

Whether and how an outlier's opinion affects a firm's earnings management can be ambiguous *ex ante*. We explore three hypotheses. The null hypothesis—the "noise hypothesis"—argues that outliers serve merely as a noise and casts doubt on any real effect of an outlier's opinion imposed on a professional and sophisticated audience. It predicts that an outlier forecast does not impel managers to manipulate earnings.

For the alternatives, we consider two competing hypotheses. The "discipline hypothesis" is based on the empirical evidence documenting the monitoring role of financial analysts (e.g., Yu 2008; Chen, Harford, and Lin 2013; Irani and Oesch 2013). When an extremely distinct opinion is voiced, it stirs more attention from fellow analysts, who then may spend more of their time on the firm under their coverage. The greater analyst attention, coupled with a potentially more active monitoring role, leads to greater public scrutiny thus less earnings management. The "discipline hypothesis" suggests that the extent of an outlier's extremism reduces the degree of earnings management.

The "pressure hypothesis", on other hand, builds on the literature examining the role of analysts (and the public market in general) in cultivating managerial myopia (e.g., Fuller and Jensen 2002; He and Tian 2013). This hypothesis argues that an outlier forecast influences the opinions of fellow analysts to raise their forecast estimates. With a rise in the overall forecast values as well as the level of optimism bias, managers face excessive pressure and have a greater incentive to manipulate earnings. The "pressure hypothesis" thus predicts that the extent of an outlier's extremism exacerbates firms' earnings management.

We test the above three hypotheses and document a real effect of extreme analyst optimism on firm corporate governance. The extremism of an outlier forecast is positively associated with firm earnings management, measured by the level of discretionary accruals based on modified Jones (1991) model. One standard deviation increase in extreme optimism is associated with an 18% increase in the level of earnings management. The results are robust to alternative sample restrictions, alternative measures of earnings management and extreme optimism, alternative empirical specifications, and alternative econometric models—including an identification strategy using a quasi-natural experiment (brokerage house mergers) to address the endogeneity concern, as well as a direct test for potential reverse causality. Our findings thus support the "pressure hypothesis" but are inconsistent with the "discipline hypothesis" and "noise hypothesis".

Next, we attempt to identify possible underlying economic mechanisms through which outlier forecasts exert excessive pressure on managers for more earnings management. Psychology literature has long established that people's assessments on value and probability are subject to the influence of a simple, sometimes even irrelevant, reference point ("anchor"), despite their effort and intension to avoid such an influence (e.g., Tversky and Kahneman 1974; Simmons et al 2010). In the context of forecast dynamics, we find that analysts are not immune to the anchoring effect. Forecasts from peer analysts become more optimistic following the arrival of the outlier forecast. This suggests that extreme optimism affects peer analysts by shaping their views about the firm. More importantly, the effect of extreme optimism on earnings management is prominent only when an outlier forecast generates more optimistic subsequent forecasts by fellow analysts.

Peer analysts are not the only financial market participants who respond to outliers' opinions. Compared to a non-outlier forecast, we find that both abnormal returns and trading volume surrounding the issuance of an outlier forecast are significantly higher. Therefore, investors are also subject to the influence of extreme analyst optimism.

In the final part of the paper, we explore three plausible sources that may contribute to extreme optimism: private information, investment banking incentive, and analyst self-motivated reasons. To investigate whether an analyst's private information leads to the issuance of outlier forecasts, we conduct two sets of tests. In the first set of tests, we find that accuracy of outlier forecasts is significantly worse than non-outlier forecasts, which suggests that analysts issuing outlier forecasts do not necessarily possess better private information than others.

In the second set of tests, we explore the effect of a regulatory event, the Regulation Fair Disclosure (Reg FD). By prohibiting publicly traded companies from selectively disclosing information to certain financial market participants, Reg FD exogenously reduced the availability of private information to sell-side analysts. If an analyst's private information accounts for his or her extreme optimism and explains our findings, we should expect that the extremism of an outlier forecast, as well as its effect on earnings management, declines after the Reg FD. Instead, there is a rise in the magnitude of extreme optimism after the Reg FD. Furthermore, the effect of extreme optimism on a firm's earnings management is larger post Reg FD than pre Reg FD. These tests thus suggest that private and accurate information is unlikely to cause an analyst to voice extreme views.

To explore whether the incentive from investment banking is the reason for extreme optimism, we first take advantage of another regulatory event—the 2002 Global Settlement (GS), which prohibits analysts from being compensated for generating investment banking business for their investment firms. This regulatory event thus serves as an exogenous change that directly affects brokerage-based incentives. If extreme optimism is motivated by such incentives, the magnitude of extreme optimism should diminish after the GS. Instead, we find that the level of extreme optimism and its effect on earnings management increased post GS. Second, we explore whether investment banks reward analysts who issue outlier forecasts with better career outcomes. If optimistic reports help generate investment banking businesses, analysts voicing the extreme optimistic view should experience better career advances. On the contrary, we find that analysts issuing outlier forecasts are more likely to leave the profession and do not have a better chance to be promoted. Both the GS and analyst career tests thus suggest that investment banking incentive is unlikely to be the dominating reason for extreme optimism.

To explore the third possible cause for extreme optimism—self-motivated reasons—we examine the traits of outlier forecasts. An outlier forecast tends to be more extreme when a higher level of *ex ante* uncertainty exists surrounding a firm's information environment. An outlier forecast is usually issued by an analyst who has covered the firm for a longer period of time, who was less accurate in the past, and who is affiliated with a smaller broker. Intuitively, the downside for such an analyst to voice an extreme view appears to be small. These results suggest evidence for a stronger personal motive for risk-taking and attention-seeking.

Overall, these tests suggest that private information and conflicts of interest are unlikely to be the dominant factor that leads an analyst to voice an extremely optimistic opinion. Instead, in a highly competitive industry with only the very few top performers reaping huge rewards, analysts' self-motivated incentives, for a strategic reason such as attention-seeking or risk-taking, or driven by his or her behavioral biases, are more likely to be the source for the extreme optimism.

To the best of our knowledge, our paper is the first study to directly evaluate the real outcomes of outliers' opinions. By documenting the significant effect of outliers on earnings management, our paper contributes to the literature on analyst optimism by focusing on the influence of the most extreme forecast rather than on the average forecast optimism. We show that the arrival of an outlier forecast shapes the subsequent forecast optimism of fellow analysts, and thus identifies a potential source for the overall forecast optimism. More importantly, by presenting direct evidence on the unintended real consequences potentially resulting from an analyst's personal motives, we show that forecast optimism, as well as its effect on corporate governance, can arise from a source beyond the well-recognized private incentives of brokerage houses.

Our paper is also related to the large literature studying the impact of financial analysts on managers. On the positive side, studies show that analysts help reduce information asymmetry (Brennan and Subrahmanyam 1995; Kelly and Ljungqvist 2012) and act as external monitors (Yu 2008; Chen, Harford, and Lin 2013; Irani and Oesch 2013). On the negative side, researchers find that analysts impose pressure on managers and induce managerial short-termism (e.g., Graham, Harvey, and Rajgopal 2005; He and Tian 2013). Most of the studies use the number of analysts to measure the scope of coverage. Instead of the aggregate effect of analysts as a group, we focus on the heterogeneity of analysts and examine how individuals with extreme opinions affect corporate governance. By exploring the dynamics of the sequence of forecasts and interactions between outliers and other market participants, we present a direct mechanism through which an individual, rather than a group of analysts, can also influence managers' decisions on financial reporting.

The rest of the paper proceeds as follows. Section 2 discusses the research design and hypotheses. Section 3 describes our data sources and sample construction. Sections 4 through 6 present the empirical results. Section 7 provides discussions of additional tests of causality and robustness. Section 8 concludes the paper. Variable definitions and constructions are in the Appendix.

2. RESEARCH DESIGN

Due to the idiosyncratic nature of outliers, it is empirically challenging to compare among economic agents' tendency to exert an extreme behavior and to then directly assess the economic consequences of such behavior. Using earnings forecasts from sell-side analysts to evaluate the real effect of outliers' opinions thus offer several advantages. First, unlike other corporate events such as security issuances and mergers and acquisitions in which the timing of the event is endogenous and individuals who voice their opinions can be sporadic and random, corporate earnings disclosure is mandated on a regular basis and analyst following tends to be stable. Second, it is easy to identify outliers—individual forecasts that are most distinct from the group consensus—in a systematic way. Lastly but more importantly, the extent to which a forecast deviates from the group's view is measurable and comparable across firms.

2.1 Hypotheses

To evaluate the impact of outliers' opinions, we explore three hypotheses. The "noise hypothesis" considers that outlier forecasts are ignored by other professional market participants, including peer analysts and managers, who view extreme forecasts as a noise. This hypothesis predicts that an outlier forecast has no effect on a manager's earnings management behavior.

As an alternative, the “discipline hypothesis” postulates that analysts’ monitoring role on earnings management is strengthened by the presence of distinct views. When an extremely distinct opinion is voiced, it stirs more attention from fellow analysts, who then may spend more time on their own to study the firm. More analyst attention could enhance their monitoring role, which potentially leads to less earnings management.

The third hypothesis, “pressure hypothesis”, predicts the opposite. This hypothesis argues that the presence of an extreme optimistic view can exacerbate managerial myopia (Stein 1988). When an outlier forecast influences the opinions of fellow analysts to raise their forecasts, the overall level of optimism bias increases, which pressures managers to more excessively manipulate earnings in line with analyst expectations. The “pressure hypothesis” thus predicts that more extreme optimism generates greater pressure for firms to manipulate their earnings.

2.2 Empirical Proxies

Our main variable of interest is “Extreme Optimism”. To capture the extent that an individual’s opinion differs from that of the group, we construct this variable at firm-year level as the difference between the most optimistic forecast and the consensus peer forecast. When calculating consensus peer forecast, which is the average of forecasts issued by other analysts covering the same firm in the same year, we include only the forecasts issued prior to the announcements of realized earnings to minimize the potential effect of reverse causality. We then scale this difference by the stock price of the previous calendar year to ensure the comparability across firms with differing characteristics such as size and growth opportunities. The greater the value of the variable, the more distinct the extreme forecast deviates from the group's average.[2] In this respect, our proxy for an outlier's opinion stands in sharp contrast to the traditional measure for analyst optimism, which is typically measured as the difference between the average of forecasts of all analysts and the realized firm earnings (e.g., Bradshaw et al. 2001; Drake and Myers 2011).

To illustrate, consider the following numerical example. A firm is covered by five analysts, who issue forecasts of $1, $2, $2, $4, and $6 earnings per share, respectively. The actual earnings is $3 per share. We identify the $6 per share forecast as the outlier forecast because it is the most extreme one away from peer consensus. In contrast, the traditional measure for analyst optimism is the difference between the consensus forecast (i.e., the average of all forecasts, $3) and the realized earnings ($3), which is $0. While the traditional proxy for average analyst optimism is benchmarked by the actual earnings, our proxy for an outlier's opinion is benchmarked by the average estimates from peer analysts.

In what follows, we label a forecast as an outlier forecast if it is the optimistic forecast that deviates the most from the consensus forecast of peer analysts. We label an analyst as a "peer analyst" if he or she covers the same firm at the same time as the one who issues the outlier forecast. "Extreme Optimism" thus measures the extremism of an outlier forecast relative to the views of peer analysts.

Following the literature (e.g., Jones 1991; Dechow et al. 1995), we measure a firm's earnings management using a modified version of Jones (1991) model. The literature on accrual-based earnings management argues that, between the two components of earnings, accounting adjustments called accruals are more vulnerable to manipulation than cash flows, because the size and sign of accruals are subject to manager's discretion. Of course, not all the accruals are

[2] By construction, we focus on forecast optimism, rather than forecast pessimism. This is because "analysts are known for excessive optimism because of conflict of interest" (Hong and Kacperczyk, 2010) and pessimism is less relevant than optimism to induce manipulations and less suitable to test the three hypotheses.

the result of earnings management: Given a firm's operational and industry conditions, certain accruals (i.e., non-discretionary accruals) are necessary and appropriate. Therefore, our proxy for a firm's earnings management is the level of discretionary accruals, computed as the difference between total accruals and non-discretionary accruals. The non-discretionary accruals are estimated from cross-sectional regressions (within each SIC two digit code industry) of total accruals on changes in sales and on property, plant, and equipment. A higher value of discretionary accruals indicates a greater extent of earnings management. Alternatively, in Section 7 we employ various proxies to measure earnings management through real activities in terms of abnormal levels of production and operating activities, instead of accounting-based accruals.

3. DATA AND DESCRIPTIVE STATISTICS

3.1 Data Sources

We draw a sample of analyst annual earnings forecasts between 1991 and 2011 from the Institutional Brokers' Estimate System (I/B/E/S) database. Since the estimates for the extremism of an outlier opinion hinge on an adequate group size for peer analyst consensus, we limit forecasts to firms that are covered by at least four analysts in a given year. Our final sample contains 1,082,395 forecasts issued by 10,144 analysts regarding 4,436 firms between 1991 and 2011.

Information on analyst employment is also obtained from the I/B/E/S database. Accounting data comes from Compustat annual data files and the stock return data comes from CRSP daily files.

3.2 Summary Statistics

Table 1 presents the descriptive statistics of our final sample. At firm-year level, Panel A shows that the average degree of accrual-based earnings management is 0.17. The most extreme forecast about earnings per share (price-adjusted) is 0.02. The analysts issuing outlier forecasts have stayed in the profession for 6.8 years (i.e., 82 months) on average, similar to the 82 months for an average peer analyst covering the same firm at the same time. The return on assets for our sample firm averages 2%, total assets average near 3.28 billion dollars, and the average ratio of market equity to book equity is 3.9.

At earnings forecast level, Panel B reveals that the professional experience at the time a forecast is issued averages 85 months. The average price adjusted forecast error is 0.01. The timing of the forecast, computed as the difference in days between the time when an analyst makes a forecast and the time when a firm announces its earnings, averages 205 days. The average forecasted earnings (unadjusted by price) is $1.31 per share. The abnormal return surrounding the issuance of a forecast is 0%. The daily shares turnover averages 4 millions in response to an issuance of earnings forecast.

4. EXTREME OPTIMISM AND EARNINGS MANAGEMENT

In this section we assess the real effect of outlier opinions and test the “noise”, “pressure” and “discipline” hypotheses. We estimate the effect of “Extreme Optimism” on a firm’s earnings management using the ordinary least squares (OLS) approach. Table 2 reports the baseline regression results. The unit of analysis is firm-year observations. Column 1 reveals that analyst extreme optimism is positively and significantly related to the extent of earnings management, after taking into account observed and unobserved time-varying and industry-specific factors with year and industry fixed effect.

In column 2, in addition to year and industry fixed effect, we control for time-varying analyst-specific, brokerage-specific and firm-specific characteristics that may explain earnings management. In terms of analyst and broker characteristics, we include: the professional experience of the analyst who issues the outlier forecast, the average professional experience of peer analysts, the broker size (calculated as the logarithm of the number of analysts employed by a broker when a forecast is issued and used as a proxy for the broker's prestige and reputation), and the size of the coverage (measured by the number of analysts covering the firm, which prior research has shown to affect earnings management). In terms of firm characteristics, we include a firm's size (measured by the natural logarithm of total assets), its profitability (measured by ROA), and its growth opportunity (measured by the market to book ratio). In column 3, we replace industry fixed effects with firm fixed effects to control for observed and unobserved firm-specific factors that may affect both earnings management and the extremism of an outlier forecast.

We observe that the positive effect of extreme optimism on earnings management is robust to the inclusion of various analyst-, brokerage-, and firm-specific characteristics, as well as firm and year fixed effects. The economic effect is also sizable. To illustrate, the coefficient for "Extreme Optimism" in column 3 is 1.03, which suggests that one standard deviation increase in extreme optimism is associated with an increase in the level of earnings management equivalent to 18% of the sample mean. Overall, the results from our baseline regressions support the "pressure hypothesis", but are inconsistent with the "noise hypothesis" and "discipline hypothesis".

5. WHO RESPONDS TO AN OUTLIER FORECAST?

5.1 Reactions from Peer Analysts

Our analyses so far have shown that the extremism of earnings forecast is linked with more earnings management. In this session we explore underlying economic mechanisms through which an individual's extreme opinion can exert effect on managers. We postulate that the arrival of the outlier forecast affects the forecast optimism of peer analysts, inducing them to adjust their earnings forecast subsequently upwards. As a group, this creates pressure on managers to alter earnings to cater to analyst expectations.

We first compare the forecasts issued by peer analysts before and after the arrival of the outlier forecast. Since an outlier forecast can occur at any time of the year and the timing of forecasts from peer analysts is difficult to standardize, we use a rolling-window framework to capture the potentially long-lasting effect of the outlier forecast on fellow analysts. Specifically, "Post Outlier Forecast (60 Days)" ("Post Outlier Forecast (90 Days)") is an indicator variable equal to one if a forecast is issued by a peer analyst within 60 days (90 days) after observing the outlier forecast, and zero if it is issued prior to the release of such a forecast.

As an alternative to the fixed time frame, we use "Post Outlier Forecast (15 Forecasts)" ("Post Outlier Forecast (20 Forecasts)"), an indicator variable equal to one if a forecast belongs to the subsequent 15 (20) forecasts following the outlier forecast, and zero if it is issued prior to the release of the most extreme forecast. By construction, the sample size for this set of analyses varies depending on the length of the rolling window and the timing of the outlier forecast.

We run OLS regressions with the dependent variable as the forecasted earnings per share issued by a peer analyst, scaled by the share price in the previous year, and the key independent variable as one of the dummies described above. To control for observed and unobserved firm-specific and time-varying factors that affect the extent of analyst optimism, we include firm ×

year fixed effects. We also control for analyst-specific characteristics such as the professional experience of the peer analyst at the time when a forecast is issued, and his/her past forecast accuracy, which is computed as the average Hong-Kubik (2003) forecast accuracy score in the previous two years.

Table 3 Panel A reports the results. The coefficients associated with various dummies for forecasts issued after the outlier forecast are positive and significant. Since all the tests include firm × year fixed effects, this indicates that, among all the peer analysts covering the same firm in the same year, forecasts issued after the outlier forecast (in a rolling-window framework) are more optimistic than those issued prior to the arrival of such a forecast.

In Panel B we explore how outlier opinion affects firm earnings management through peer analyst reactions. We define the reaction from peer analysts as being "strong" ("weak") if the average of forecasted earnings issued by peer analysts after the outlier forecast is higher (lower) than that of forecasted earnings issued before the outlier. In columns 1 through 4, we split the sample based on the "strong" or "weak" peer reaction using the 60- and 90-day post outlier windows, respectively. In columns 5 through 8, the sample split is based on a rolling window with a fixed number of forecasts (15 and 20 forecasts) instead of a fixed time interval.

We repeat the baseline regressions of Table 2 for each set of subsamples. Panel B reveals that when peer analysts respond strongly to the outlier forecast (columns 2, 4, 6, and 8), "Extreme Optimism" is significantly related to a firm's earnings management. By contrast, when the peer reaction is weak, the extremism of the outlier forecast itself hardly affects earnings management (columns 1, 3, 5 and 7).

To illustrate, the coefficient for "Extreme Optimism" is 1.76 when the average forecasted earnings in the 90-day post-outlier forecast window is higher than the average forecasted earnings prior to the outlier (column 4), and it is statistically significant. This indicates that a one percent increase in “Extreme Optimism” is associated with 1.76% more earnings management in the presence of a strong reaction from peer analysts. The effect of the extremism of the outlier on earnings management dwindles to 0.57% when the peer reaction is weak. It also becomes statistically insignificant.

Table 3 presents evidence that fellow analysts respond to the outlier forecast and such a forecast moves the forecast consensus. Potentially this creates a long-lasting pressure on managers to meet the higher earnings expectation from analysts as a group.

The existing literature on analysts’ forecasts mostly focuses on the latest forecasts before earnings announcements. In contrast, we show some earlier forecasts still contain useful information and appear to influence the subsequent forecasts from peer analysts over an extended period of time. The results in Table 3 thus help shed light on our understanding about the path-dependent nature of analysts.

While the reasons for the peer analyst reaction—whether it be by herding (Graham 1999 and Welch 2000) or information cascade (Welch 1992)—are beyond the scope of the paper, our findings are broadly consistent with the substantial evidence in psychology on anchoring and adjustment. For instance, a seminal work by Tversky and Kahneman (1974) shows that a simple, sometime even irrelevant, reference point (“anchor”) can significantly influence people’s assessment of valuation and probability. Simmons et al. (2010) further demonstrate that it is difficult to avoid anchoring—even for people who intentionally try to shun the influence of an irrelevant anchor. In the context of this study, an extreme forecast, even though it may look unreasonable or come from a weak analyst, serves as a salient anchor for all the peer analysts to follow. Put differently, in the context of forecast dynamics, analysts are not immune to the anchoring effect.

5.2 Reactions from Investors

Instead of fellow analysts, we now examine whether the market moves following the release of an outlier forecast, and whether investors' reaction differs between the most extreme forecast and other forecasts. On the day when an earnings forecast is issued, we calculate both the abnormal return ("CAR", which is the difference between the stock return and the CRSP value-weighted return) and the trading volume (measured as the natural logarithm of shares traded). The key independent variable is "Outlier Forecast", a dummy variable equal to one if a forecast is the most optimistic one and zero otherwise. To control for firm-specific and time-variant observed and unobserved factors that may affect the extent of market reaction to a forecast, we include firm × year fixed effects for all analyses.

Table 4 presents the results for abnormal returns (columns 1 and 2) and trading volumes (columns 3 through 5) at the time when an analyst issues earnings forecast. In columns 2, 4, and 5, we include additional controls for analyst-specific characteristics that may affect the market reaction such as the analyst's professional experience, track record of past forecast accuracy, the size of the broker with which the analyst is affiliated, and the timing of the forecast.

Columns 1 through 4 reveal that the coefficients for "Outlier Forecast" are positive and significant. Among all the forecasts issued by the analysts covering the same firm at the same time, the abnormal return is 0.6% higher, and the trading volume is nearly 5% greater, for the outlier forecast than for non-outlier forecasts.

It is possible that the findings in columns 3 and 4 are driven by a mechanical reason, as trading volumes are usually higher when price movements are larger. In column 5, we control contemporaneous abnormal returns at the time of earnings forecasts.[3] While the magnitude of price movement is indeed positive and significant, the "Outlier Forecast" dummy remains positively and significantly associated with trading volume. The magnitude of the coefficient is also similar to those in columns 3 and 4.

Overall, the results in Table 4 indicate that investors are influenced by extreme analyst optimism. Not only does the market move in response to the release of the outlier forecast, but also the reaction generated is stronger for the outlier forecast than for other forecasts.[4] The fact that investors react strongly to the most extreme forecast may suggest another channel through which outlier opinions can generate more pressure on managers.

Lastly, it is worth pointing out that by comparing market reactions between the outlier and non-outlier forecasts, we essentially take into account the effect of any news release and firm announcement before or after the arrival of the outlier forecast. This is because if the outlier forecast is issued in response to the newly available firm-specific information, then the market should react at the time when the news is released, instead of when the outlier forecast is issued. Put differently, if an outlier forecast happens to be the one that most timely reflects the most recently available information, then we should not expect that the market reacts strongly to the outlier forecast itself.

6. POTENTIAL SOURCES FOR EXTREME OPTIMISM

[3] Since both the buyer-initiated and seller-initiated orders contribute to the trading volumes of a firm's shares, we take the absolute value of the contemporaneous abnormal return. Using signed contemporaneous abnormal returns does not alter our findings.

[4] We are not able to conduct the earnings management test directly in this setting. This is because earnings management is constructed on an annual basis, whereas the abnormal return and trading volume are computed surrounding the day when the outlier forecast is issued. Since on average the outlier forecast occurs at the early part of the year, it is not expected to exert long-lasting effect on variables constructed based on data at the fiscal year end.

In this section, we explore three sources that potentially contribute to analyst extreme optimism. First, an analyst issuing outlier forecasts may be the one who has the most accurate private information. Second, analysts may issue overoptimistic reports in order to secure current and future investment banking businesses for their brokerage firms (e.g., Lin and McNichols 1998; Michaely and Womack 1999). Lastly, analyst may issue outlier forecasts due to self-motivated incentives, which can be strategic reasons such as attention-seeking and tournament, or behavioral biases such as overconfidence (Hilary and Menzly 2006).[5]

6.1 Private Information

We conduct two sets of tests to investigate whether an analyst's private information leads to his or her extreme optimism. In the first set of tests, we examine the accuracy associated with outlier forecasts. The dependent variable is the forecast error, and the key independent variable is "Outlier Forecast". To avoid the potential contamination effect from an outlier forecast, we exclude all forecasts issued after the occurrence of the outlier forecast. We control for firm × year fixed effects as well as analysts' experience, track record of past accuracy, the size of brokers, and the timing of the forecast.

Table 5 Panel A presents the OLS regression results. In column 1, an analyst's experience is measured by his or her general experience in the profession, whereas in column 2, the experience is firm-specific. We observe that the coefficient for the dummy for the outlier forecast is positive and significant. With the inclusion of firm × year fixed effects, this result indicates that among all the analysts covering the same firm at the same time, outlier forecasts

[5] For example, in the early 2000's, a well-known analyst, Jack Grubman from Salomon Smith Barney, held a very optimistic view on a group of telecommunication companies, including Worldcom, Global Crossing, and Winstar Communications, when most of his peers were more pessimistic on those firms. There can be multiple reasons for why Grubman issued those optimistic forecasts: (1) He held an informational edge with the telecommunication industry. As a formal employee of AT&T, he had thorough knowledge of the industry and had tight connections with executives through his network. (2) He was deeply involved in investment banking business and used his influence to secure IPOs and M&A deals for his firm. (3) On the street, he was known for his exuberant and confident personality. His early career success reinforced those traits.

have a larger error than non-outlier forecasts. This implies that analysts issuing the most extreme forecast do not necessarily possess better private information.

In the second set of tests, we explore a regulatory event—the implementation of Regulation Fair Disclosure (Reg FD) in 2000—that exogenously affects the sources for analysts' private information. By prohibiting publicly traded companies to selectively disclose information to certain financial market participants, Reg FD has largely eliminated the benefits of private access to management (Koch, Lefanowicz, and Robinson 2012). If an analyst's private information accounts for his or her extreme optimism regarding a firm under coverage, we should expect the level of extreme optimism, and thus its effect on the firm's earnings management, to decline after the Reg FD.

Table 5 Panel B reports the OLS regression results. In column 1, we use the entire firm-year sample to detect whether the implementation of the Reg FD reduces the magnitude of analyst extreme optimism by limiting the information advantage of selected analysts. The dependent variable is "Extreme Optimism". The key independent variable is "Post Reg FD", a dummy variable equal to one if a forecast is issued after the Reg FD and zero if before. The coefficient for the "Post Reg FD" dummy is positive and significant. This suggests a rise instead of a drop in the magnitude of extreme optimism after the Reg FD, when many analysts' sources for private information are severed.

In columns 2 and 3, we repeat our baseline regression by splitting the sample into the 1991-2000 pre-Reg FD subsample and the 2001-2011 post-Reg FD subsample. The coefficient for "Extreme Optimism" not only remains positive and significant in both periods, but also is larger during the post-Reg FD period (1.325) than during the pre-Reg FD period (0.424). The effect of outlier forecast on earnings management appears stronger, rather than weaker, after the Reg FD.

To summarize, the results from Table 5 suggest that private information is less likely to be the main cause for extreme analyst optimism.

6.2 Conflicts of Interest—Brokerage-based Incentive

Existing literature has documented extensive evidence that analysts issue biased and overoptimistic reports in an attempt to secure current and future investment banking business for their brokerage firms. Researchers, along with regulators and the mass media, have argued that analysts' compensation structure created such an incentive, as a significant portion of their compensation is tied to trading profits and, until recently, to the underwriting activities of their employers (e.g., Dorfman, 1991; Boni and Womack, 2002).

In this section, we employ two sets of tests to explore whether the brokerage-based incentives are the reason behind the issuance of an extremely optimistic forecast. In the first set of tests, we explore whether a change in analysts' compensation structure leads to a change in analysts' extreme optimism, and thus a change in its effect on earnings management. In the second set of tests, we investigate whether analysts issuing the extremely optimistic forecasts are rewarded with a better career outcome.

6.2.1 Mitigating Conflicts of Interest: The Global Settlement

The data on sell-side analysts' compensation is not publicly available, preventing researchers from directly measuring the existence of incentives that drive conflicted research. Instead, we use a regulatory event—the 2002 Global Settlement (GS)—allowing us to explicitly identify a change in analysts' compensation structure that is directly linked to analysts' incentives. One of the prominent outcomes from the GS is a mandated change in analysts' compensation structure, which prohibits analysts from being compensated for generating investment banking business for their brokerage firms. This mandate thus serves as an exogenous change to analyst compensation that directly affects analysts' incentives. If extreme optimism is motivated by analysts' private incentives, we should observe that the level of extreme optimism and the extent it influences firm's earnings management diminish after the GS.

Following Kadan et al. (2009), we restrict our sample of firms to two years before (2000-2001) and two years after (2003-2004) the implementation of the GS, and require sample firms to retain analyst coverage both before and after the GS. The unit of analysis is firm-year observations.

In column 1 of Table 6, we regress "Extreme Optimism" on "Post GS" for the combined sample covering both the pre- and post-GS periods. "Post GS" is a dummy variable equal to one if a forecast is issued during the post GS period and zero otherwise. We observe that the coefficient for the dummy is positive and significant, suggesting a rise in the magnitude of extreme optimism following the GS. In columns 2 and 3 of Table 6, we repeat the baseline regressions for the pre- and post-GS sample periods, respectively. While the coefficient of "Extreme Optimism" is positive and significant in both periods, it is much larger rather than smaller, during the post GS period (2.83) than the pre GS period (1.03).

The results thus indicate that not only the extremism of an outlier forecast continues to engender more aggressive earnings management post GS, but its effect is also stronger than that before the GS. These findings suggest that, while brokerage-based incentives may affect the optimism of analysts as a group, they do not appear to be the main reason behind an individual analyst's decision to issue the most extremely optimistic forecast.

6.2.2 Career Consequences of Extremely Optimistic Analysts

Hong and Kubik (2003) show that the labor market in general favors optimistic analysts, who get promoted faster and more likely to stay in the profession. If extreme optimism arises from analysts' incentives to boost revenue related to investment banking and trading for their brokerage firms, then we expect that such analysts are more likely to be promoted and are less likely to leave the profession.

We track the career movement of analysts who issue outlier forecasts. First we explore whether issuing the extremely optimistic forecast reduces the propensity for an analyst to leave the profession. In this set of tests, the dependent variable is "Leave", a dummy variable equal to one if the analyst disappears from the I/B/E/S database for three or more years following a forecast, and zero otherwise. The key independent variable is "Top 5% Extreme Optimism". Following Hong and Kubik (2003), we rank each analyst each year based on the percentage of his/her forecasts turning out to be outlier forecasts, and set this dummy variable equal to one if an analyst in a given year belongs to the top 5% of all analysts based on this ranking.

Throughout the entire set of analyses, we include year fixed effects and analyst fixed effects to absorb time-varying and analyst-specific characteristics that can drive an analyst's propensity to depart from the profession. In addition, Hong and Kubik (2003) indicate that good past forecasting performance decreases an analyst's chances of experiencing such an unfavorable outcome. We thus control for the effect of past forecast accuracy on an analyst's moving out the profession. Specifically, we estimate each analyst's past performance by computing his/her average Hong-Kubik (2003) forecast accuracy score from year t to $t-2$. We then include dummies for whether or not an analyst's past performance falls into the bottom 5, 5-10, 10-25, 25-50, and 50-75 percentiles.

Columns 1 and 2 of Table 6 Panel B report the results. Controlling for forecast accuracy, professional experience, year and analyst fixed effects, the coefficient for "Top 5% Extreme Optimism" is positive and significant. This indicates that among all the forecasts issued by the same analyst, more outlier forecasts increase the propensity for the analyst to depart from the profession. In column 3, we include the interaction term between the dummy for "Top 5% Extreme Optimism" and the analyst's professional experience to take into account the possibility that an analyst grows more extreme if he or she has been in the profession for a sufficiently long period of time. The coefficient for the interaction term is positive and significant, indicating that analysts issuing the most extreme forecasts are especially more likely to leave if they have already stayed longer in the profession.

In columns 4 and 5 we concentrate on the observable career movement among analysts who do not leave the sell-side analyst profession. Following Hong and Kubik (2003), we set the dependent variable to "Promotion" in column 4 and "Demotion" in column 5. "Promotion" and "Demotion" are dummy variables equal to one if an analyst moves to and out from a reputable broker in the following year, respectively. Hong and Kubik (2003) define a reputable broker as a broker whose size, measured by the number of analysts it employs in a year, falls into the top 10 percentile of all brokers. In our sample, a broker's size falls into the top 10 percentile if the broker employs at least 36 analysts in a year.

Columns 4 and 5 reveal that issuing an extremely optimistic forecast makes an analyst less likely to move up to a more prestigious brokerage houses. On the contrary, it makes them more likely to move down to a less prestigious brokerage houses than his or her current one. However, both effects are not statistically significant.

Table 6 Panel B provides evidence that analysts are more likely to leave the profession if they are more inclined to issue extremely optimistic forecasts, and doing so does not help them to move into more prestigious brokerage houses. These findings imply that brokerage firms do not reward analysts who issue extremely optimistic forecasts with better career outcomes. Together with the findings in Panel A, conflicts of interest—though a widely believed motive for analysts to issue optimistic reports in general—do not appear to be the main reason for an individual analyst to issue the most extreme forecast.

6.3 Analysts' Self-Motivated Incentives

We now turn to the third plausible source behind issuing outlier forecasts: analyst's self-motivated incentives, which can arise from strategic reasons such as attention-seeking and tournament or behavioral biases such as overconfidence. We first look at factors that may contribute to the *magnitude* of the outlier extremism, and then explore how analyst characteristics at the time of issuing a forecast affect its *propensity* to become the outlier.

6.3.1 What Affects the Extremism of an Outlier Forecast?

The first element of interest is information uncertainty at the time when an outlier forecast arrives. We postulate that a higher level of information uncertainty increases the extremism of an outlier forecast. We use analysts' opinion diffusion as a proxy to capture firm-specific information environment (Zhang 2006). Specifically, for each firm in each year, "Forecast Divergence" is the standard deviation of forecasts issued prior to the arrival of an outlier, scaled by last year's price. With a greater value of this variable, there will be more disagreement among analysts on the firm's earnings.

We run an OLS regression estimating the effect of forecast divergence on "Extreme Optimism" based on our sample of firm-year observations. We control for proxies for analyst-specific and forecast-specific traits such as the timing of the forecast, analyst's professional experience or firm-specific experience, and the size of the brokerage house, as well as proxies for firm-specific traits such as the size of analyst coverage, profitability, firm size, and growth opportunities. We include year and firm fixed effects to absorb time-varying and firm-specific observed factors that may affect the extent of extremism of a forecast.

Column 1 in Panel A of Table 7 reveals that a bigger disagreement among analysts is associated with a greater magnitude of extreme optimism. When analysts' views about the firm's earnings are more diverse, and thus the firm's *ex ante* information environment is less certain, an outlier forecast becomes more extreme. This is consistent with Evgeniou et al (2013) who find that when luck is more important in determining outcomes, such as when the market is more volatile, the average deviation from the consensus forecast is larger.

Related to this finding, "Timing of the Forecast" is positively linked to the extent of extreme optimism. This variable is calculated as the logarithm of the number of days between the earnings announcement date and the date when a forecast is issued. The larger the number, the earlier the forecast is issued. When outlier forecasts are issued during the earlier stage—rather than later stage—of forecast cycles (the time frame when the disagreement among analysts is usually higher), they tend to be more extreme.

The positive correlation between the forecast divergence and extremism of an outlier forecast may arise mechanically due to the fact that "Extreme Optimism" by construction is benchmarked against the consensus forecasts by peer analysts; a higher forecast divergence may mask a low level of consensus forecasts. In column 2, we include the average value of forecasts issued prior to the arrival of the most extreme one, as an additional control. We observe that while the average forecast value indeed is negatively linked to the degree of extreme optimism, the divergence of opinion remains positive and significant.

Next, we split the sample into the “High” and “Low” forecast divergence subsamples, depending on whether or not a firm-year observation falls into the top (bottom) quartile of the value of “Forecast Divergence”. We repeat the baseline regressions in Table 2 relating extreme analyst optimism on earnings management for each of the two sub-samples.

Panel B of Table 7 reveals that the effect of extreme analyst optimism on earnings management is only prominent when there is a strong *ex ante* uncertainty about a firm’s earnings. By contrast, when there is little *ex ant* uncertainty among analysts in forecasting a firm’s earnings, the extremism of the outlier forecast itself does not affect earnings management.

The findings in Table 7 also likely help with a better understanding of the results in Table 3: when there is a higher degree of uncertainty in estimating a firm’s earnings, the outlier forecast becomes more extreme. This may stir greater attention from peer analysts and impose more prolonged influence on their subsequent forecasts.

6.3.2 Who Issues an Outlier Forecast?

To explore self-motivated incentive as a potential reason behind extreme optimism, we examine the traits associated with outlier forecasts. Clement and Tse (2005) show that the likelihood of being bold increases with an analyst’s previous forecast accuracy, suggesting overconfidence. In addition, both brokerage size and analyst’s professional experience are linked with the propensity to issue bold rather than herded forecasts. Furthermore, bold forecasts tend to be more accurate than herded forecasts. Thus, bold forecasts incorporate analysts’ private information more completely and provide more relevant information to investors.

We estimate a conditional logistic regression on the propensity for an earnings forecast to be the outlier. The dependent variable is the dummy variable “Outlier Forecast”. The independent variable captures the experience of the analyst when the forecast is issued. We measure an analyst’s experience in two ways: first, we measure general experience by how long an analyst has stayed in the profession by the total number of months between the current forecast and the first forecast issued by an analyst. Second, we measure firm-specific experience by the total number of months between the current forecast and the first forecast for a given firm by an analyst. We control for firm × year fixed effects and account for the timing of a forecast.[6]

Table 8 reports the odds ratios from the conditional logistic regressions. Columns 1 and 2 show that it is an analyst's firm-specific experience at the time when a forecast is issued, rather than general experience, that is significantly positively related to the likelihood of an outlier forecast. The longer an analyst has covered the firm, the more likely his/her forecast becomes the most extreme one.

In columns 3 and 4, we examine the role of the size of broker with which the analyst is affiliated and the accuracy of the past forecast. Forecasts issued by an analyst who is affiliated with a smaller broker and who has been less accurate in the past are more likely to be outliers. This is consistent with the findings of Evgeniou et al. (2013) that the gain in risk taking is greater for low-skilled than high-skilled analysts.

The coefficient of "Timing of the Forecast" is positive for all columns, suggesting that outlier forecasts often occur at the early, rather than late, stage of a forecast cycle. The average length of time between when an outlier forecast is issued and when a firm announces earnings is 254 days (a median of 286 days), approximately 8-9 months before earnings announcement.

When including all the variables at the time of issuance in the model (column 5), all the coefficient estimates reserve the same sign. The economic magnitudes are also consistent and sizable. For example, the odds ratio for "Firm-Specific Experience" is 1.02, which translates to a 4.4% higher probability that a forecast becomes the outlier for each additional year that the

[6] We cannot include the forecast error as a control variable in this regression because by construction, the error associated with a forecast is mechanically related to the dependent variable whether or not a forecast is an extremely optimistic one.

analyst covers the firm. In comparison, the unconditional probability for a forecast to be the outlier is 2.5%. One standard deviation increase in the size of a broker (equivalent to three more analysts) reduces the probability of issuing outlier forecasts by 9%. One standard deviation increase in an analyst's past accuracy can reduce such a probability by 5%. The odds ratio for "Timing of the Forecast" is 1.85. This is equivalent to an 82% increase in the probability of an analyst issuing an outlier forecast if the duration between the release dates of forecasted and realized earnings moves from the 25th percentile to the 75th percentile.

In summary, Table 8 shows that an outlier forecast tends to be issued by analysts who have covered the firm for a longer period of time, who were less accurate in the past, and who are affiliated with smaller, thus less prestigious, brokers. Outlier forecasts arrive earlier than later during annual forecast cycles. Given that an analyst who issues inaccurate forecasts in the past and who has stayed longer in the profession is more likely to leave (Table 6 Panel B), the downside for such an analyst to issue an extremely optimistic forecast appears to be small. These findings are consistent with the hypothesis that analysts' incentives for risk-taking and attention-seeking are likely sources of outlier forecasts.

7. EXTENSIONS AND ROBUSTNESS

7.1 Exogenous Variation of Analyst Optimism

Identifying the casual effect of extreme optimism on firms' earnings management is challenging, because analysts issue optimistic forecasts based on firm characteristics that may not be observable to econometricians.[7] In our main analyses, we control for various fixed effects to take into account the observed and unobserved firm-specific, industry-specific, and year-

[7] For instance, Bradshaw et al. (2001) find that over-optimism is greater for firms with high accruals. Drake and Myers (2009) show that analyst over-optimism can be related to accruals.

specific characteristics that can affect the extent of accrual-based earnings management. In this section, we adopt an identification strategy to further address the concern that unobserved firm heterogeneity correlated with both analysts' extreme optimism and firm earnings management could bias the result.

Our identification strategy relies on a quasi-natural experiment, brokerage house mergers, which generate an exogenous variation in analyst coverage and optimism. Hong and Kacperczyk (2010) argue that, since brokers involved in mergers often have redundant coverage, such events usually lead to an exogenous reduction in analyst coverage. The broker merger events studied in Hong and Kacperczyk (2010) are particularly relevant to our analysis because they show that the direct consequence of this exogenous reduction of coverage is an increase in analyst optimism, due to the decline of competition among peers. In the context of our study, brokerage mergers generate a plausibly exogenous variation in analyst coverage and optimism that affects a firm's earnings management only through its effect on the firm's analyst optimism.

We first verify that the exogenous impact of brokerage mergers also affects the extreme optimism of individual analysts. We use Hong and Kacperczyk's (2010) list of brokerage merger events during the 1980-2005 period, with the requirement that both merging brokerage houses cover at least two of the same stocks before the merger. Hong and Kacperczyk (2010) have carefully verified that their brokerage merger events are exogenous to the characteristics of the firms under coverage, which makes the analysis here less prone to endogeneity concerns. Within our sample period, there are a total of 13 brokerage mergers that affect our sample firms.

For the difference-in-difference analysis, we restrict our event window to one year before and one year after each merger event. To construct the sample of treatment firms, we follow procedures similar to those described in Hong and Kacperczyk (2010), and identify treated firms as those under coverage by both brokers prior to their merger and those that had remained covered afterwards. Our treatment sample includes 660 unique firm-year observations.

To construct the control group, we match each firm in the treatment sample with a firm in the same tercile of total assets one year prior to the merger, and require that the characteristics of the firm and its analysts are available during the event window. If multiple candidates are available, we first select one with the closest number of analysts to the treated firm. If this step fails to produce a unique match, we next choose the firm with the closest total assets to the treated firm. The final sample contains 2,640 firm-year observations for treated and matched firms.

To capture the effect of broker mergers on earnings management, we construct an interaction term, "Treated" × "After". "Treated" is a dummy variable equal to one if two brokers covering the same firm are merged and zero otherwise, and "After" is a dummy variable equal to one if a forecast is issued after the brokerage merger year and is zero before the event year.

Our control for analyst-specific characteristics includes the general experience of the outlier analyst, the average experience of peer analysts covering the same firm, and the size of coverage. We also control for firm characteristics such as profitability (ROA), size, and market to book, as well as broker merger fixed effects, year fixed effects and industry fixed effects. Following Irani and Oesch (2013), we cluster standard errors at broker merger event level.

Column 1 of Table 9 presents the results. Our difference-in-difference estimate captured by the coefficient for "Treat" × "After" is positive and significant at the 1% level, suggesting that the rise in extreme optimism is particularly strong among treated firms. This finding is broadly consistent with Hong and Kacperczyk (2010), who document a rise in analyst forecast optimism following the (exogenous) decrease in coverage caused by brokerage mergers.

Next, we split our sample between firms that are affected by brokerage mergers and their matched firms that do not experience a brokerage merger. We repeat the analysis in Table 2 with the extra interaction term "After"×"Extreme Optimism". Columns 2 and 3 of Table 9 show that the coefficient for the interaction term is positive and significant only in the treated group. The effect of extreme optimism on earnings management is only evident after the exogenous decrease in analyst coverage, which gives rise to analyst optimism.

The economic significance also improves, compared to the OLS regression results in Table 2. Compared to a similar firm without any decrease in analyst coverage, one standard deviation increase in extreme optimism due to an exogenous loss of analyst coverage causes a 26% increase in earnings management from the mean level for the treated firms.[8] Overall, the results in Table 9 lend further credence to causal inference of the effect of extreme optimism on earnings management.

7.2 Placebo Test for Potential Reverse Causality

As an alternative to the tests using the exogenous brokerage house mergers as a quasi-natural experiment to address the potential endogeneity concern, we conduct a placebo test to address the possible reverse causality issue that firms with more manipulation of earnings generate more extreme forecast optimism. We estimate a regression model in which the dependent variable is a firm's earnings management lagged by one year. The key independent variable, "Extreme Optimism", is measured for the current year. The estimation includes the same set for analyst-specific, firm-specific, and time-varying characteristics, as well as various fixed effects as in the baseline regressions. If the reverse causality explains our findings, then the

[8] The magnitude of the economic significance is computed as follows: The standard deviation of "Extreme Optimism" in the treatment sample is 0.017. The corresponding increase in the level of earnings management is therefore 0.04 (2.337 × 0.017). The mean value of earnings management in the treatment sample is 0.155. The 0.04 increase is equivalent to 0.04/0.155 = 26%.

firm's earnings management level in the previous year should be positively related to the current year's analyst extreme optimism. Furthermore, this regression specification helps tease out the time-trend effect. That is, if the relationship between earnings management and extreme optimism is spurious, for instance if both earnings management and extreme optimism exhibit an upward time trend, then the current year's extreme analyst optimism should be mechanically correlated with the firm's earnings management in the previous year.

The regression results (untabulated) reveal that a firm's previous year's earnings management is negatively, instead of positively, related to the current year's extreme analyst optimism. Nevertheless, the effect is insignificant. This indicates that while it is possible that the average level of analyst optimism can arise in response to a firm's manipulated earnings, an individual analyst's extremely optimistic forecast is unlikely to be affected.

7.3 Earnings Management through Operations

Instead of managing accounting accruals, managers can also manipulate earnings through operations. In this subsection, we check whether our findings are robust to alternative measures for earnings management.

The recent accounting literature develops methods to identify the magnitude of earnings manipulation through real operation activities (e.g., Roychowdhury 2006; Barton et al 2010; Irani and Oesch 2013). Following Roychowdhury (2006), we construct multiple proxies to detect real earnings management based on the abnormal level of operating cash flow ("RM1"), cost of goods sold ("RM2"), change of inventory level ("RM3"), production cost ("RM4"), discretionary expense based on current sales ("RM5"), and discretionary expense based on lagged sales ("RM6"). All the above proxies for real earnings management are presented as a percentage of lagged total assets, and are winsorized at the 5% level.

Table 10 reports the results where we repeat the baseline tests but replace accrual-based earnings management with various proxies for real earnings management as the dependent variable. We note that the extremism of the outlier forecast is also linked to a greater degree of manipulation of real activities to avoid reporting annual losses. The results indicate that our findings are robust to this alternative specification of earnings management.

8. CONCLUSIONS

The most vocal and extreme opinion is prevalent in many social dimensions. Whether such opinions are reflective of private information, or are oblivious to it, they may still exert their influence upon others and cause real consequences. In this paper, we examine the effect of outliers' opinions on economic agents in the context of extreme analyst optimism and corporate governance, and document the economic consequence of outliers. Furthermore, we explore the extent to which an outlier's opinion shapes the opinion of the group, and how an outlier's view influences other market participants.

We find that when analysts issue outlier forecasts for firms under their coverage, these firms tend to manage accounting accruals with a greater intensity. The arrival of an outlier forecast increases the forecast optimism of peer analysts, and generates stronger investor reactions. Further analyses suggest that private information and conflicts of interest are less likely to be the main reason behind the effect of extreme analyst optimism on earnings management. Instead, an analyst's self-motivated incentives are the likely cause.

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Appendix: Variable Definition and Construction

Variables	Definition
# of Analysts	The number of analysts covering the same firm in the same year.
ABS(CAR)	The absolute value of CAR. Winsorized at 0.5% level for both tails.
Accuracy Scores Indictor	Following Hong and Kubik (2003), we first calculate the accuracy score for each analyst in a year and then take an average of accuracy score in three years (year t, $t-1$ and $t-2$) to obtain a measure of general accuracy for each analyst – forecast year. "Accuracy Scores Indictors" are dummy variables to capture whether an analyst's general accuracy falls into the bottom 5 percentile, between 5 and 10 percentile, between 10 and 25 percentile, between 25 and 50 percentile, or between 50 and 75 percentile.
Broker Size	The natural logarithm of the number of analysts employed by a broker in a year.
CAR	Abnormal return on the day when an analyst issues a forecast. Computed as the difference between the stock return and the value-weighted CRSP index on the announcement day.
Earnings Forecast	Forecasted earnings per share divided by the last year's price.
Earnings Management	Absolute level of discretionary accruals, estimated by cross-sectional version of the modified Jones model. Winsorized at 0.5% level for both tails.
Experience	The natural logarithm of an analyst's experience plus one, where an analyst's experience is computed as the number of months between an analyst's current earnings forecast and his/her first forecast in the I/B/E/S database. For the firm-year sample, it refers to the experience of the analyst issuing the most optimistic forecast.
Extreme Optimism	For each firm-year, we compute this variable as the difference between the most optimistic forecast and the consensus peer forecast, scaled by the share price of the previous year, where the consensus peer forecast is the average value of all forecasts issued to each firm during each year, excluding the most optimistic one. Winsorized at 0.5% level for both tails.
Firm-Specific Experience	The natural logarithm of an analyst's firm specific experience plus one, where an analyst's firm specific experience is computed as the number of months between an analyst's current earnings forecast and his/her first forecast covering the firm in the I/B/E/S database.
Forecast Divergence (Pre Outlier Forecast)	The standard deviation of forecasts issued by analysts covering the same firm in the same year prior to the arrival of the most extreme forecast divided by last year's price. Winsorized at 0.5% level for both tails.

Forecast Error	The absolute value of the difference between forecasted earnings and actual earnings, scaled by share price in the previous year. Winsorized at 0.5% level for both tails.
Market to Book	The natural logarithm of one plus market value equity divided by book value of equity.
Mean Forecast Value (Pre Outlier Forecast)	The mean value of forecasts issued by analysts covering the same firm in the same year prior to the arrival of the most extreme forecast divided by last year's price. Winsorized at 0.5% level for both tails.
Leave Analyst Profession	A dummy variable equal to one if, following a forecast issued in year t, an analyst disappears from the I/B/E/S database for three or more consecutive years starting from year $t+1$, and zero otherwise.
Outlier Forecast	A dummy variable equal to one if a forecast is the most optimistic one among all the forecasts regarding the annual earnings per share of a firm, and zero otherwise.
Past Forecast Accuracy	The average accuracy score of an analyst in the past two years (year $t-1$ and year $t-2$). The accuracy score is calculated based on Hong and Kubik (2003). It is adjusted for firm-year characteristics and scaled to a range between 0 and 100. Bigger value indicates higher accuracy.
Peer Analysts' Experience	The natural logarithm of one plus the average experience of analysts covering the same firm in the same year, excluding the experience of the analyst who issues the most optimistic forecast.
Post Outlier Forecast (60/90 Days) (15/20 forecasts)	A dummy variable equal to one if a forecast is issued by an analyst covering the same firm within 60/90 days or 15/20 forecasts following the arrival of the most extreme forecast, and zero otherwise.
Post GS	A dummy variable equal to one if a forecast is issued after the implementation of the Global Settlement (GS), i.e., in years 2003 and 2004, and zero if the forecast is issued in years 2000 and 2001.
Post Reg FD	A dummy variable equal to one if the forecasts are issued after year 2000's Regulation Fair Disclosure (Reg FD), and zero if issued before 2000.
Promotion (Demotion)	A dummy variable equal to one if the analyst moves from a less (more) reputable broker to a more (less) reputable broker in year $t+1$ and zero otherwise. Following Hong and Kubik's (2003) definition, a more reputable broker is the one whose size, measured by the number of analysts it employs in a year, falls into the top 10 percentile of the sample distribution.
RM1-RM6	Following Roychowdhury (2006), we construct multiple proxies to detect real earnings management based on the abnormal level of operating cash flow ("RM1"), cost of goods

	sold ("RM2"), change of inventory level ("RM3"), production cost ("RM4"), discretionary expense based on current sales ("RM5"), and discretionary expense based on lagged sales ("RM6")
ROA	Return on assets. Computed as net income divided by total assets.
Size	The natural logarithm of the book value of total assets.
Timing of the Forecast	The natural logarithm of the difference in days between the actual earnings announcement date and the date when an analyst issues his/her forecast.
Top 5% Extreme Optimism	For each analyst-forecast year, we calculate the ratio of the number of the most extreme forecasts to the total number of forecasts issued by an analyst. "Top 5% Extreme Optimism" is a dummy variable set to one if this ratio belongs to the top 5% of the sample distribution for each analyst-forecast year, and zero otherwise.
Trading Volume	The natural logarithm of the number of shares traded on the day when an analyst issues an earnings forecast.

Table 1: Descriptive Statistics

This table reports the descriptive statistics. The sample period is between 1991 and 2011. Panel A is based on firm-year observations, and Panel B is based on forecast level observations.

Panel A: Firm-Year Level Observations

Variable	N	Mean	SD	5th Percentile	Median	95th Percentile
Earnings Management	27173	0.17	0.5	0	0.06	0.55
Extreme Optimism	27153	0.02	0.03	0	0.01	0.07
Experience (Peer Analyst)	27173	82.05	29.54	37.26	80	133.74
Experience (Most Extreme Analyst)	27167	82.27	65.51	5	67	209
# of Analysts	27173	11.49	7.89	4	9	28
Broker Size	23835	48.57	46.72	4	32	149
ROA	27173	0.02	0.18	-0.26	0.05	0.17
Total Assets (in Billions US$)	27173	3.28	18.05	0.047	0.526	12.46
Market to Book Ratio	27173	3.9	43.69	0.89	2.59	10.16

Panel B: Forecast Level Observations

Variable	N	Mean	SD	5th Percentile	Median	95th Percentile
Experience	1082248	85.06	66.36	6	71	214
Forecast Error	1082157	0.01	0.02	0	0	0.05
Timing of the Forecast	1082395	204.91	107.51	36	198	364
EPS Forecast	1082395	1.31	3.27	-0.51	1	4.23
CAR	1071905	0	0.06	-0.08	0	0.08
Volumes (million shares)	1071908	4.01	13.07	0.03	0.89	15.66

Table 2: Extreme Analyst Optimism and Earnings Management

This table reports the results from the OLS regressions estimating the effects of extreme analyst optimism on firm earnings management. The sample period is 1991-2011. The dependent variable is "Earnings Management", computed based on the John's (1991) model. The rest of variables are defined in the text and Appendix. Industry classification is based on the two digit SIC code. Robust standard errors are clustered at firm level reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable	Earnings Management		
	(1)	(2)	(3)
Extreme Optimism	0.933***	0.906***	1.030***
	(0.132)	(0.153)	(0.265)
Peer Analysts' Experience		-0.051***	-0.037**
		(0.009)	(0.015)
Experience		0.001	0.001
		(0.003)	(0.004)
# of Analysts		0.003***	0.005***
		(0.001)	(0.001)
Broker Size		-0.002	-0.003
		(0.003)	(0.003)
ROA		-0.068***	0.009
		(0.021)	(0.040)
Size		-0.018***	-0.027**
		(0.003)	(0.012)
Market to Book		0.042***	0.042***
		(0.007)	(0.013)
Year Fixed Effects	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	No
Firm Fixed Effects	No	No	Yes
# of obs.	27,153	23,672	23,672
R-squared	0.169	0.182	0.314

Table 3: Analyst Peers' Reaction to Outlier Forecast

This table examines the forecast optimism of peer analysts following the arrival of the outlier forecast. The sample period is 1991-2011. In Panels A, the dependent variable is the earnings forecast issued by a peer analyst, scaled by the stock price in the previous year. The samples for regressions include all the forecasts issued before the outlier forecast as well as those issued after the outlier forecast in various windows (i.e., within 60 and 90 days after the outlier forecast, or among 15 and 20 forecasts issued after the outlier forecast). In Panel B, the unit of analysis is firm-year observations. The dependent variable is earnings management. Robust standard errors clustered at firm × year level (Panel A) and clustered at the firm level (Panel B) are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Subsequent Forecast Optimism

Dependent Variable	Earnings Forecast			
	(1)	(2)	(3)	(4)
Post Outlier Forecast (60 Days)	0.003***			
	(0.000)			
Post Outlier Forecast (90 Days)		0.002***		
		(0.000)		
Post Outlier Forecast (15 Forecasts)			0.001***	
			(0.000)	
Post Outlier Forecast (20 Forecasts)				0.001***
				(0.000)
Experience	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Past Forecast Accuracy	0.000**	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Broker size	0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Firm × Year Fixed Effects	Yes	Yes	Yes	Yes
# of obs.	361,023	426,705	471,049	513,479
R-squared	0.966	0.965	0.966	0.966

Table 3 Continued.

Panel B: Peer Analyst Optimism and Earnings Management

Dependent Variable	Earnings Management							
	60 Days		90 Days		15 Forecasts		20 Forecasts	
	Weak	Strong	Weak	Strong	Weak	Strong	Weak	Strong
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Extreme Optimism	0.612*	1.720***	0.572	1.760***	0.524	1.973***	0.408	2.121***
	(0.366)	(0.597)	(0.349)	(0.596)	(0.334)	(0.644)	(0.291)	(0.735)
Peer Analysts' Experience	-0.035*	-0.048*	-0.037*	-0.040	-0.032	-0.046	-0.032*	-0.040
	(0.021)	(0.028)	(0.021)	(0.027)	(0.020)	(0.030)	(0.019)	(0.030)
Experience	0.002	0.001	0.000	0.002	0.003	0.003	0.003	0.002
	(0.005)	(0.007)	(0.005)	(0.007)	(0.004)	(0.008)	(0.004)	(0.008)
# of Analysts	0.004**	0.005**	0.004***	0.005**	0.004**	0.006**	0.005***	0.006***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Broker size	-0.000	-0.006	0.002	-0.003	0.001	-0.002	-0.001	-0.000
	(0.005)	(0.007)	(0.005)	(0.007)	(0.005)	(0.007)	(0.005)	(0.007)
ROA	0.008	-0.091	0.012	-0.043	0.005	-0.044	0.002	-0.061
	(0.049)	(0.090)	(0.051)	(0.078)	(0.050)	(0.081)	(0.050)	(0.085)
Size	-0.014	-0.039*	-0.011	-0.036*	-0.015	-0.038*	-0.016	-0.041*
	(0.016)	(0.022)	(0.015)	(0.021)	(0.015)	(0.023)	(0.015)	(0.023)
Market to Book	0.025	0.061**	0.027	0.069***	0.027	0.067**	0.023	0.065**
	(0.016)	(0.026)	(0.017)	(0.026)	(0.016)	(0.027)	(0.016)	(0.028)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
# of obs.	13,548	10,124	13,463	10,209	14,148	9,524	14,338	9,334
R-squared	0.419	0.410	0.422	0.404	0.419	0.412	0.415	0.417

Table 4: Investors' Reactions to Outlier Forecast

This table relates outlier forecast to market reactions. In columns 1 and 2, the dependent variable is the abnormal return surrounding the time when a forecast is issued. In columns 3 through 5, the dependent variable is the trading volume at the time of the forecast. Robust standard errors clustered at firm × year level are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable	Abnormal Return		Trading Volume		
	(1)	(2)	(3)	(4)	(5)
Outlier Forecast	0.006***	0.006***	0.046***	0.048***	0.048***
	(0.000)	(0.000)	(0.005)	(0.006)	(0.006)
Experience		-0.000**		0.021***	0.014***
		(0.000)		(0.001)	(0.001)
Past Forecast Accuracy		-0.000		0.002***	0.001***
		(0.000)		(0.000)	(0.000)
Broker size		-0.000***		0.044***	0.030***
		(0.000)		(0.001)	(0.001)
Timing of the Forecast		0.001***		0.001	-0.007***
		(0.000)		(0.003)	(0.002)
ABS(CAR)					9.814***
					(0.051)
Firm × Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
# of obs.	1,071,905	759,069	1,071,908	759,071	759,069
R-squared	0.115	0.130	0.858	0.858	0.895

Table 5: Forecast Accuracy and Private Information

This table relates analyst forecast error and private information to extreme optimism. The sample period is 1991-2011. In Panel A the dependent variable is the “Forecast Error”. In Panel B, the dependent variable is “Extreme Optimism” in column 1 and “Earnings Management” in columns 2 and 3. The pre-Reg FD period is 1991-2000 and the post-Reg FD period is 2001-2011. “Outlier Forecast” is a dummy variable equal to one if a forecast is the most optimistic one, and zero otherwise. Robust standard errors clustered at firm × year level (Panel A) and at firm level (Panel B) are reported in parentheses, respectively. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Accuracy of Outlier Forecast

Dependent Variable	Forecast Error	
	(1)	(2)
Outlier Forecast	0.005***	0.005***
	(0.000)	(0.000)
Experience	-0.000***	
	(0.000)	
Firm-Specific Experience		-0.000***
		(0.000)
Past Forecast Accuracy	-0.000***	-0.000***
	(0.000)	(0.000)
Broker Size	-0.000	-0.000
	(0.000)	(0.000)
Timing of the Forecast	0.007***	0.007***
	(0.000)	(0.000)
Firm × Year Fixed Effects	Yes	Yes
# of obs.	307,401	307,401
R-squared	0.850	0.850

Table 5 Continued.

Panel B: Reg FD and Extreme Optimism

Dependent Variable	Extreme Optimism	Earnings Management	
	Full Sample	Pre Reg FD	Post Reg FD
	(1)	(2)	(3)
Post Reg FD	0.009***		
	(0.002)		
Extreme Optimism		0.424*	1.325***
		(0.231)	(0.419)
Peer Analysts’ Experience	0.001**	-0.026	-0.031
	(0.001)	(0.017)	(0.026)
Experience	-0.000	-0.000	0.000
	(0.000)	(0.003)	(0.006)
# of Analysts	-0.000	0.004***	0.008***
	(0.000)	(0.001)	(0.002)
Broker Size	-0.000**	0.001	-0.005
	(0.000)	(0.004)	(0.006)
ROA	-0.018***	0.066	-0.025
	(0.003)	(0.055)	(0.043)
Size	-0.001	0.007	-0.065***
	(0.001)	(0.016)	(0.022)
Market to Book	-0.007***	0.038**	-0.000
	(0.001)	(0.018)	(0.020)
Year Fixed Effects	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes
# of obs.	23,672	11,209	12,463
R-squared	0.603	0.509	0.324

Table 6: Brokerage-Motivated Incentives

This table relates the conflicts of interest between analysts and the firms under coverage to extreme optimism. In Panel A, the sample is constructed following Kadan et al. (2009), and is restricted to firms that are under analyst coverage during both the pre-GS and post-GS periods, where the pre-GS period is 2000-2001, and the post-GS period is 2003-2004. The combined sample includes firm-year observations in both the pre- and post-GS periods. The dependent variable in column 1 is "Extreme Optimism", and is earnings management in columns 2 and 3. Industry classification is based on the two digit SIC code. Robust standard errors clustered at firm level are reported in parentheses. In Panel B, the sample period is 1991-2011. The unit of analysis is analyst-announcement year observations. Robust standard errors clustered at analyst level are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A: The Effect of Global Settlement

Dependent Variable	Extreme Optimism	Earnings Management	
	Combined Sample	Pre GS	Post GS
	(1)	(2)	(3)
Post GS	0.002***		
	(0.001)		
Extreme Optimism		1.031**	2.828*
		(0.440)	(1.587)
Peer Analysts' Experience	0.001	0.018	-0.168**
	(0.001)	(0.031)	(0.071)
Experience	-0.000	-0.017	0.033
	(0.000)	(0.010)	(0.022)
# of Analysts	-0.000	0.002	0.010***
	(0.000)	(0.002)	(0.003)
Broker Size	-0.001**	0.012	-0.014
	(0.000)	(0.009)	(0.021)
ROA	-0.024***	-0.025	0.133
	(0.005)	(0.069)	(0.171)
Size	-0.001***	-0.024***	-0.046***
	(0.000)	(0.008)	(0.017)
Market to Book	-0.006***	0.104***	0.043
	(0.001)	(0.037)	(0.046)
Year Fixed Effects	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes
# of obs.	3,619	1,785	1,834
R-squared	0.228	0.241	0.411

Table 6 Continued.

Panel B: Analyst Career Consequences

Dependent Variable	Leave Analyst Profession			Promotion	Demotion
	(1)	(2)	(3)	(4)	(5)
Top 5% Extreme Optimism	0.042***	0.048***	0.006	-0.010	0.007
	(0.010)	(0.010)	(0.018)	(0.007)	(0.007)
Experience		0.189***	0.186***	0.004	0.002
		(0.006)	(0.006)	(0.005)	(0.004)
Top 5% Extreme Optimism × Experience			0.028**		
			(0.011)		
Bottom 5% Accuracy Scores Indicator	0.372***	0.310***	0.309***	-0.006	0.034***
	(0.017)	(0.017)	(0.017)	(0.010)	(0.013)
5-10% Accuracy Scores Indictor	0.254***	0.194***	0.194***	-0.007	0.001
	(0.015)	(0.015)	(0.015)	(0.009)	(0.008)
10-25% Accuracy Scores Indicator	0.166***	0.107***	0.107***	-0.012**	0.006
	(0.008)	(0.008)	(0.008)	(0.006)	(0.005)
25-50% Accuracy Scores Indicator	0.072***	0.015**	0.015**	-0.002	0.002
	(0.006)	(0.006)	(0.006)	(0.005)	(0.004)
50-75% Accuracy Scores Indicator	0.037***	-0.019***	-0.019***	-0.002	0.003
	(0.005)	(0.005)	(0.005)	(0.005)	(0.004)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Analyst Fixed Effects	Yes	Yes	Yes	Yes	Yes
# of obs.	44,065	44,065	44,065	33,439	33,439
R-squared	0.451	0.469	0.469	0.202	0.217

Table 7: When does an Analyst Issue an Outlier Forecast?

The sample period is 1991-2011. The unit of analysis is firm-year observations. Panel A reports the results from OLS regressions on factors affecting the magnitude of extreme optimism. The dependent variable is "Extreme Optimism". For each firm each year, "Forecast Divergence (Pre Outlier Forecast)" is the standard deviation of forecasts issued prior to the arrival of the most extreme one by analysts covering the same firm in the same year. "Average Forecast Value (Pre Outlier Forecast)" is the mean value of forecasts issued by analysts covering the same firm in the same year. Both variables are scaled by last year's price. Panel B reports the OLS regression estimates relating extreme analyst optimism to earnings management in a subsample analysis. The subsamples are constructed based on the standard deviation of analyst forecasts prior to the arrival of the most optimistic forecast. The dependent variable is "Earnings Management". Robust standard errors clustered at firm level are reported in parentheses, respectively. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A: What Affects the Magnitude of Extreme Optimism?

Dependent Variable	Extreme Optimism	
	(1)	(2)
Forecast Divergence (Pre Outlier Forecast)	1.439***	1.435***
	(0.060)	(0.060)
Mean Forecast Value (Pre Outlier Forecast)		-0.029**
		(0.014)
Timing of the Forecast	0.003***	0.003***
	(0.000)	(0.000)
Firm-Specific Experience	-0.000	-0.000
	(0.000)	(0.000)
Past Forecast Accuracy	-0.000*	-0.000*
	(0.000)	(0.000)
# of Analysts	0.000	0.000
	(0.000)	(0.000)
Broker Size	-0.000**	-0.000**
	(0.000)	(0.000)
ROA	-0.007***	-0.004*
	(0.002)	(0.002)
Size	0.000	0.000
	(0.001)	(0.001)
Market to Book	-0.002***	-0.002***
	(0.001)	(0.001)
Year Fixed Effects	Yes	Yes
Firm Fixed Effects	Yes	Yes
# of obs.	13,091	13,091
R-squared	0.775	0.776

Table 7 Continued.

Panel B: Divergence of Opinions, Extreme Optimism, and Earnings Management

Dependent Variable	Earnings Management	
	(1)	(2)
	Low Forecast Divergence	High Forecast Divergence
Extreme Optimism	-0.371	1.255**
	(1.685)	(0.601)
Peer Analysts' Experience	-0.102**	-0.027
	(0.044)	(0.089)
Experience	0.004	-0.008
	(0.008)	(0.020)
# of Analysts	0.001	0.010*
	(0.003)	(0.006)
Broker Size	0.018*	-0.025
	(0.009)	(0.019)
ROA	0.065	0.062
	(0.191)	(0.101)
Size	-0.016	-0.024
	(0.036)	(0.053)
Market to Book	0.046	-0.065
	(0.044)	(0.045)
Year Fixed Effects	Yes	Yes
Firm Fixed Effects	Yes	Yes
# of obs.	4,517	3,751
R-squared	0.509	0.538

Table 8: Who Issues Extremely Optimistic Forecasts?

This table relates analyst-specific and forecast-specific characteristics to the likelihood of a forecast being the most extreme one. We estimate a conditional logistic regression and report the odds ratios. The sample period is 1991-2011. The unit of analysis is earnings forecast observations. The dependent variable is a dummy variable equal to one if a forecast turns out to be the most extreme one, and zero otherwise. “Experience”, “Firm-Specific Experience”, “Broker Size”, “Past Forecast Accuracy” and “Timing of the Forecast” are measured at the time when a forecast is issued. Robust standard errors clustered at firm-year level are reported in parentheses. Robust standard errors clustered at firm level are reported in parentheses, respectively. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable	Outlier Forecast				
	(1)	(2)	(3)	(4)	(5)
Experience	0.993				
	(0.006)				
Firm-Specific Experience		1.010*			1.017**
		(0.005)			(0.007)
Broker Size			0.914***		0.919***
			(0.006)		(0.007)
Past Forecast Accuracy				0.991***	0.992***
				(0.001)	(0.001)
Timing of the Forecast	1.710***	1.710***	1.824***	1.735***	1.847***
	(0.027)	(0.027)	(0.031)	(0.031)	(0.036)
Firm × Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
# of obs.	1,082,114	1,082,114	939,670	753,770	654,377
Pseudo R2	0.015	0.015	0.020	0.016	0.021

Table 9: Exogenous Brokerage Mergers, Extreme Optimism, and Earnings Management

This table reports the difference-in-difference tests following exogenous brokerage houses merger events identified in Hong and Kacperczyk (2010). In column 1, the dependent variable is "Extreme Optimism". In columns 2 and 3, the dependent variable is "Earnings Management", computed based on Jones' (1991) model. The rest of the variables are defined in the text and Appendix. Industry classification is based on the two digit SIC code. Robust standard errors clustered at brokerage merger level are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable	Extreme Optimism	Earnings Management	
	Combined Sample	Treatment Sample	Control Sample
	(1)	(2)	(3)
Treated × After	0.004***		
	(0.001)		
Extreme Optimism × After		2.337***	1.601
		(0.706)	(1.789)
Extreme Optimism		-0.426	1.818
		(0.413)	(1.278)
Peer Analysts' Experience	0.002*	-0.095	-0.650***
	(0.001)	(0.061)	(0.127)
Experience	-0.002**	0.011	0.087
	(0.001)	(0.007)	(0.059)
# of Analysts	0.000**	-0.004	-0.009***
	(0.000)	(0.003)	(0.002)
ROA	-0.018**	-0.123	0.949
	(0.006)	(0.158)	(0.670)
Size	-0.000	-0.017	0.053**
	(0.000)	(0.011)	(0.022)
Market to Book	-0.009***	0.106**	0.142*
	(0.001)	(0.041)	(0.073)
After	0.001**	-0.023	-0.075*
	(0.001)	(0.021)	(0.038)
Treated	-0.006***		
	(0.002)		
Year Fixed Effects	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes
Merger Fixed Effects	Yes	Yes	Yes
# of obs.	2,639	1,320	1,319
R-squared	0.387	0.379	0.550

Table 10: Real Earnings Management

This table relates extreme optimism to real earnings management. The sample period is 1991-2011. Following Roychowdhury (2006), we construct dependent variables for real earnings management based on the abnormal level of operating activities – net cash flow ("RM1"), cost of goods sold ("RM2"), change of inventory level ("RM3"), production cost ("RM4"), discretionary expense based on current sales ("RM5"), and discretionary expense based on lagged sales ("RM6"). All these variables are presented as percentage of lagged total assets and winsorized at the 5% level. Robust standard errors clustered at firm level are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable	RM1	RM2	RM3	RM4	RM5	RM6
	(1)	(2)	(3)	(4)	(5)	(6)
Extreme Optimism	14.150***	19.737***	4.918**	14.676**	23.307***	18.421**
	(4.816)	(6.170)	(2.254)	(6.345)	(8.118)	(8.717)
Peer Analysts' Experience	0.106	0.317	0.228	0.257	0.901*	0.663
	(0.287)	(0.384)	(0.139)	(0.417)	(0.490)	(0.541)
Experience	-0.007	0.014	-0.041	0.005	0.052	-0.073
	(0.065)	(0.068)	(0.031)	(0.075)	(0.093)	(0.104)
# of Analysts	0.112***	0.160***	0.034***	0.177***	0.192***	0.158***
	(0.030)	(0.042)	(0.010)	(0.046)	(0.047)	(0.054)
Broker Size	-0.066	-0.039	-0.019	0.046	0.085	0.062
	(0.063)	(0.076)	(0.032)	(0.081)	(0.101)	(0.107)
ROA	-1.634	6.378***	0.436	5.605***	-8.651***	-8.367***
	(1.674)	(1.322)	(0.409)	(1.442)	(2.359)	(2.328)
Size	-3.032***	-6.191***	-1.621***	-6.092***	-5.602***	-5.152***
	(0.322)	(0.466)	(0.140)	(0.472)	(0.601)	(0.681)
Market to Book	2.452***	2.887***	0.171	2.771***	2.744***	3.462***
	(0.345)	(0.387)	(0.109)	(0.390)	(0.474)	(0.513)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
# of obs.	17,617	17,617	17,617	17,617	17,617	17,617
R-squared	0.567	0.738	0.455	0.692	0.703	0.656