Standing out from the Crowd: The Real Effects of Outliers*

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Abstract

We study the impact of outlier opinions – extreme views voiced by individuals – in financial markets. Using analyst forecasts as a laboratory, we show that market participants respond to the arrival of extremely optimistic forecasts, instead of ignoring them as noise. An outlier forecast subsequently moves group consensus and begets more extreme forecasts by peers. Outlier forecasts also generate stronger market reactions from investors, more media coverage, and more conservative management guidance. Further analyses reveal that issuing outlier forecasts increases an analyst's chance to cover more important clients of his employer. Outlier forecasts are also more likely to take place when an analyst's reputation cost is lower and information uncertainty is high. These findings suggest that the propensity for expressing extreme views is situational and that personal incentives are the likely cause at play.

Keywords: social influence, polarization, financial analyst, extreme opinions, outliers

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1. Introduction

Herding – the tendency for individuals to conform to their groups – appears widespread among financial market participants. How and why individuals' beliefs evolve towards the standards and views of groups with which they interact have attracted extensive academic attention in the past few decades (e.g., Trueman 1994; Grinblatt, Titman, and Wermers 1995; Zwiebel 1995; Wermers 1999; Welch 2000). What largely remains under-explored, however, is the effect of outliers — individual views and beliefs that radically deviate from those of the group.[1] On the one hand, discounting outliers when gauging consensus is a common yet often taken-for-granted practice in a broad range of contexts.[2] On the other hand, society has increasingly gravitated towards polarization, where extreme views, no matter how groundless or irrational, attract media attention and stir public sentiment.

In this paper, we explore the impact of outlier opinions in financial markets. Are outliers just noise that a rational economic agent tends to ignore, or do they influence people's decisions and behaviors? Empirically, however, it is challenging to compare individuals' tendencies to broadcast extreme views, let alone assess the real consequences of these views. This is because an outlier opinion originates from an individual instead of a cohort of agents, and the extremism of the opinion depends on the context of the subject. Demarzo, Vayanos, and Zwiebel (2003), among others, highlight the difficulty in measuring absolute disagreement in beliefs across many

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[1] Only until recently, finance and accounting researchers began to investigate how outliers and influential observations in the datasets bias the empirical findings (see, e.g., Guthrie, Sokolowsky, and Wan 2012; Leone, Minutti-Meza, and Wasley, 2019).

[2] Outliers are often discarded completely in real world practice. For instance, economists apply winsorization or trimming on key variables in econometric analyses. Judges for the Olympic Games vacate the highest and lowest scores during gymnastic and diving competitions. When the British Bankers' Association (BBA) compiles LIBOR, for many years, they would throw away the highest and lowest 25% entries before averaging the rest.

contexts, as agents may hold very dissimilar views on certain issues but share extremely close views on other topics.

To surmount these challenges, we employ financial analyst forecasts as a laboratory and examine how market participants react when an analyst voices an extreme view about a firm's future earnings. Since self-selection influences how extreme an analyst's view is likely to be, we focus on the most optimistic opinion.[3] Our research setting offers several unique and important advantages. First, we can quantify the extent to which an individual disagrees with the rest of the cohort over the same subject, overcoming the challenge that extreme views are often subject-oriented and thus incomparable across topics. Second, unlike corporate events such as security issuances and mergers and acquisitions, in which the timing is endogenous, and individuals who voice their opinions can be sporadic and random, mandatory earnings disclosure dates are largely set well in advance, and analyst following tends to be stable. Lastly, the consequences of extreme opinions are measurable in multiple dimensions.

We compile a sample of analyst forecasts about firms' annual earnings from 1990 to 2019 and adopt a dynamic approach to identify outlier forecasts. For each forecast, we calculate the extent to which it deviates from the most optimistic one among all prior forecasts issued by peer analysts covering the same firm in the same year. This approach mitigates the look-ahead bias and reflects, at a given time point, how radical a forecast differs from those of existing peers. To capture the extreme but rare nature of an outlier opinion, we classify a forecast to be an outlier if the extent of its deviation falls into the top 1% of the sample.[4]

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[3] Put differently, measuring outlier opinions based on extremely optimistic instead of pessimistic views is less prone to sample selection bias. Since analysts can self-select the firms they follow, terminating the coverage about a firm is more preferable than voicing extremely negative views in their forecasts (e.g., McNichols and O'Brien 1997; Hayes 1998).

[4] We also explore the robustness of our results to the use of alternative measures for outliers.

We document a significant peer reaction to the outlier forecast. Forecasts from peer analysts become more optimistic following the arrival of an outlier forecast. To illustrate, the next three post-outlier forecasted earnings issued by peers are on average 0.682 higher than those forecasts issued prior to the outlier forecast, accounting for 18% of the sample mean forecast value. The effects can persist through the next twenty peer forecasts. In the context of forecast dynamics, an outlier forecast appears to serve as an "anchor" that shapes the judgment of peer analysts.[5]

Not only do outliers move peer analyst consensus, but they beget more outliers. Following the issuance of an outlier forecast, peer analysts are more likely to also broadcast extreme views about the firm's earnings. With more extreme outlier forecasts, we have a higher probability of observing subsequent outliers and more radical subsequent outliers. To this end, these results connect well to Cialdini's (1984) seminal work on the principles of influence, particularly social proof, which implies that individuals look to the behavior and opinions of others when forming their own opinions, especially in situations of uncertainty.

Besides peer analysts, there is evidence that other market participants are also subject to the influence of outlier forecasts. First, both abnormal returns and trading volume are significantly higher surrounding the issuance of an outlier forecast than that of a non-outlier one. This indicates that investors react to an individual's extreme opinion. Second, the news media reports not only more related news about the firm that is subject to an analyst's extreme view, but also more favorable news. This suggests that the arrival of outlier forecasts generates media attention and stirs media sentiment about the firm. Lastly, managers from firms subject to an

[5] The psychology literature, including the seminal work of Tversky and Kahneman (1974) and Simmons, LeBoeuf, and Nelson (2010), 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 intention to avoid such an influence.

outlier opinion are less likely to issue guidance that beats the consensus. Arguably, by elevating consensus peer forecast and inducing more extreme views subsequently, the arrival of an outlier forecast renders the firm less capable to meet inflated expectations. These findings offer evidence consistent with the major heuristics identified by Tversky and Kahneman (1974) which suggests that market participants might overweigh the implications of the extreme forecasts due to their salience and the ease with which they come to mind, leading to stronger market reactions.

All results are obtained by controlling for firm-level and analyst-level characteristics and including firm and time-fixed effects. Thus, our findings cannot be interpreted as being driven by time- or firm-specific shocks. The inclusion of firm × year fixed effects in some regression specifications helps to narrow down our comparison of reactions by market participants for the same firm in the same year but with and without exposure to outlier forecasts.

Overall, we document the impact of outlier forecasts not only on peer analysts, but also on investors, media, and management. This suggests that a broad range of market participants respond to outlier opinions instead of treating them as noise.

What circumstance gives rise to extreme views? We postulate that the tendency for an individual to broadcast his outlier opinion is situational, hinging on the environment and characteristics of his peers. Scharfstein and Stein (1990) predict that agents with less uncertainty about their ability, for whom reputation concerns are no longer relevant, are more likely to deviate from the rest of the group. Consistent with their prediction, we show that analysts are more likely to issue outlier forecasts if they are relatively more experienced or are affiliated with bigger brokers than their peers. In this set of analyses, it is crucial to include analyst × year fixed effects, which allow for the likelihood of the *same* analyst voicing extreme opinion about a firm in his coverage portfolio in a given year to vary depending on the peer cohorts with whom he interacts. In addition, we show that an outlier forecast becomes more radical when there exists a greater prior disagreement among peer analysts regarding the firm's future earnings. These findings suggest that the propensity for expressing extreme views is situational rather than an innate (static) attribute of certain individuals. An environment in which reputation cost is smaller or it is easier to swing peer opinions fosters the tendency of voicing extreme views.

Is issuing outlier forecasts rewarding? To explore the potential personal motives behind being extreme, we evaluate whether outlier forecasts help analysts promote their status. Following Harford et al. (2019), we develop a measure for analysts' career advancement based on the change in the quality of firms that they cover due to the reassignment of stocks in their coverage portfolios. Because analysts' compensation and internal promotion are not publicly observable, existing studies have largely relied on analyst turnover to identify their career transitions (Hong and Kubik 2003; Gao, Wang, and Yu 2023). In comparison, our proxy allows us to capture the change in an analyst's status within his brokerage firm over time, free from being contingent on relatively infrequent incidences of turnover. We show that the frequency of issuing outlier forecasts is associated with an analyst being subsequently assigned to more important clients of his employer — firms with higher market value and greater institutional ownership. This suggests that analysts issuing outlier forecasts tend to experience favorable career outcomes.

Finally, we consider alternative motives behind outlier forecasts. An outlier forecast may simply reflect the analyst's private information (Chen and Jiang 2006); consequently, market participants react to an informative signal, rather than an extreme one. The existing literature has also documented ample evidence that analysts issue over-optimistic reports to secure the investment banking business for their brokerage firms (Lin and McNichols 1998; Michaely and

Womack 1999). As such, an outlier forecast may capture an analyst's brokerage-based incentive. Nevertheless, the results from our tests to evaluate these possibilities suggest that private information and brokerage-based incentives are unlikely to justify analysts' extreme position. Instead, personal incentives are likely the source for analysts to voice opinions that are distinct from those of their peers.

Our study contributes to several strands of literature. First, it is related to existing studies on the impact of outliers (e.g., Guthrie, Sokolowsky, and Wan 2012; Adams et al. 2019). We complement this line of literature by identifying a clean setting to examine the direct effect of outliers. We provide novel evidence that various market participants succumb to the influence of extreme opinions. In particular, outlier forecasts elevate group sentiment and breed more radical views among peer analysts. Our findings thus highlight contributing factors toward the path of polarization that is increasingly prevalent in capital market and society.

Our findings also add to the understanding of analyst coverage. On the one hand, prior studies document that analysts mitigate information asymmetry and improve corporate governance (e.g., Brennan and Subrahmanyam 1995; Yu 2008; Irani and Oesch 2013; Chen, Harford, and Lin 2015). On the other hand, analysts can impose pressure on managers and induce managerial short-termism (e.g., Graham, Harvey, and Rajgopal 2005; He and Tian 2013). Most studies use the number of analysts to measure the scope of coverage and do not consider heterogeneity within the analyst group. By exploring the within-group interaction dynamics, our findings help to reconcile the above debate, suggesting that the effectiveness of analysts as a group can vary depending on how individuals can swing the views of their peers with whom they interact. In this respect, our findings echo those of Harford et al. (2019), who show that analysts as a group improve a firm's information environment *only* when a large portion of them allocate their efforts to the underlying firm relative to the rest of the stocks in their coverage portfolios.

Lastly, our paper is related to prior studies examining analyst forecast boldness (e.g., Hong, Kubik, and Solomon 2000). Most of them consider boldness as the personal, invariant trait of an individual.[6] In contrast, social psychology studies have long established that the predominant factors influencing human behavior are situational rather than personality-driven (e.g., Mischel 1968; Ross and Nisbett 1991). Accordingly, our classification of outlier opinions focuses on the extremism of a forecast and allows for the same individual to express distinct views on certain subjects while still concurring with the rest of the group on others. Our findings suggest that the tendency to express extreme opinions depends on the environment to which an individual is exposed. Not only are individuals and their efforts heterogeneous within the same cohort of analysts, but also the same individual may behave differently depending upon the cohorts of peers to which he or she is assigned. By capturing the within-group dynamics between the most radical view and those of peers, our measure allows us to explore the externalities of being extreme, a topic that existing proxies of forecast boldness are not suited to address.

The rest of the paper proceeds as follows. Section 2 describes the methodology and data. Sections 3 through 6 present the results. Section 7 concludes. Variable definitions are in the Appendix.

[6] For instance, Hong, Kubik, and Solomon (2000) estimate boldness at analyst-year level, computing how much an analyst forecast deviates from the consensus *on average* each year. By construction, their boldness measure captures any deviations, large or small, for all analysts. Clement and Tse (2005) classifies forecasts "as bold if they are above both the analyst's own prior forecast and the consensus forecast immediately prior to the analyst's forecast, or else below both". An analyst is considered bold as long as he/she revises away from the consensus, even for a revision as small as one cent.

2. Methodology and Data

2.1 Measuring Outlier Forecasts

The Merriam-Webster Dictionary defines an "outlier" as an observation that is "markedly different in value from the others of the sample." An outlier opinion thus exhibits two essential traits: (1) being markedly distinct from the others, and (2) originating from an individual instead of a cohort of agents. Using analyst earnings forecasts to evaluate the effect of outlier opinions offers several advantages. First, unlike corporate events such as security issuances and mergers and acquisitions, in which the timing is endogenous and individuals who voice their opinions can be sporadic and random, mandatory earnings disclosure dates are largely set well in advance, and analyst following tends to be stable. Second, there is an unambiguous and systematic way to extreme opinions: individual forecasts that are most distinct from those from peers. Lastly, the extent to which a forecast deviates from the group's view is measurable and comparable across firms.

We adopt a dynamic approach to identify outlier opinions. For each firm-year, we sort all forecasts by the time of issuance. For each forecast, we measure the extent to which it deviates from the most optimistic one among all prior forecasts. Specifically, "*Deviation*" is the percentage deviation in earnings per share of the current forecast from the most optimistic forecast out of all prior forecasts. Doing so allows us to mitigate the look-forward bias and capture how market participants view the extent of deviation of a forecast *at the time when it is issued*, which is critical for our empirical investigation of their reactions. To reflect the nature of an outlier opinion being "markedly distinct from the others", we classify a forecast to be an outlier if the extent of its deviation falls into the top 1% of the entire sample.[7]

[7] To illustrate, consider Analyst Amy who issued a forecast of $1.88 annual earnings per share of a firm called Best Electronics. At time there are five forecasts issued prior to Amy's to predict Best Electronics' annual earnings per

This approach is intuitive and suitable for identifying outlier views for the following reasons. First, it is dynamic because the set of prior forecasts varies for each forecast and outliers are determined at the time when they are issued. Second, it is extreme because we not only compare a forecast with the most optimistic one among prior peer forecasts but also consider it as an outlier if the extent of deviation falls to the top 1% of the sample. Lastly, it does not impose restrictions on the frequency of outliers per firm per year. Firms with certain characteristics in certain periods may attract more extreme opinions, while others may be less prone to radical views and do not experience outlier forecasts at all. Our method of classifying outlier forecasts thus fully reflects the time-varying heterogeneity among firms.

By construction, our classification of outlier forecast originates from the extent to which an individual opinion differs from that of their peers, where a peer is defined as an analyst covering the same firm in the same year. In this respect, it stands in sharp contrast to the typical measure for analyst optimism, which is calculated as the difference between the average of analyst forecasts and the realized firm earnings (Bradshaw et al. 2001; Drake and Myers 2011). Put differently, the traditional proxy for analyst optimism is a static measure averaged over all analysts and benchmarked by the actual earnings; it is available for all firm-year observations. By contrast, our proxy is dynamically benchmarked against all previous forecasts issued by peers to the same firm-year; outlier forecasts rarely emerge for every firm in each year.

Focusing on the optimistic side of analyst opinion mitigates the impact of selection bias on the extent of extremism in an outlier forecast. This is because the existing incentive structure enervates an analyst's willingness to voice extremely pessimistic forecasts (Kadan et al. 2009);

share: \$1, \$0.5, \$1.6, \$0.99, and \$1.66. Since \$1.66 is the most optimistic one among all five prior forecasts, we compare to what extent Amy's forecast deviates from the most optimistic prior: (\$1.88-\$1.66)/\$1.66 = 13.25%. We calculate the extent of deviation for each forecast in our sample. For a forecast to qualify as an outlier, we require the extent of its deviation falls into the top 1% of the sample.

an analyst can always opt for the alternative — terminating his coverage on firms that he views negatively (McNichols and O'Brien 1997; Hayes 1998). As such, the observed pessimistic forecast is less likely to reflect the actual extremism in an analyst's opinion and hence introduces a larger bias in opposition to the optimistic ones.

We acknowledge, however, that there is no clear consensus on how extreme an opinion must be in order to be classified as an outlier. In the Internet Appendix IA.1, we explore alternative ways to identify outlier forecasts.

2.2 Data Sources and Descriptive Statistics

We compile a sample of analysts' annual earnings forecasts from 1990 to 2019 from the Institutional Brokers' Estimate System (I/B/E/S) database.[8] Since assessing the extent to which an individual's opinion deviates from that of peers requires an adequate cohort size, we limit the sample to firms that are covered by at least four analysts each year. To ensure a reasonable size of prior peer forecasts, we also require a firm-year to have a minimum of five prior forecasts, or at least six forecasts in total, to identify an outlier forecast. After matching with the Compustat annual files and CRSP daily files, we obtain 1,786,367 forecasts issued by 12,616 analysts regarding 5,341 firms (37,371 firm-year observations). After dropping missing values of our key variables used in baseline regressions, our sample contains 1,481,477 forecasts issued by 8,174 analysts to 5,238 firms (36,089 firm-year observations).

Table 1 presents the descriptive statistics of the full sample. Depending on our research questions, we organize our data into different levels of analysis. We investigate market participants' reactions to outlier forecasts at the forecast level and firm-year level, respectively,

[8] I/B/E/S already screens for what it considers to be outlier forecasts due to either mistakes or inconsistent estimation criteria. It then makes various adjustments to correct these erroneous forecasts, such as obtaining corrected estimates from the issuing analysts, or looking into exclusions/inclusions. In the I/B/E/S database, these forecasts are referenced as "outlier estimates" and singled out in an "Excluded Estimates" file. Our analysis is based on the cleaned version of the I/B/E/S file, so the outlier forecasts we identify are not from the "Excluded Estimates" file.

and we explore the incentives and consequences of issuing outlier opinions at the analyst-firm-year level and analyst-year level.

At the forecast level, outlier forecasts account for 1% of the sample (by construction). On average, a forecasted EPS is 38% lower than the most optimistic forecasted value among all prior forecasts. However, the EPS in an outlier forecast is 12% higher than the most optimistic prior forecast. The CAR and trading volume on the day when a forecast is issued is -0.07% and 4.8 million shares, respectively. An average analyst has approximately 12 years of professional experience with a 51.31 of Hong-Kubik (2003) forecast accuracy score in the previous two years. An average broker employs 66 analysts per year.

At the firm-year level, an average sample firm is exposed to 0.44 outlier forecasts. Conditional on a firm-year with at least one outlier forecast, the EPS from the first outlier forecast is 33% higher than the most optimistic one among all prior forecasts. On average, 0.67 outlier forecasts are subsequently issued after the arrival of the first outlier forecast. There is preliminary evidence of escalated extremism, as the EPS from a subsequent outlier forecast is 43% greater than that of the most optimistic prior forecast, and higher than the extent of deviation of the first outlier (33%). An average sample firm is covered by 14 analysts per year, has total assets worth 4.95 billion dollars, a market-to-book ratio of 6, and an ROA of -1%.

At the analyst-firm-year level, we can compare an analyst's relative position to the cohort of peer analysts predicting the earnings of the same firm in the same year. An average analyst is 5% more experienced than his peers, 4% more experienced with firms under coverage, and is affiliated with a broker that is 5% larger than the brokers of his peers. At the analyst-year level, 20% of analysts in our sample issue outlier forecasts in a year, and an average analyst issues 0.31 outlier forecasts in a year. 39% of analysts cover firms with a higher market value compared with last year, and 44% of analysts cover firms with higher institutional ownership compared with last year.

3. Peer Analysts

3.1 Peer Reactions

In this section, we explore whether and how outlier opinion affects fellow analysts. On the one hand, peer analysts are skilled and sophisticated professionals, thereby should not react to one individual's extreme view. On the other hand, the "anchor-and-adjustment" effect, first theorized by the seminal work of Tversky and Kahneman (1974), suggests that an outlier forecast can form an anchor and influence peers. Despite that people had every intention to make accurate predictions, their forecasts can inevitably be influenced by an existing anchor, even if it is a randomly assigned number (Tversky and Kahneman 1974; Simmons, LeBoeuf, and Nelson 2010).

We compare forecasts issued by peer analysts before and after the arrival of an outlier forecast. "*EPS Forecast*" is the forecasted annual earnings per share (EPS), scaled by the firm's share price in the previous year, and multiplied by 100. 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 adopt a rolling-window approach for the post-outlier horizon. "*Post Outlier Forecast*" is a dummy variable set to one if an analyst's forecast belongs to, respectively, the 3, 5, 10, 15, and 20 forecasts issued after observing an outlier forecast, and zero otherwise. We then compare the EPS value forecasted by peers during these post-outlier horizons with the most recent five forecasts issued prior to the arrival of the outlier. Using all pre-outlier forecasts instead of a fixed pre-outlier horizon does not alter our main findings. 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.

Specifically, we examine whether peer analysts react to an outlier forecast by estimating the following regression model:

$$y_{i,t} = \beta \times Post\ Outlier\ Forecast_{j,t} + \boldsymbol{\gamma X_{i,t}} + \theta_{b,t} + \epsilon_{i,t}, \tag{1}$$

where $y_{i,t}$ is the EPS forecast issued by peer analyst i during the above-described horizons in year t. If a fellow analyst is influenced by the arrival of an extremely optimistic forecast issued by analyst j, then we expect $\beta > 0$. $\boldsymbol{X_{i,b,b',t}}$ includes controls for time-varying analyst-specific and brokerage-specific characteristics, such as an analyst's total years of professional experience and past forecast accuracy, as well as the size of the broker, which captures the prestige and reputation of his employer. Specifically, to gauge an analyst's professional experience, we calculate "*Experience*", which is the total number of years between the current forecast and the first forecast issued by an analyst appearing in the I/B/E/S database. It captures an analyst's general experience by reflecting on how long he has remained in the profession. To measure an analyst's past forecast accuracy, we calculate Hong and Kubik's (2003) forecast accuracy scores and average then over the previous two years. We also include firm × year fixed effects ($\theta_{b,t}$) to control for the confounding effects on the forecast optimism of a peer analyst brought about by time-varying and firm-specific unobserved heterogeneity. This fixed effects strategy helps to narrow down our comparison to all peer analysts covering the *same firm* in the *same year*.

Columns 1-5 of Table 2 report the regression results. The unit of analysis is at the forecast level. Standard errors are clustered at the firm-year level. We observe a positive and significant coefficient associated with the dummy for peer forecast issued over various post-outlier horizons. Among all the peer analysts covering the same firm in the same year, forecasts issued after the arrival of an outlier forecast are more optimistic than those issued prior to the arrival of such a forecast. The effect prevails through the post-outlier 20-forecast horizon with negligible decay in the magnitude of the coefficient, suggesting a persistent influence of an outlier on peer analysts.

In terms of the economic magnitude, column 1 indicates that the annual earnings per share forecasted by peer analysts over the post-outlier 3-forecast horizon are on average 0.682 higher than those forecasts issued prior to the outlier forecast. This accounts for approximately 18% of the sample mean forecast value (3.79).[9]

Despite the rare nature of an outlier, our classification of outlier forecast allows for a firm-year to have multiple outliers. In this case, a peer analyst's forecast may be categorized as both a pre-outlier forecast and a post-outlier one if multiple outlier forecasts are issued within a short time window. The more optimistic post-outlier forecasts by peers that we document could thus be attributed to a subsequent outlier forecast, rather than to forecast optimism of peers in general. In the main tests, we take into account this possibility by employing a fixed and short pre-outlier horizon and varying post-outlier horizons. To further mitigate this concern, we distinguish between the first outlier and subsequent outliers issued in a firm-year.

In columns 6-10 of Table 2, we restrict our comparison of peer forecasts to the arrival of the first outlier in a year and repeat the baseline regression using this cleaner subsample. The results are consistent with an extremely optimistic opinion subsequently moving up the consensus of peer analysts.

The results that outlier forecasts can shift group consensus can be connected to Cialdini's (1984) work on the principles of influence, particularly social proof. The principle suggests that

[9] Prior studies find that analyst forecast optimism declines over time during the forecast period (Richardson, Teoh, and Wysocki 2004; Hutton 2005), suggesting that the longer an analyst waits to issue his forecast, the less optimistic his forecast is. In light of this evidence, the economic effect of an outlier forecast on peer analysts could be underestimated.

individuals look to the behavior and opinions of others when forming their own opinions, especially in situations of uncertainty. In addition, our findings are broadly consistent with the substantial evidence in psychology on anchoring and adjustment. For instance, Tversky and Kahneman (1974) show that a simple, sometimes 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. An extreme forecast, even though it may look unreasonable or originate from an analyst lacking acuity, appears to serve as a salient anchor for all peer analysts.

3.2 Self-fulfilling Extremism

The results so far show that a radically optimistic forecast moves up fellow analysts' consensus. In this subsection, we explore to what extent the arrival of an outlier affects the likelihood of peers to also issue outlier forecasts and the extremism of their views.

To do so, we first restrict the sample to firm-year observations with at least one outlier forecast and calculate "*# of Subsequent Outliers*", the number of outlier forecasts issued after the first outlier forecast in a firm-year. We then regress this variable on the extent of extremism of the first outlier (i.e., the degree of its deviation from the most optimistic prior forecast). For this set of analyses, we control for the characteristics of the analyst who issues the first outlier forecast, including his professional experience, past forecast performance, and the size of his broker. Since observed and unobserved firm characteristics may attract outlier views, we also control for a firm's profitability (ROA), size, growth opportunities (captured by the market-to-book ratio), the size of analyst coverage, as well as year-, industry- and firm- fixed effects.

Columns 1-2 of Table 3 reveal that the extent of the first outlier's deviation from previous forecasts is positively and significantly associated with the number of subsequent outlier forecasts. This suggests that outliers tend to beget more outliers. The economic magnitude is also significant. Column 1 suggests that a one-standard-deviation increase in the first outlier's deviation from the previous peer forecast (0.78) is associated with 0.07 more subsequent outliers in the same firm-year. This accounts for approximately 10% of the sample mean of subsequent outliers (0.67).

Next, we evaluate the impact of outlier opinions on the extremism of subsequent outliers. This set of tests requires the sample to consist of firm-year observations with at least two outlier forecasts. For each firm-year, we calculate "*Subsequent Outlier Deviation*", which is the average deviation of all outliers issued after the first outlier forecast. A higher value of this variable indicates that subsequent outlier forecasts are more extreme.

Columns 3-4 of Table 3 show that the extremism of the first outlier amplifies that of subsequent outliers. The more radical the first outlier is, the larger deviations of subsequent outliers are from previous peer forecasts. Column 3 suggests that a one-standard-deviation increase in the first outlier's deviation from prior forecasts (0.78) raises the deviation of subsequent outliers on average by 0.13, approximately 30% of the sample average of subsequent deviation (0.43).

To summarize, the results in Table 3 provide evidence consistent with self-fulfilling extremism. Not only do outliers beget more outliers, but also earlier outliers boost the extremism of subsequent ones.

3.3 Which Peer Analysts React to Outliers?

In this section, we explore the heterogeneity within peer analysts in their response to an outlier forecast. To alleviate the potential confounding effect that a peer analyst may subsequently become an outlier analyst, we focus on peer reactions to the arrival of the first outlier forecast in a firm-year.

We consider three common analyst traits: work experience, past forecast accuracy, and the reputation of the broker they are affiliated with, proxied by the size of the broker. Using the sample median as the cutoff, we distinguish between peer analysts that have more or less experience, better or worse past forecast performance, or come from larger or smaller brokers. We then interact the dummy variable for the post-outlier forecast with peer analysts of different levels of experience, past performance, and broker size. For brevity, we report regression results using the 3-forecast window following the issuance of the first outlier forecast. Expanding post-outlier windows to include 20 forecasts produces consistent results.

The results from Table 4 suggest that peer analysts, regardless of their professional experience (column 1) and past performance (column 2), react in a similar magnitude to outlier forecasts. In column 3, the F-statistic of testing the difference in coefficients of the two interaction terms is 5.99, suggesting that peer analysts employed by smaller brokers react statistically significantly stronger to an outlier forecast than those from larger brokers. Nevertheless, the economic magnitude of the difference between the two is qualitatively small.

Overall, Table 4 reveals that the effect of outlier opinions on peers prevails across analysts with heterogenous backgrounds. These findings are consistent with Simmons et al. (2010) that it is challenging to shun the "anchor effect", even for agents with traits that make them more capable of doing so otherwise.

3.4 Robustness

3.4.1 Alternative Measures of Outliers

In our main analysis, we classify a forecast as an outlier if the extent of its deviation from the most optimistic forecast among all previous forecasts falls into the top 1% of the sample. Since there is no definitive boundary for a forecast to be considered as rare and extreme, we consider two alternative cutoffs to identify outliers: the top 5% and the top 10% of the sample. Internet Appendix IA.1 presents the baseline results using these two alternative ways to define outliers. While relaxing the constraint for forecast deviation leads to an augmented sample size and a lesser degree of extremism, we always find a consistent and robust pattern of peer reactions to outlier forecasts.

3.4.2 Concurrent News Events

It is possible that an extremely optimistic forecast is issued following the arrival of significantly favorable news about the firm. Peer analysts may react to the concurring news itself, not to the outlier forecast.

We extract news reports for U.S. firms from the “Global Equities” section of the RavenPack News Analytics (RPNA) and merge them with I/B/E/S. To address the concern that firm-specific news may confound with the timing of outlier forecasts, we proceed as follows. We first construct a “without-good-news” sub-sample, excluding all forecasts issued on the day that observes significantly favorable news, as well as forecasts issued up to two days before the arrival of such news to mitigate the effect of news leakage. Within this sub-sample, we repeat our main analysis. Alternatively, we re-estimate our baseline results using the full sample but directly control for both the total number of news and the number of favorable news arriving in the periods of $[t-2, t]$ and $[t-1, t]$, as well as on day t when a forecast is issued. Untabulated regressions suggest that our findings are unlikely driven by concurrent news.

3.4.3 Private Information

Another relevant concern is that analysts may issue biased forecasts that overshoot the consensus based on the direction of their private information (Bernhardt, Campello, and Kutsoati 2006). Chen and Jiang (2006) show that analysts tend to overweight their private information when issuing favorable forecasts. Clement and Tse (2005) find that the likelihood of being bold increases with an analyst's previous forecast accuracy. Chen and Matsumoto (2006) show that more optimistic analysts may receive more private information from managers. As such, an outlier forecast may capture the superior private information from the issuing analyst, and peer analysts react to the arrival of a more accurate forecast.

To evaluate this possibility, we first directly compare the accuracy of outlier and non-outlier forecasts. Internet Appendix IA.2 shows that outlier forecasts have a larger, rather than a smaller, error than non-outlier forecasts.

We also explore the implementation of Regulation Fair Disclosure (Reg FD) in 2000, a regulatory event that exogenously affects the sources of analysts' private information. By prohibiting firms from selectively disclosing information to certain financial market participants, Reg FD has significantly reduced the benefits of private access to management (Koch, Lefanowicz, and Robinson 2013). If private information arises from an analyst's exclusive access to management and accounts for his extreme optimism, analysts should become less extreme in their forecasts following the Reg FD. Instead, Internet Appendix IA.3 provides no evidence that outlier forecasts occur less frequently after the Reg FD, when many analysts' sources of private information were severed. Overall, it appears that private information cannot sufficiently justify the extreme positions of outlier analysts.

4. Other Market Participants

One major heuristics from Tversky and Kahneman (1974), representativeness, suggests that market participants might overweigh the implications of the extreme forecasts due to their salience and the ease with which they come to mind, leading to stronger market reactions. We have so far documented the influence of an outlier forecast on fellow analysts. In this section, we examine whether other market participants, such as investors, media, and management, are subject to the influence of outlier forecasts.

4.1 Investors

We examine whether investors respond differently between outlier and non-outlier forecasts. On the day a 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 logarithm of shares traded). We control for analyst-specific characteristics that may affect the market reaction, such as the analyst's professional experience, past forecast accuracy, the size of the broker with which the analyst is affiliated, and the timing of the forecast. Importantly, we include firm × year fixed effects to control for firm-specific and time-variant factors that may affect the way the market reacts to a forecast.

Table 5 presents the forecast-level regression results for abnormal returns (column 1) and trading volumes (columns 2-3). Among all the forecasts issued regarding the annual earnings of the same firm in the same year, the abnormal return is 1.3% higher, and the trading volume is 10%

larger, on the day when an outlier forecast is issued, compared to the days when non-outlier forecasts are made.

Since trading volumes are usually higher when price movements are larger, the findings in column 2 may be mechanical. In column 3, we control for, additionally, abnormal returns at the time of earnings forecasts.[10] While the magnitude of price movement is indeed positively and significantly linked to trading volume, we continue to observe a larger volume of trades placed on the day of an outlier forecast than on the day when a non-outlier forecast arrives.

Overall, the results in columns 1-3 of Table 5 indicate that outlier forecasts generate stronger market reactions than non-outlier ones. This is consistent with Lundholm and Rogo's (2016) finding that excessively volatile forecasts contribute to stock market volatility. Importantly, Kirk, Reppenhagen, and Tucker (2014) document that investors use key analyst forecasts as additional benchmarks to evaluate earnings, as the consensus forecast under-utilizes private information contained in individual forecasts. In this respect, by moving up group consensus and inducing more radical forecasts from peers, the view of an outlier analyst, rather than just the average forecasts, can influence investor expectations. The results are also consistent with some investors being naive regarding the incentives of analysts and responding to analysts' optimistic recommendations regardless of underlying bias (Malmendier and Shanthikumar 2007).

4.2 News Media

We also examine whether outlier forecasts have a differential impact on news media than non-outlier ones. In doing so, we restrict to firm-year observations that have at least one outlier forecast. As described previously, we extract news reports for U.S. firms from the "Global

[10] 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.

Equities" section of the RPNA and merge them with I/B/E/S.[11] Since RPNA began its data coverage in 2000, we restrict the sample period to 2000-2019. We classify a piece of news as relevant if its RPNA Relevance Score is 100. A news article is considered good news if its Composite Sentiment Score exceeds 50.[12]

For each forecast, we calculate the change in media coverage intensity surrounding the time of issuance. "*Increase in Total News*" and "*Increase in Good News*" are, respectively, the percentage change in the total number of news and the percentage change in the number of good news from the pre-forecast $[t-3, t-1]$ period to the post-forecast $[t+1, t+3]$ period, when a forecast is issued on day t. We also consider the change in the fraction of news being good news in the two 3-day periods. "*Increase in % Good News*" is the difference between the percentage of good news out of all news released during the pre-forecast $[t-3, t-1]$ period and that during the post-forecast $[t+1, t+3]$ period. If news media is subject to the influence of an individual analyst's radically optimistic view about a firm, then we would expect that the number of news reports about the firm, especially the number of good news, increases following the issuance of an outlier forecast.

Consistent with the above conjecture, column 4 of Table 5 indicates that the percentage increase in the number of news related to a firm is 10.9% higher following the issuance of an outlier forecast than a non-outlier one. This responds to approximately 30% of the sample

[11] RPNA provides real-time structured sentiment, relevance, and novelty data for entities and events detected in the unstructured text published by reputable sources. Publishers include the Dow Jones Newswires, the Wall Street Journal, Direct Regulatory and PR feeds, and over 19,000 other traditional and social media sites. Its Global Equities section detects news and produces analytics data on over 40,000 listed stocks from the world's equity markets.

[12] As a comprehensive database on corporate news, RPNA records all the news reports related to a firm, including news pieces in which the firm is only briefly mentioned. For each news report, RPNA ranks the relevance of the content for a specific firm. A Relevance Score of 0 means that the entity was passively mentioned while a score of 100 means the entity was prominent in the news story. RPNA also combines various sentiment analysis techniques and designs a Composite Sentiment Score (CSS) to track the sentiment of news about a firm. The CSS ranges from 0 (the least favorable) to 100 (the most favorable), with 50 being neutral. We classify a news report about a firm as "favorable" if its CSS rating exceeds 50.

average of "*Increase in Total News*", which is 36%. The results suggest that news media increases coverage intensity about a firm following an outlier forecast than a non-outlier.

The results are more striking when we focus on good news instead of all news. Column 5 of Table 5 indicates that the percentage increase in favorable news reports about a firm is 12.5% higher following an outlier forecast than a non-outlier one. When considering the magnitude of the change in news coverage, column 6 reveals that outlier forecasts bring a bigger jump in favorable news coverage than non-outlier ones: the increase of the percentage of good news from the pre-forecast three-day window to the post-forecast three-day window is 1.6% larger for an outlier forecast than a non-outlier.

Overall, results from columns 4-6 of Table 5 suggest that outlier forecasts not only generate more media coverage intensity than non-outlier ones, they also elevate media sentiment. The news media report more positive news about the firm after an outlier forecast than a non-outlier.

4.3 Corporate Management

While analysts issue forecasts on a firm's future earnings, management also provides their expectations of future earnings through guidance. In our context, management guidance offers an opportunity to directly observe management's responses to an outlier forecast.

We compile a sample of management guidance issued within 90 days after the first outlier forecast in a given firm-year, which allows us to focus on guidances likely provided in response to the outlier forecast. The sample consists of 3,058 guidance events. We then examine how the extent of extremism of the first outlier forecast affects the management's assessment of the likelihood of beating analyst consensus. In this test, the unit of analysis is a firm-year. We control for the experience, past accuracy, and broker size of the analyst who issues the first outlier forecast, as well as time-varying firm characteristics such as the size of coverage, ROA, firm size, and the market-to-book ratio. We include firm-fixed effects and year-fixed effects to absorb firm-specific and time-varying characteristics that affect the management guidance.

Column 7 of Table 5 reports the results. We observe that management is less likely to predict that the firm beat the analyst consensus when the outlier forecast is more radical. Since the outlier forecasts affect peer analysts to revise their earnings upwards and move up group consensus, it becomes more difficult for a firm to meet the evaluated analyst expectation. In response, the management is less likely to issue a guidance of beating the inflated consensus, to avoid disappointment later from investors.

5. What Cultivates Outlier Opinions?

Why would an individual hold extreme opinions on certain subjects but not on others? Why doesn't every analyst broadcast extreme views? In this section, we consider that individuals have different utility functions and explore personal motives that may contribute to extreme optimism. We postulate that the costs and benefits of voicing extreme views vary significantly across analysts; as such, an individual's incentive to issue outlier forecasts is exacerbated when doing so can generate significant personal benefits while the potential cost is limited.

5.1 Which Peers Promote Outlier Views?

An important feature of an outlier opinion is that individuals may hold extreme views on certain subjects while sharing similar views with the rest of the group on others. To gauge why an analyst issues outlier forecasts for some firms but not for others, we leverage the theoretical insights of Scharfstein and Stein (1990) to guide our analysis. Scharfstein and Stein (1990) predict that agents with less uncertainty about their ability, for whom reputation concerns are no longer relevant, are less likely to herd with others. In the context of our study, their model implies that analysts are more likely to deviate from the rest of the group when their reputation concern is less relevant than that of their peers.

We consider the uncertainty about an analyst's ability in three dimensions: general experience, firm-specific experience, and brokerage reputation. Specifically, to gauge an analyst's professional experience, we consider not only an analyst's general experience by reflecting on how long he has remained in the profession, but also his firm-specific experience, calculated as the total number of years between the analyst's current forecast and his/her first forecast for a given firm. This variable allows us to consider the fact that an agent may hold extreme views on certain subjects while agreeing with the consensus of others. It also considers that a young analyst may have more experience covering a firm than a senior analyst. Lastly, an analyst working for a bigger broker presumably comes from a more prestigious brokerage house, signaling less uncertainty regarding his ability in comparison to those working for smaller brokers.

For a given firm-year, we then rank all analysts based on each of these proxies for uncertainty about ability. Since the size of analyst coverage varies across firms, we convert their ranks to a Hong and Kubik (2003) type score to ensure these ranks are compatible and meaningful across firms. A higher (firm-specific) rank score suggests less uncertainty about an analyst's ability and thus a smaller reputation cost perceived by the analyst.

Lastly, we compare these firm-specific rank scores within each analyst's coverage portfolio. Specifically, for each analyst-firm-year, we divide an analyst's rank score by the average of the scores of the peer analysts covering the same firm in the same year, and minus one. "*More Experienced*", "*More Firm-Specific Experienced*", and "*Bigger Broker*" thus indicate the extent of the (reduced) reputation concern of an analyst relative to that of the peers for each firm in his coverage portfolio.

We estimate a linear probability model on the propensity for an analyst to be the outlier analyst and report the results in Table 6 Panel A. The unit of analysis is at the analyst-firm-year level. For this set of analyses, it is crucial to include analyst × year fixed effects to purge the potential influence of time-varying analyst heterogeneity. As such, this fixed effects strategy allows us to compare different propensities for voicing extreme views by the same analyst in the same year that vary with the different peer cohorts to which he is assigned.

Columns 1-3 relate an analyst's rank of reputation concern relative to that of his peers to the propensity of being an outlier analyst. We observe that when an analyst is more established and thus has less reputation concern than the rest of peers covering the same firm, the analyst is more likely to become an outlier analyst. The results are generally consistent with the prediction of Scharfstein and Stein (1990).

When including all the proxies for analyst reputation rank relative to peers in the model (column 4), all the coefficient estimates reserve the same sign. Since all the tests include analyst × year fixed effects, the findings essentially isolate how the extent of difference in reputation concerns between an analyst and his peer cohorts affects differently the propensity for him to issue an outlier forecast in a year.

In terms of the economic magnitude, the coefficient for "*More Firm-Specific Experienced*" in column 4 suggests that a one-standard-deviation increase in an analyst's rank of firm-specific experience is associated with around 0.5% higher probability that the analyst becomes the outlier analyst, which is approximately 16% higher than the average probability of becoming an outlier analyst in the whole sample (3.15%).

Overall, Table 6 Panel A suggests that being extreme is situational rather than being an invariant, innate trait of an individual. An analyst broadcasts outlier forecasts only when he is more established, and thus reputation concern matters less to him than it does to his peers. In this case, exerting impact and swinging peer opinions are easier and thus less costly. In a highly competitive industry with only the very few top performers reaping gigantic payoffs, the potential cost for such an individual to issue an extremely optimistic forecast appears to be small.

5.2 Disagreement among Peers

We postulate that the cost of expressing extreme views drops when there already exists a strong disagreement among peers. We capture the within-group opinion diffusion by calculating the uncertainty among peer analysts regarding their predictions about a firm's future earnings. Empirically, we calculate the forecast dispersion before the issuance of the first outlier forecast ("*Pre-outlier Forecast Dispersion*") and relate such dispersion to the value of the outlier forecast itself. "*Pre-outlier Forecast Dispersion*" thus captures the extent of disagreement among analysts. At the same time, we control for the average forecasted earnings prior to the outlier forecast ("*Average of Pre-outlier Forecasts*").

Columns 1-2 of Panel B of Table 6 show that pre-outlier disagreement among analysts has a positive and significant impact on the value of an outlier forecast. This indicates that a larger *ex-ante* disagreement among analysts is associated with a more extreme outlier forecast about a firm's earnings. Put differently, an outlier forecast becomes more radical only after the issuing analyst observes that their peers hold more diverse views about a firm's future earnings.

A one-standard-deviation increase in the pre-outlier forecast dispersion (1.6) will increase an outlier's EPS forecast value by 2.5, equivalent to 63% of the sample mean (3.99). This is consistent with Evgeniou et al. (2013)'s findings that when luck is more important in determining outcomes, such as when the market is more volatile, the average deviation of outlier forecasts from the consensus forecast is greater. It is also consistent with Zarnowitz and Lambros (1987), who document that forecast dispersal increases when forecast uncertainty is high (as subjectively reported by forecasters).

In columns 3-4 of Panel B, we explore how a firm's general information environment affects the level of extremism in analyst forecasts. Instead of focusing on the forecast dispersion of pre-outlier forecasts as in columns 1-2, which anchors around an outlier forecast and requires a sample of firm-year observations with at least one outlier forecast, we use all forecasts issued in a firm-year. We calculate a firm's analyst forecast dispersion in the previous year ("*Previous Year's Forecast Dispersion*") and relate it to the frequency that the firm experiences outlier forecasts in the current year. We control for the average value of value of these forecasts.

Columns 3-4 of Panel B provide results consistent with those related to pre-outlier forecast dispersion. The more divergent analysts' opinions are regarding a firm's future earnings in the previous year, the more outlier forecasts the firm witnesses in the following year. A one-standard-deviation increase in forecast dispersion (1.39) in the previous year is associated with 0.23 more outlier forecasts in the current year. This is equivalent to approximately 52% of the sample average of the number of outlier forecasts (0.44).

The findings in Table 6 thus help us better understand the results in Table 2: when there is a stronger disagreement among peer analysts in estimating a firm's future earnings, the outlier forecast tends to be more extreme. This may stir greater attention from peer analysts and impose a prolonged influence on their subsequent forecasts.

5.3 Can Outlier Forecasts Promote Analysts' Careers?

Laster, Bennett, and Geoum (1999) model a scenario in which forecasters' payoff maximization can give rise to their efforts to differentiate their views from the consensus in equilibrium. Their model thus predicts that a forecaster's desire to maximize his expected payoffs, whether wages or upward career mobility, exacerbates the incentive to broadcast outlier opinions. This is especially the case in highly competitive industries such as the financial service industry, where only a small set of individuals garner huge payoffs.

Assessing whether issuing outlier forecasts is associated with favorable career outcomes requires data for promotions and demotions over the professional life of an analyst. However, as neither analysts' compensation nor their internal career paths are publicly observable, the existing studies rely on turnover information to infer an analyst's career path. For instance, Hong, Kubik, and Solomon (2000) and Hong and Kubik (2003) consider an analyst moving to a larger (smaller) broker as a promotion (demotion).

In light of Harford et al. (2019), we develop a different method to identify analyst career progress. Our proposed measure relies on the change in the quality of an analyst's coverage portfolio over time due to the reassignment of stocks. We capture the importance of a stock to an analyst's career in his coverage portfolio by, respectively, market capitalization and institutional ownership. If brokers reward analysts by assigning important stocks to them, then their coverage portfolios should consist of more firms with a larger market capitalization or higher institutional ownership.

The economic rationale hinges on the fact that firms with large market capitalization or high institutional ownership are key sources of commission revenues for brokerage houses (Frankel, Kothari, and Weber 2006). In turn, the broker assigns its best-performing analysts to cover its important clients. Analysts covering these high-profile firms not only harvest higher year-end bonuses, usually as a result of the larger commission revenue they help generate, but they also gain better access to the network of institutional investors, who can directly affect their career through, for instance, electing all-stars (Emery and Li 2009; Groysberg, Healy, and Maber 2011).[13] Empirical evidence and field interviews indicate that brokers often use client assignments to incentivize analysts (Roger 2018). Consequently, Harford et al. (2019) show that career concerns motivate analysts to allocate their effort to firms that provide more lucrative commission revenues for their employers relative to the rest of the firms in their coverage portfolios. In particular, they use similar proxies to identify which stock in an analyst's portfolio is relatively more important and thus receives more analyst effort.

We construct our measures for analyst career advancement by identifying whether there is a change in stock composition in an analyst's coverage portfolio. "*Higher Market Value*" ("*Higher Institutional Ownership*") is then defined as an indicator variable set to one if, in a given year, the average market value (percentage of institutional ownership) of stocks in an analyst's current coverage portfolio is higher than that of stocks in his previous coverage portfolio, and zero otherwise. Averaging the market value or institutional ownership in an analyst's coverage portfolio mitigates the concern that our research design instead captures that analysts issuing extreme forecasts are demoted to smaller brokerages and consequently need to cover more firms.

By construction, these two proxies allow us to compare the values of two different sets of stocks covered by the same analyst in the same year. Put differently, if the composition of a

[13] Brochet, Miller, and Srinivasan (2014) document an increase in the market capitalization of coverage portfolios when analysts experience a change in firms they cover. Groysberg, Healy, and Maber (2011) find that aggregate market capitalization of the portfolio of firms that analysts cover is an important determinant of sell-side analyst compensation.

coverage portfolio remains unchanged but the average market value or institutional ownership increases from the previous year, we do not consider it as a career advancement maneuver.[14]

Broadly speaking, a broker can award an analyst by allowing him to continue covering its most important clients, or to cover the same clients who have otherwise become more important to the broker over time, as captured by a rise in market valuation and institutional ownership. Restricting our proxies to the incidences of stock reassignment within an analyst coverage portfolio thus potentially underestimates the real effects of our findings. Nevertheless, doing so helps prevent our analysis from being contaminated by mechanical relations, as the average market capitalization or institutional ownership in a coverage portfolio may rise for other reasons.

An advantage of our measures for career progression is that they are based on the quality of the coverage portfolio and thus do not rely on the availability of turnover information to infer analyst promotion or demotion. Because these proxies can capture internal career outcomes, they are better suited in the context of this study to understand the impact of outlier forecasts than proxies based on career turnovers. Voicing an extreme opinion usually does not lead to an immediate job change; however, it can directly affect internal evaluation and an analyst's portfolio assignment in the next period.

In Table 7, we examine how the quality of an analyst's coverage portfolio changes following the issuance of an outlier forecast. The unit of observations is at the analyst-year level. The dummy for outlier analyst is set to one if an analyst issues at least one outlier forecast in a given year. Since a change in the composition of a coverage portfolio may come from an

[14] To illustrate, consider an analyst who covers firms A, B, and C in 2010 and 2011; covers firms A, C, and D in 2012 and 2013; and covers firms A, D, and E in year 2014. "*Higher Market Value*" is set to zero in 2011 and 2013, as his coverage portfolio remains unchanged, even if the average market cap of firms in the same portfolio increases from the previous year. In 2012, this variable is set to one if the average market cap of A, C, and D in 2012 is higher than that of A, B, and C (his previous portfolio) valued in 2012, and zero otherwise. In 2014, this variable is set to one if the average market cap of A, D, and E in 2014 is higher than that of A, C, and D valued in 2014, and zero otherwise.

analyst's comparative advantages over other analysts (Brochet, Miller, and Srinivasan 2014), we follow Hong and Kubik (2003) and control for an analyst's experience and past performance, measured by their average forecast accuracy. Importantly, we include analyst fixed effects and year fixed effects to absorb analyst-specific and time-specific characteristics that may correlate with variations in market capitalization and institutional ownership in the coverage portfolio.

Table 7 shows that the dummy for outlier analysts is significantly related to an increase in the average market value (columns 1-4) and institutional holdings (columns 5-8) of firms in the analyst's coverage portfolio in the following year. The economic magnitude also appears to be sizeable. With the inclusion of analyst and year fixed effects, column 1 suggests that, on average, the same analyst issuing at least one outlier forecast in the current year is 3% more likely to cover client firms with a greater market capitalization in the next year, compared with an average likelihood of 39% for the entire sample. Similarly, the same analyst issuing at least one outlier forecast in the current year is 2% more likely to cover client firms with greater institutional ownership in the next year, compared with an average likelihood of 44% for the entire sample.

Table 7 provides evidence that brokerage firms reward analysts who issue outlier forecasts. These findings are consistent with Laster, Bennett, and Geoum's (1999) prediction that forecasters' wages foster their incentive to differentiate from peers. Although consensus prediction tends to be more accurate (Zarnowitz and Braun 1993), analysts whose forecasts are in line with the group consensus have little opportunity to distinguish themselves and promote their careers.[15]

[15] It is possible that the market value of the covered stocks changes coincidentally in the year of stock re-assignment within an analyst's coverage portfolio, or that the economic magnitude of value change is marginal. In these cases, our proxies may pick up pure luck rather than an analyst's career move within the brokerage firm. This should be less of a concern in the context of our study since different analysts cover different sets of stocks. *Ex ante*, it is also unclear whether this on average biases the size of coverage portfolio upwards or downwards. Using the dummy version helps to mitigate the impact of noise in these proxies to certain extent. Furthermore, the random and

7. Conclusion

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. In a review of 3,572 papers published in the top four finance journals, Adams et al. (2019) show that the most common practices to deal with outlier observations involve winsorizing (52%), trimming (16%), or dropping (17%). Presumably, except for bringing in noises and biasing the true interpretation of an empirical analysis, the presence of outliers themselves is considered economically negligible.

Real-world anecdotes often suggest otherwise. The most vocal and extreme opinions are common in many social dimensions. For instance, during political election campaigns, only the extreme views occupy the attention of the mass media and the public for a considerable period (Hirano, Synder, and Ting 2009). Regardless of whether such opinions reflect private information, they may still affect others (Demarzo, Vayanos, and Zwiebel 2003). The voice of outliers does not appear to be lost in the crowd but ripples across the market to influence various participants.

By exploring the within-group dynamics and documenting that a single outlier can influence the entire group, this paper demonstrates the impact of outlier opinions on market participants in the context of extreme analyst optimism. We find that an outlier forecast not only generates subsequently more optimistic forecasts by peer analysts, but also breeds more radical outliers. Outlier forecasts also cause greater market reactions from investors, more intensive media coverage, and more conservative management guidance.

Lastly, there is evidence that broadcasting extreme views is situational rather than originating from an invariant, innate personal trait. Outlier forecasts are more likely to take place

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idiosyncratic nature of luck prohibits it from contributing to systemic evidence. That is, it is possible that luck plays out at an individual level; at a systemic level, the effect of randomness should cancel out.

when an analyst's reputation cost is lower relative to that of his peer cohort, and information uncertainty is high. Further analyses reveal that personal career motives, instead of private information or investment banking incentives, are the likely cause for outlier forecasts.

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Appendix: Variable Definition and Construction

Variable	Definition
# of Subsequent Outliers	The number of outlier forecasts issued in a firm-year after the first outlier forecast.
Average of Pre-outlier Forecasts	The average of price adjusted-EPS forecasts issued prior to the first outlier forecast in a firm-year. Winsorized at 0.5% level for both tails.
Average of Previous Year's Forecasts	The average of price adjusted-EPS forecasts about a firm in year $t-1$. Winsorized at 0.5% level for both tails.
Beat Consensus	A dummy variable set to one if the earnings guidance provided by the management within 90 days following the emergence of the first outlier forecast implies that the firm is expected to beat earnings for the period indicated, and zero otherwise.
Bigger Broker; More Experienced; More Firm-Specific Experienced	An analyst's relative rank in terms of experience, firm-specific experience, and broker size, respectively to the peer analysts. Following Hong and Kubik (2003), we first rank all analysts forecasting the same firm-year based on their experience, firm-specific experience, or broker size, respectively, and convert their ranks to a Hong-Kubik (2003) type of score. For each analyst-firm-year, we divide an analyst's score on experience, firm-specific experience, and broker size, by the average score of his/her peers and minus one.
Broker Size	The number of analysts employed by a broker in a year. In regressions, we use the natural logarithm of the broker size.
CAR; ABS(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, multiplied by 100. ABS(CAR) is the absolute value of CAR. Winsorized at the 0.5% level for both tails.
Deviation	The percentage change in the value of an EPS forecast from the most optimistic one among all prior forecasts issued by peers. Winsorized at the 0.5% level for both tails.
EPS Forecast	An analyst's earnings forecast from I/B/E/S, divided by last year's stock price, multiplied by 100.
Experience	The natural logarithm of one plus the number of years between an analyst's current earnings forecast and his first forecast in the I/B/E/S database.
Firm Size	The book value of total assets. In regressions, we take the natural logarithm of firm size.
Firm-Specific Experience	The natural logarithm of one plus an analyst's firm-specific experience, which is the number of years between an analyst's current earnings forecast and his first forecast covering the firm in the I/B/E/S database.
Forecast Horizon	The natural logarithm of the difference in days between the actual earnings announcement date and the date when an analyst issues the forecast.

Frequency of Outlier Forecasts	At the analyst-year level, this variable is the number of outlier forecasts an analyst has issued in a year. At the firm-year level, this variable is the number of outlier forecasts issued to the firm.
Higher Institutional Ownership	A dummy variable set to one if the difference in average institutional ownership (measured in year t) of firms in an analyst's coverage portfolio between years t and $t-1$, is greater than zero. This variable is set to zero if the difference is less than or equal to zero, or if there is no change in stock composition of the coverage portfolio.
Higher Market Value	A dummy variable set to one if the difference in average market capitalization (measured in year t) of firms in an analyst's coverage portfolio between years t and $t-1$, is greater than zero. This variable is set to zero if the difference is less than or equal to zero, or if there is no change in stock composition of the coverage portfolio.
Increase in Total News	The change in the number of news articles from $[t-3, t-1]$ to $[t+1, t+3]$, where day t is when an EPS forecast is issued, scaled by the number of news articles over the period of $[t-3, t-1]$. Winsorized at the 0.5% level for both tails.
Increase in Good News	The change in the numbers of good news from $[t-3, t-1]$ to $[t+1, t+3]$, where day t is when an EPS forecast is issued, scaled by the number of good news over the period of $[t-3, t-1]$. Winsorized at the 0.5% level for both tails.
Increase in % Good News	The difference between the fraction of news articles being good news in the $[t-3, t-1]$ period and that in the $[t+1, t+3]$ period, where day t is when an EPS forecast is issued. Winsorized at the 0.5% level for both tails.
Market to Book	The natural logarithm of one plus the market value of equity divided by the book value of equity.
Outlier Analyst	A dummy variable set to one if an analyst has issued an outlier forecast in a year, and zero otherwise.
Outlier Forecast	A dummy variable set to one if the deviation of a forecast from the most optimistic prior forecast falls into the top 1% of the sample, and zero otherwise.
Past 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. Larger values indicate higher accuracy.
Peer > Median Accuracy / > Median Experience / > Median Broker	A dummy variable set to one if, respectively, a peer analyst's past forecast accuracy, experience, and broker size is above the sample median, and zero otherwise.
Peer < Median Accuracy / < Median Experience / < Median Broker	A dummy variable set to one if, respectively, a peer analyst's past forecast accuracy, experience, and broker size is below the sample median, and zero otherwise.

Post Outlier Forecast	A dummy variable equal to one if a forecast is issued by an analyst covering the same firm within, respectively, 3, 5, 10, 15, and 20 forecasts following the arrival of an outlier forecast, and zero otherwise.
Pre-outlier Forecast Dispersion	Standard deviation of the price adjusted-EPS forecasts issued prior to the first outlier forecast in a firm-year. Winsorized at 0.5% level for both tails.
Previous Year's Forecast Dispersion	Standard deviation of the price adjusted-EPS forecasts about a firm's EPS in year $t-1$. Winsorized at 0.5% level for both tails.
ROA	Return on assets. Computed as net income divided by total assets. Winsorized at 0.5% level for both tails.
Size of Coverage	The number of analysts covering the same firm in the same year.
Subsequent Outlier Deviation	For each firm-year with multiple outlier forecasts, this variable is calculated as the average deviation of all subsequent outlier forecasts issued after the first outlier forecast.
Trading Volume	The number of shares traded on the day an analyst issues an earnings forecast. In regressions, we use the natural logarithm of the traded shares.

Table 1: Descriptive Statistics

This table reports the descriptive statistics. The sample period is between 1990 and 2019. All variables are defined in the Appendix.

Variables	# of obs.	Mean	Median	Std. Dev.
Forecast level:				
Broker Size	1,481,477	66	46	62
CAR	1,461,533	-0.07	-0.03	5.42
Deviation				
All forecasts	1,325,067	-0.38	-0.12	1.02
Outlier forecasts	13,137	0.12	0.14	0.03
EPS Forecast (unadjusted by price)	1,481,477	1.78	1.25	2.31
EPS Forecast (adjusted by price x 100)	1,481,477	3.79	4.28	5.42
Experience (in years)	1,481,477	12.41	11	8.18
Forecast Horizon	1,481,477	210	203	104
Increase in Total News	1,022,271	0.36	-0.88	3.88
Increase in Good News	810,118	-0.18	-1	2.67
Increase in % Good News	683,123	-0.01	0	0.46
Outlier Forecast (1% cutoff)	1,481,477	0.01	0	0.09
Outlier Forecast (5% cutoff)	1,481,477	0.05	0	0.21
Outlier Forecast (10% cutoff)	1,481,477	0.09	0	0.29
Past Accuracy	1,481,477	51.31	51.04	5.41
Trading Volume (in million shares)	1,461,533	4.81	1.34	13.99
Firm-year level:				
Average of Previous Year's Forecasts	30,561	3.35	3.95	5.8
Frequency of Outlier Forecasts	30,561	0.44	0	0.93
Previous Year's Forecast Dispersion	30,561	0.87	0.41	1.39
Firm-year level (at least one outlier forecast):				
# of Subsequent Outliers	7,998	0.67	0	1.14
Average of Pre-outlier Forecasts	7,998	1.57	2.82	7.95
Beat Consensus	7,998	0.09	0	0.28
Firm Size (total assets in $ billions)	7,998	4.95	0.82	19.15
First Outlier Analyst's Accuracy	7,998	50.73	50.72	5.83
First Outlier Analyst's Broker Size	7,998	61	42	60
First Outlier's Deviation	7,998	0.33	0.13	0.78
First Outlier Analyst's Experience	7,998	12.75	11	8.04
First Outlier Analyst's Forecast Horizon	7,998	271	289	90
Market to Book	7,998	6	2.69	66.9
Pre-outlier Forecast Dispersion	7,998	0.93	0.45	1.6
ROA	7,998	-0.01	0.04	0.18
Size of Coverage	7,998	14	11	9
Subsequent Outlier Deviation	3,008	0.43	0.17	0.91

Analyst-firm-year level:				
Bigger Broker	450,054	0.05	0	0.71
More Experienced	450,054	0.05	0	0.71
More Firm-Specific Experienced	450,054	0.04	0	0.68
Analyst-year level:				
Frequency of Outlier Forecasts	42,058	0.31	0	0.76
Higher Institutional Ownership	42,058	0.44	0	0.5
Higher Market Value	42,058	0.39	0	0.49
Outlier Analyst	42,058	0.2	0	0.4

Table 2: Peer Reaction to Outlier Forecasts

The sample period is 1990-2019. The unit of observations is at the peer forecast level. The dependent variable is the EPS forecast issued by a peer analyst, scaled by the covered firm's stock price in the previous year and multiplied by 100. We report the regression estimates of peer reactions to all outlier forecasts issued in a firm-year in columns 1-5 and to the first outlier forecast in a firm-year in columns 6-10. The sample includes five forecasts issued prior to an outlier forecast as well as, respectively, 3, 5, 10, 15, and 20 forecasts issued after the outlier forecast. All variables are defined in the Appendix. Robust standard errors clustered at the firm-year level are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Dependent Variable: *EPS Forecast*									
Sample:	Peer Reactions to All Outlier Forecasts					Peer Reactions to First Outlier Forecasts				
Time Horizon:	3 Forecasts	5 Forecasts	10 Forecasts	15 Forecasts	20 Forecasts	3 Forecasts	5 Forecasts	10 Forecasts	15 Forecasts	20 Forecasts
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Post Outlier Forecast	0.682***	0.687***	0.690***	0.678***	0.668***	0.631***	0.645***	0.665***	0.668***	0.668***
	(0.021)	(0.020)	(0.021)	(0.022)	(0.023)	(0.021)	(0.020)	(0.021)	(0.022)	(0.023)
Experience	0.014	0.01	-0.008	-0.009	-0.006	0.024*	0.016	0.006	-0.001	0.001
	(0.013)	(0.012)	(0.010)	(0.010)	(0.009)	(0.014)	(0.013)	(0.011)	(0.010)	(0.010)
Past Accuracy	0.005***	0.004***	0.003**	0.002*	0.002**	0.003	0.002	0.001	0.001	0.001
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
Broker Size	0.011	0.004	-0.000	-0.002	-0.003	0.002	0.002	-0.000	-0.001	-0.004
	(0.009)	(0.008)	(0.007)	(0.006)	(0.006)	(0.009)	(0.008)	(0.007)	(0.006)	(0.006)
Firm x Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	90,868	108,984	147,641	179,370	205,817	63,951	79,018	113,603	144,006	170,512
R-squared	0.931	0.931	0.93	0.93	0.93	0.959	0.954	0.948	0.944	0.942

Table 3: Self-fulfilling Extremism

The sample period is 1990-2019. The unit of observations is at the firm-year level. In columns 1-2, the sample includes firm-year observations with at least one outlier forecast. The dependent variable is the number of outlier forecasts issued in a firm-year after the first outlier forecast. In columns 3-4, the sample includes firm-year observations with at least two outlier forecasts. The dependent variable is the average deviation of all subsequent outlier forecasts issued in a firm-year after the first outlier forecast. Control variables include the experience, past forecast accuracy, and broker size of the analyst who issues the first outlier forecast in a firm-year, as well as firm characteristics such as the size of coverage, ROA, size, and market-to-book ratio. All variables are defined in the Appendix. Robust standard errors clustered at the firm are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable:	*# of Subsequent Outliers*		*Subsequent Outlier Deviation*	
Sample:	At least one outlier forecast		At least two outlier forecasts	
	(1)	(2)	(3)	(4)
First Outlier's Deviation	0.095***	0.066**	0.164***	0.187**
	(0.022)	(0.031)	(0.040)	(0.086)
First Outlier Analyst's Experience	0.015	0.028	-0.029	-0.029
	(0.019)	(0.031)	(0.027)	(0.065)
First Outlier Analyst's Accuracy	0.010***	0.008**	-0.003	-0.005
	(0.002)	(0.004)	(0.003)	(0.006)
First Outlier Analyst's Broker Size	0.047***	0.047**	-0.001	0.001
	(0.012)	(0.020)	(0.015)	(0.038)
Size of Coverage	0.008***	-0.003	0.010***	0.030**
	(0.002)	(0.005)	(0.003)	(0.012)
ROA	0.449***	0.918***	-0.066	0.469
	(0.076)	(0.181)	(0.107)	(0.297)
Firm Size	-0.052***	-0.110**	-0.038**	-0.148*
	(0.012)	(0.053)	(0.017)	(0.081)
Market to Book	0.077***	0.125***	-0.045	-0.04
	(0.022)	(0.046)	(0.030)	(0.071)
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	No	Yes	No
Firm FE	No	Yes	No	Yes
Observations	7,998	7,998	3,008	3,008
R-squared	0.065	0.385	0.089	0.492

Table 4: Which Peers React to Outlier Forecast?

The sample period is 1990-2019. The unit of observations is at the forecast level. The sample includes five forecasts issued prior to the first outlier forecast in a firm-year and three forecasts issued after the outlier forecast. The dependent variable is the EPS forecast issued by a peer analyst, scaled by the stock price in the previous year and multiplied by 100. All variables are defined in the Appendix. Robust standard errors clustered at the firm-year level are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable: *EPS Forecast*			
	(1)	(2)	(3)
Post Outlier Forecast x Peer > Median Experience	0.622***		
	(0.024)		
Post Outlier Forecast x Peer < Median Experience	0.641***		
	(0.031)		
Post Outlier Forecast x Peer > Median Accuracy		0.624***	
		(0.026)	
Post Outlier Forecast x Peer < Median Accuracy		0.642***	
		(0.023)	
Post Outlier Forecast x Peer > Median Broker			0.584***
			(0.027)
Post Outlier Forecast x Peer < Median Broker			0.671***
			(0.028)
Peer > Median Experience	0.032		
	(0.021)		
Peer > Median Accuracy		0.028*	
		(0.017)	
Peer > Median Broker			0.031
			(0.021)
Past Accuracy	0.002		0.003
	(0.002)		(0.002)
Broker Size	0.002	0.004	
	(0.009)	(0.007)	
Experience		0.007	0.023*
		(0.009)	(0.014)
Firm x Year FE	Yes	Yes	Yes
Observations	63,951	77,150	63,951
R-squared	0.959	0.957	0.959

Table 5: Reactions from Other Market Participants

In columns 1-3, the sample period is 1990-2019. The unit of observations is at the forecast level. The dependent variable in column 1 is "*CAR*", the abnormal return surrounding the time when a forecast is issued, and the trading volume at the time of the forecast in columns 2-3. In columns 4-6, the sample period is 2000-2019. The unit of observations is at the forecast level. We obtain our news data from the Ravenpack database. The dependent variable is the percentage increase in the total number of news (column 4), the number of good news (column 5), and the difference between the fraction of news being good news in the $[t-3, t-1]$ period and that in the $[t+1, t+3]$ period, when a forecast is issued on day t (column 6). In column 7, the sample period is 1990-2019. The unit of observations is at the firm-year level. We use the first outlier forecast issued to a firm-year and relate the characteristics of the first outlier forecasts to the likelihood of having a management guidance event. The dependent variable is an indicator variable for whether a firm's management predicts the firm to beat analyst consensus. All variables are defined in the Appendix. Robust standard errors (in parentheses) are clustered at the firm-year level in columns 1-6 and at the firm level in column 7. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable:	*CAR*	*Trading Volume*		*Increase in Total News*	*Increase in Good News*	*Increase in % Good News*	*Beat Consensus*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Outlier Forecast	1.307***	0.102***	0.059***	0.109***	0.125***	0.016**	
	(0.062)	(0.007)	(0.006)	(0.042)	(0.031)	(0.007)	
Experience	-0.016***	0.022***	0.013***	-0.031***	-0.007	-0.000	
	(0.006)	(0.001)	(0.001)	(0.007)	(0.005)	(0.001)	
Past Accuracy	-0.001	0.001***	0.001***	0.003***	0.002***	0.000	
	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)	
Broker Size	-0.020***	0.031***	0.020***	0.088***	0.068***	0.006***	
	(0.004)	(0.001)	(0.000)	(0.005)	(0.004)	(0.001)	
Forecast Horizon	0.097***	0.040***	0.025***				
	(0.012)	(0.002)	(0.002)				
ABS(CAR)			10.084***				
			(0.038)				
First Outlier's Deviation							-0.008**
							(0.004)
First Outlier Analyst's Experience							-0.008
							(0.008)
First Outlier Analyst's Accuracy							0.000
							(0.001)
First Outlier Analyst's Broker Size							-0.001

							(0.004)
First Outlier Analyst's Forecast Horizon							0.031***
							(0.007)
Size of Coverage							-0.001
							(0.001)
ROA							0.082**
							(0.033)
Firm Size							0.019
							(0.012)
Market to Book							0.025**
							(0.010)
Year FE	No	No	No	No	No	No	Yes
Firm FE	No	No	No	No	No	No	Yes
Firm x Year FE	Yes	Yes	Yes	Yes	Yes	Yes	No
Observations	1,461,533	1,461,533	1,461,533	895,623	712,875	607,469	7,998
R-squared	0.125	0.856	0.903	0.104	0.141	0.166	0.419

Table 6: What Cultivates Outlier Opinions?

Panel A: Who Issues Outlier Forecasts

This table estimates a linear probability model relating the likelihood of being an outlier analyst to the relative position of an analyst to peer analysts forecasting the earnings of the same firm-year. The sample period is 1990-2019. The unit of observation is at the firm-year-analyst level. The dependent variable is "*Outlier Analyst*", a dummy variable indicating whether an analyst has issued any outlier forecast to a firm-year under coverage. "*More Experienced*", "*More Experienced with Firm*", and "*Bigger Broker*" capture, respectively, the relative position of an analyst's general experience, firm-specific experience, or broker reputation to the rest of analysts forecasting earnings of the same firm in the same year. All variables are defined in the Appendix. Robust standard errors clustered at the analyst-year level are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Dependent Variable: *Outlier Analyst*			
	(1)	(2)	(3)	(4)
More Experienced	0.004***			0.001
	(0.001)			(0.001)
More Firm-Specific Experienced		0.007***		0.007***
		(0.001)		(0.001)
Bigger Broker			0.003***	0.002**
			(0.001)	(0.001)
Size of coverage	-0.001***	-0.001***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
ROA	0.014***	0.014***	0.014***	0.014***
	(0.002)	(0.002)	(0.002)	(0.002)
Firm Size	-0.004***	-0.004***	-0.004***	-0.004***
	(0.000)	(0.000)	(0.000)	(0.000)
Market to Book	0.003***	0.003***	0.003***	0.003***
	(0.001)	(0.001)	(0.001)	(0.001)
Industry FE	Yes	Yes	Yes	Yes
Analyst x Year FE	Yes	Yes	Yes	Yes
Observations	450,054	450,054	450,054	450,054
R-squared	0.189	0.190	0.189	0.190

Table 6 continued.

Panel B: Ex-ante Uncertainty

This table relates *ex-ante* information uncertainty to the extremism and frequency of outlier forecasts. The sample period is 1990-2019. The unit of observation is at the firm-year level. In columns 1-2, the sample includes firm-year observations with at least one outlier forecast. If a firm-year receives multiple outlier forecasts, we use the first outlier forecast. The dependent variable is the magnitude of an outlier forecast, calculated as the value of the outlier forecast scaled by the previous year's price and multiplied by 100. In columns 3-4, we relate a firm's previous year's forecasts to the number of outlier forecasts that the firm receives in the current year based on the sample of all firm-year observations. All variables are defined in the Appendix. Robust standard errors clustered at the firm level are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable:	*Outlier EPS Forecast*		*Frequency of Outlier Forecasts*	
	(1)	(2)	(3)	(4)
Pre-outlier Forecast Dispersion	1.540***	1.386***		
	(0.092)	(0.092)		
Average of Pre-outlier Forecasts	0.940***	0.936***		
	(0.014)	(0.020)		
Previous Year's Forecast Dispersion			0.163***	0.172***
			(0.008)	(0.011)
Average of Previous Year's Forecasts			0.006***	0.019***
			(0.002)	(0.003)
First Outlier's Experience	0.041	-0.011		
	(0.043)	(0.057)		
First Outlier's Accuracy	-0.012**	-0.01		
	(0.005)	(0.006)		
First Outlier's Broker Size	-0.02	-0.029		
	(0.023)	(0.034)		
First Outlier's Forecast Horizon	-0.311***	-0.343***		
	(0.066)	(0.093)		
Size of Coverage	-0.015***	-0.006	0.019***	0.007***
	(0.005)	(0.007)	(0.001)	(0.002)
ROA	0.574	1.792**	0.210***	0.527***
	(0.482)	(0.821)	(0.052)	(0.076)
Firm Size	0.069**	0.097	-0.056***	-0.069***
	(0.027)	(0.105)	(0.006)	(0.019)
Market to Book	-0.131**	-0.058	0.038***	0.042**
	(0.051)	(0.092)	(0.013)	(0.019)
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	No	Yes	No
Firm FE	No	Yes	No	Yes
Observations	7,998	7,998	30,561	30,561
R-squared	0.888	0.951	0.136	0.334

Table 7: Career Incentives of Outlier Analysts

The unit of observations is at the analyst-year level. The dependent variable in columns 1-4 is a dummy variable set to one if the average market capitalization of firms in an analyst's year t coverage portfolio is greater than that in year t of firms in his year $t-1$ coverage portfolio. In columns 5-8, the dependent variable is a dummy variable set to one if the average institutional ownership of firms in an analyst's year t coverage portfolio is greater than that in year t of firms in his year $t-1$ coverage portfolio. "*Outlier Analyst*" is an indicator variable equal to one if an analyst has issued an outlier forecast in year $t-1$. "*Frequency of Outlier Forecasts*" is the number of outlier forecasts that an analyst has issued in year $t-1$. All variables are defined in the Appendix. Robust standard errors clustered at the analyst level are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable:	*Higher Market Value*				*Higher Institutional Ownership*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Outlier Analyst	0.026***		0.026***		0.015*		0.016**	
	(0.008)		(0.008)		(0.008)		(0.008)	
Frequency of Outlier Forecasts		0.012***		0.012***		0.012***		0.013***
		(0.004)		(0.004)		(0.004)		(0.004)
Experience	0.006	0.006	0.008	0.008	0.001	0.001	0.007	0.007
	(0.016)	(0.016)	(0.015)	(0.015)	(0.016)	(0.016)	(0.016)	(0.016)
Past Accuracy	-0.001*	-0.001*			-0.001**	-0.001**		
	(0.000)	(0.000)			(0.000)	(0.000)		
Bottom 5% Accuracy Dummy			0.033**	0.034**			0.022	0.022
			(0.017)	(0.017)			(0.017)	(0.017)
5%-10% Accuracy Dummy			0.040***	0.040***			0.003	0.003
			(0.015)	(0.015)			(0.016)	(0.016)
10%-25% Accuracy Dummy			0.020**	0.020**			-0.003	-0.003
			(0.010)	(0.010)			(0.011)	(0.011)
25%-50% Accuracy Dummy			0.015	0.015*			-0.019**	-0.019**
			(0.009)	(0.009)			(0.009)	(0.009)
50%-75% Accuracy Dummy			0.014	0.014			-0.008	-0.008
			(0.009)	(0.009)			(0.009)	(0.009)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Analyst FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	42,058	42,058	42,058	42,058	42,058	42,058	42,058	42,058
R-squared	0.204	0.204	0.204	0.204	0.200	0.200	0.200	0.201

Internet Appendix for

"Standing out from the Crowd: The Real Effects of Outliers"

This online appendix consists of the following tables:

IA.1: Alternative Cutoffs for Outliers

IA.2: Forecast Errors of Outliers

IA.3: Reg-FD

Internet Appendix IA.1: Alternative Cutoffs for Outliers

The sample period is 1990-2019. The unit of observations is at the forecast level. We report regression results based on all outlier forecasts issued to a firm-year. A forecast is considered an outlier if its deviation from prior peers falls into the top 5% (columns 1-5) and 10% (columns 6-10) of the sample. The samples include five forecasts issued before the outlier forecasts as well as 3, 5, 10, 15, and 20 forecasts issued after the outlier forecast. The dependent variable is the EPS forecast issued by a peer analyst, scaled by the firm's stock price in the previous year and multiplied by 100. All variables are defined in the Appendix. Robust standard errors clustered at the firm x year level are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Dependent Variable: *EPS Forecast*									
Alternative Cutoff:	Cutoff Point = 5%					Cutoff Point = 10%				
Time Horizon:	3 Forecasts	5 Forecasts	10 Forecasts	15 Forecasts	20 Forecasts	3 Forecasts	5 Forecasts	10 Forecasts	15 Forecasts	20 Forecasts
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Post Outlier Forecast	0.295***	0.307***	0.316***	0.309***	0.300***	0.263***	0.280***	0.285***	0.271***	0.254***
	(0.007)	(0.007)	(0.008)	(0.009)	(0.009)	(0.006)	(0.006)	(0.007)	(0.008)	(0.009)
Experience	0.013***	0.012***	0.005	0.004	0.004	0.010***	0.010***	0.005	0.004	0.004
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Past Accuracy	0.005***	0.004***	0.004***	0.003***	0.003***	0.004***	0.004***	0.004***	0.003***	0.003***
	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Broker size	0.003	0	-0.002	-0.004*	-0.005**	0	-0.002	-0.003	-0.005***	-0.006***
	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Firm x Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	354,288	407,273	510,213	587,438	648,087	480,688	532,694	631,694	705,440	763,537
R-squared	0.955	0.954	0.952	0.951	0.95	0.957	0.956	0.954	0.952	0.951

Internet Appendix IA.2: Forecast Errors of Outliers

This table compares forecast accuracy between an outlier forecast and a non-outlier forecast. The sample period is 1990-2019. The unit of observations is at the forecast level. The dependent variable is "*Forecast Error*", calculated as the absolute value of the difference between forecasted earnings and actual earnings, scaled by share price in the previous year, multiplied by 100. All variables are defined in the Appendix. Robust standard errors clustered at the firm x year level are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable: *Forecast Error*		
	(1)	(2)
Outlier Forecast	0.402***	0.402***
	(0.032)	(0.032)
Experience	-0.020***	
	(0.002)	
Firm-specific Experience		-0.010***
		(0.002)
Past Accuracy	-0.006***	-0.006***
	(0.000)	(0.000)
Broker Size	-0.004***	-0.005***
	(0.001)	(0.001)
Forecast Horizon	0.449***	0.449***
	(0.006)	(0.006)
Firm x Year FE	Yes	Yes
Observations	1,481,477	1,481,477
R-squared	0.716	0.716

Internet Appendix IA.3: Reg-FD

This table compares the frequency of outlier forecasts before and after the Regulation Fair Disclosure. The sample period is 1990-2019. The unit of observations is at the firm-year level. The dependent variable is, "*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. All variables are defined in the Appendix. Robust standard errors clustered at the firm level are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable: *Frequncy of Outlier Forecast*		
	(1)	(2)
Post Reg FD	0.106***	0.065***
	(0.006)	(0.010)
Average Experience	-0.012	-0.013
	(0.008)	(0.012)
Average Broker Size	0.034***	-0.011
	(0.006)	(0.008)
Size of Coverage	0.008***	0.002***
	(0.001)	(0.001)
ROA	-0.005	0.156***
	(0.014)	(0.030)
Firm Size	-0.032***	-0.004
	(0.003)	(0.006)
Market to Book	0.021***	0.048***
	(0.005)	(0.007)
Industry FE	Yes	No
Firm FE	No	Yes
Observations	37,346	37,346
R-squared	0.075	0.285