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Tournaments of Financial Analysts

Huifang Yin and Huai Zhang*

ABSTRACT

We argue that financial analysts can be viewed as participants of two tournaments (the "All-star" tournament and the intrafirm tournament) and examine whether analysts are incentivized by the tournament compensation structure. Using data from 1991 to 2007, we find that interim losers are more likely to increase the boldness of their forecasts in the remainder of the tournament period than interim winners. This finding survives several robustness checks and is more pronounced when the interim assessment date is closer to the end of the tournament period, when analysts are inexperienced, and when the market activity is high. In addition, we show that interim losers' changes in boldness are less informative than interim winners'. Collectively, our findings suggest that viewing financial analysts as participants of tournaments provides a useful framework for understanding analysts' behavior.

Keywords: Tournament theory; Boldness; Financial analysts.

JEL Classification: G20, G17, G24, M40, M41.

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1. Introduction

Understanding analysts' incentives provides key insights about properties of analysts' forecasts. For example, analysts' incentives to please the management help to explain the optimistic bias in analysts' forecasts. This bias is puzzling at first glance, because analysts are well-educated, well-informed and well-paid information intermediaries and it's natural to expect them to form unbiased earnings estimates. This paper adds to our understanding of analysts' incentives by examining whether analysts are motivated by the tournament compensation structure. We also provide evidence that the incentive to win the tournament does not always induce outcomes in the best interest of investors.

Anecdotal and academic evidence suggests that analysts participate in two tournaments: the "All-star" tournament and the intrafirm tournament. Financial analysts who perform well relative to other analysts covering the same industry are recognized by *Institutional Investors*, an influential magazine, as "All-stars". Popular press suggests that a large pay discrepancy exists between all-star analysts and non-all-star analysts. Using proprietary actual compensation data from a top-tier investment firm, Groysberg et al. (2011) find that "All-star" recognition substantially increases analysts' compensations. This compensation structure implies that financial analysts can be viewed as participants in the "All-star" tournament, in which relative performance matters and the winner receives disproportionately larger payoffs than the loser.

In addition to the "All-star" tournament, which is among all analysts following the same industry, financial analysts also participate in the intrafirm tournament, competing with other analysts employed by the same brokerage house. Anecdotal evidence suggests that at the end of each year, brokerage houses first set aside a pool of bonuses and then allocate it among employees. For example, Bloomberg reported that in December 2007, Goldman Sachs set aside $12.1 billion bonus pool for employees.[1] Conceivably,

[1] The web link is http://www.bloomberg.com/apps/news?pid=newsarchive&sid=aUHCJ33.KB.Q&refer=us. Grosberg et al. (2011) implicitly acknowledged this practice in their paper: "Collectively, the evidence indicates that during periods of high market activity and correspondingly high trading commissions and corporate finance fees, a bank's bonus pool expands……"

the allocation of the bonuses is based on current year performance. The top performer within the brokerage house typically gets a much bigger share of the pool than a lowly ranked analyst (Grosberg et al., 2011). Since year-end bonuses are a significant source of income, analysts have strong incentives to win the intra-firm competition on an annual basis.

We examine whether financial analysts' behavior is affected by the tournament compensation structure, which provides analysts with strong incentives to win the tournament. In order to win, interim losers (financial analysts whose interim performance is below average) need to improve their relative performance by a great margin to make up their prior "deficit". They are unlikely to herd with other analysts in the remainder of the tournament period because herding does not differentiate them from their peers and thereby does not help to improve their relative ranking. Instead, they are likely to issue bold forecasts, i.e., forecasts that deviate from both financial analysts' prior forecasts and the analysts' consensus, to distinguish their performance in an effort to catch up with interim winners (financial analysts whose interim performance is above average). As for interim winners, they are motivated to "lock in" their current rankings and are less inclined to issue bold forecasts. Thus, the central testable hypothesis of our study is that interim losers are more likely to increase the boldness of their forecasts than interim winners in the remainder of the tournament period.[2] Kadous et al. (2009) show that forecast boldness magnifies the effect of forecast accuracy on investors' assessment of analysts' abilities. To the extent that issuing bold forecasts is ex ante more risky, our central hypothesis is consistent with the well-known research finding that interim losers tend to adopt more risky strategies than interim winners (Bronars, 1987; McLaughlin, 1988; Ehrenberg and Bognanno, 1990; Brown et al., 1996; Kempf and Ruenzi, 2007; Grund et al., 2010).

[2] Analysts' career concerns do not affect our prediction. To illustrate it, assume that the lowest ranked analyst will be fired. The analyst with the lowest interim ranking has strong incentives to issue bold forecasts, because, if she herds in the remainder of the period, her ranking likely remains the lowest, while, if she issues a bold forecast, there is a chance that her ranking may improve and she may avoid being fired.

We subject our hypothesis to empirical tests, using analysts' forecasts data from I/B/E/S for the period of 1991-2007. We measure analysts' performance mainly through forecast accuracy. Stickel (1992) and Leone and Wu (2007) document that all-star analysts produce more accurate earnings forecasts, suggesting that forecast accuracy is an important indicator of analysts' performance in the "All-star" tournament.[3]. Mikhail et al. (1999), Hong and Kubik (2003) and Wu and Zang (2009) show that forecast accuracy is used by brokerage houses to judge analysts' performance in promotion and turnover decisions. If brokerage houses evaluate analysts' annual performance in the same way, forecast accuracy is likely an important determinant of the allocation of year-end bonuses.

Our definition of boldness follows Clement and Tse (2005). A forecast is defined as "bold" if it deviates from both the consensus and the prior forecast made by the same analyst; otherwise, it is deemed as "non-bold". Our empirical results from ordered logit regressions are supportive of our hypothesis: interim rankings in both the "All-star" tournament and the intrafirm tournament are negatively and significantly related to changes in forecast boldness. After controlling for current boldness and several known determinants of changes in boldness, we find that the odds of the analyst becoming bolder are lower by about 15-25% for the highest ranked analyst than for the lowest ranked analyst.

We conduct two robustness checks on this primary finding. First, we show that our results are similar if we use a continuous boldness measure instead of a binary boldness measure. Second, to address the concern that forecast accuracy is only one dimension of analysts' performance, we consider other dimensions, such as stock picking ability, forecast frequency and investment banking business generating ability. Our main conclusions continue to hold.

We then develop and test several predictions stemming from our central hypothesis. Results supportive of these predictions not only are informative by themselves but also provide additional support to our central hypothesis. First, drawing on the findings in Bronars (1987) and Grund et al. (2010) that

[3] We do not claim that forecast accuracy is the most important criterion in evaluating analysts' performance in the tournaments. Our conclusions are valid as long as forecast accuracy is positively related to the likelihood of winning the tournaments.

losing sports teams are more likely to take “desperate” (i.e., more risky) moves when time is running out, we predict that the effect of interim ranking on changes in boldness is more pronounced, when the interim assessment date is closer towards the end of the tournament period. Second, we predict that the effect of interim ranking on changes in boldness is stronger for inexperienced analysts, who have more incentives to win the tournament than analysts with extensive history. Third, we predict that the effect is more pronounced in years with high market activity, when the pay discrepancy between winners and losers is wider. Higher premium for winning the tournament provides stronger incentives to win. Finally, we predict that interim losers’ changes in boldness are less informative than interim winners’, because interim losers’ decision to issue bold forecasts is contaminated by their incentives to win the tournament. This prediction suggests that the tournament compensation structure does not always induce outcomes in the best interest of investors. All our predictions are supported by empirical results.

Our study makes several contributions. First, we contribute to the large body of literature on analysts’ incentives. Francis and Philbrick (1993) find that earnings forecasts are more optimistic for stocks with “sell” or “hold” recommendations than for stocks with “buy” recommendations, suggesting that analysts have the incentive to maintain good relationships with managers when issuing negative stock recommendations. Dugar and Nathan (1995), Lin and McNichols (1998), and Michaely and Womack (1999) show that underwriter analysts issue more optimistic opinions than other analysts, consistent with the notion that the business dealings between the underwriter and the firm provide analysts extra incentives to please the management. Das et al. (2006) suggest that analysts selectively provide coverage for firms about which analysts’ underlying expectations are positive while Ke and Yu (2006) document that analysts who issue initial optimistic earnings forecasts followed by pessimistic earnings forecasts before the earnings announcement produce more accurate earnings forecasts and are less likely to be fired by their employers. Results from these two papers suggest that analysts have incentives to curry favor with the management in order to gain access to insider information and to win future investment banking business. [4] Our study contributes to this line of literature by showing that analysts' behavior is also affected by the incentive to win the "All-star" tournament and the intrafirm tournament. Thus, viewing analysts as participants of a tournament provides additional insights for a better understanding of analysts' behavior.

Second, prior literature has examined determinants and consequences of issuing bold forecasts. Hong et al. (2000) document that inexperienced analysts are less likely to issue bold forecasts. Clement and Tse (2005) show that the likelihood of issuing bold forecasts increases with the analyst's experience, prior accuracy, and brokerage size and declines with the number of industries the analyst follows. Gleason and Lee (2003) report that bold forecasts have greater impact on security prices, especially those issued by star analysts, while Clement and Tse (2005) find that bold forecasts are on average more accurate than herding forecasts, suggesting that issuance of bold forecasts is based on information. Our study contributes to this line of literature by documenting another determinant of the likelihood of issuing bold forecasts: the incentive to win the tournament. Moreover, we show that interim losers' changes in boldness are not based on information, suggesting that the incentive to win the tournament contaminates analysts' decision to issue bold forecasts. Our evidence thus presents a more comprehensive view of the determinants and consequences of issuing bold forecasts and sounds a cautionary note to investors who tend to react more to bold forecasts.

Third, our study contributes to the line of literature on tournaments. Lazear and Rosen (1981) argue that competition in many hierarchical organizations can be viewed as tournaments. Consistent with this view, Cichello et al. (2009) find that promotion of division manager is positively related to relative performance of one division to that of other divisions. Brown et al. (1996), Orphanides (1996), Koski and Pontiff (1999) and Kempf and Ruenzi (2007) provide evidence that mutual fund managers take on more risks in the remainder of the year when their interim rankings are low, suggesting that mutual fund

[4] Please refer to Ramnath et al. (2008) and Beyer et al. (2010) for comprehensive reviews of the literature.

managers can be viewed as participants of tournaments. Our study extends this line of literature by showing that financial analysts, a topic of substantial academic interest, behave in the same way as tournament participants.

The paper is organized as follows. Section 2 reviews the tournament literature and develops testable hypotheses. Section 3 describes the data and defines variables. Section 4 discusses the empirical results and Section 5 concludes.

2. Literature review and hypotheses development

2.1. The Economics of Tournaments

Tournaments refer to competitions in which the outcome is determined by relative performance and the winner takes a disproportionally larger award than the loser (Lazear and Rosen, 1981). Examples of tournaments include golf and tennis competitions, such as PGA Tour and Wimbledon. Competitions in most hierarchical organizations can be considered as tournaments in which employees compete for a smaller number of positions at the next higher level and the promotion decision is based on relative performance assessments. Consistent with this view, Cichello et al. (2009) show that the division manager is more likely to be promoted if his division performs well relative to other divisions. A long line of theoretical literature exists on normative aspects of corporate tournaments (e.g., Lazear and Rosen, 1981; Nalebuff and Stiglitz, 1983; Green and Stokey, 1983; Rosen, 1986; Bognanno, 2001) [5]and it suggests that a tournament reward structure is particularly useful in situations where an agent's effort is not observable and the performance of all agents depends on the realization of random states. In such a case, relative performance measures allow the principal to distinguish the agent's contributions from the effect of the state of nature.

[5] Please refer to Prendergast (1999) and Lazear and Oyer (2009) for a review of this line of literature.

Prior studies have documented the effect of tournament compensation structure on mutual fund managers' risk taking behavior. Brown et al. (1996) examine the tournament on the segment level and find that the tournament reward structure provides incentives for fund managers to change the riskiness of their portfolios before the end of the assessment period. Specifically, they show that interim losers increase the risk of the portfolios to a greater extent than interim winners in an effort to make up their prior "deficit". Koski and Pontiff (1999) investigate investment managers' use of derivatives and find that the relation between the change in fund risks and prior fund performance is weaker for funds that use derivatives than for funds that do not use derivatives, suggesting that derivatives are used to reduce the impact of performance on risks. Kempf and Ruenzi (2007) show that mutual fund managers adjust the risk they take according to their relative ranking within their fund family, consistent with the notion that fund managers participate in an intrafirm tournament.

2.2. Financial Analysts as Participants of Tournaments: Intuition and Testable Hypotheses

The underlying premise of this study is that financial analysts can be viewed as participants of tournaments. We argue that financial analysts participate in two types of tournaments: the "All-star" tournament and the intrafirm tournament.

Each year, *Institutional Investor* magazine sends questionnaires covering different industries to a large number of consumers of sell-side analyst research, including portfolio managers, investment officers and buy-side analysts employed by major money management institutions. Financial analysts are evaluated along several performance dimensions, such as earnings estimates, industry knowledge, written reports, stock picks, timely communication with investors and responsiveness to investor requests. Among all analysts covering the industry, a few are conferred the title of "All-star" based on the survey results. Anecdotal evidence suggests that being recognized as an "All-star" gives financial analysts substantial bargaining power in compensation negotiations. Recent academic research provides supportive evidence. Using actual compensation data from a leading investment bank for years from 1998 to 2005, Groysberg et al. (2011) find that the "All-star" status is positively related with analysts' compensation: "All-star" analysts on average are paid 61% more than non-all-star analysts after controlling for other determinants of compensation, such as analyst experience. Similar evidence is available in Stickel (1992).

In addition to the "All-star" tournament, financial analysts also participate in the intrafirm tournament, which is among all analysts employed by the same brokerage house. Their incentives to outperform others are related to their year-end bonuses, which constitute a substantial proportion of their annual pay. Typically, at the end of the year, brokerage house first determine the size of the bonus pool and then allocate it among employees. For example, in December 2007, Bloomberg reported that the size of the bonus pool was $12.1 billion at Goldman Sachs. The allocation of the bonus is likely based on current year performance and it is far from equal. Grosberg et al. (2011) report that the pay at the 90th percentile can be as high as 6.1 times the pay at the 10th percentile among analysts at a reputable investment bank. To get a bigger slice of the pie, analysts have strong incentives to perform well relative to their colleagues. .

The tournament-like payoff structure introduces convexity to financial analysts' compensation, which typically includes a fixed component (the salary) and a variable component (the bonuses). The convexity lies in the fact that if the analyst wins the "All-star" tournament or wins the intrafirm competition, her compensation will increase substantially while her compensation will not go below the fixed salary even if she ranks the lowest in the tournaments. This call-option-like payoff structure provides analysts the incentive to alter their risk-taking behaviors according to the interim relative performance ranking. Financial analysts positioned at an interim assessment period as losers (i.e., having performed worse than average) will need to improve their relative performance to a greater extent to compensate for their first period "deficit". One feasible approach to achieve this is to issue bold forecasts, i.e., forecasts that are above or below both their own prior forecasts and the consensus forecast. As for financial analysts who have superior interim performance relative to their peers (interim winners), they are motivated to keep their current rankings and are less likely to issue bold forecasts.[6] Our reasoning above yields our central hypothesis: interim losers are more likely to increase the boldness of their forecasts in the remainder of the tournament period than interim winners.[7]

Kadous et al. (2009) show that forecast accuracy has a more pronounced impact on investors' assessment of analysts' abilities when the forecasts are bolder. While a bold and accurate forecast increases analysts' credibility more dramatically, a bold and inaccurate forecast does more harm to analysts' reputation, relative to a herding forecast. To the extent that issuing bold forecasts is ex ante more risky, our central hypothesis is consistent with research findings that interim losers tend to adopt more risky strategies than interim winners in the remainder of the tournament period (Bronars, 1987; McLaughlin, 1988; Ehrenberg and Bognanno, 1990; Brown et al., 1996; Kempf and Ruenzi, 2007; Grund et al., 2010).[8] For example, Grund et al. (2010) show that the National Basketball Association (NBA) teams are more likely to increase the likelihood of three-point shots (an indicator of risky behavior) when they are behind than when they are ahead.

[6] In our reasoning above, we assume that there is no strategic interaction between interim winners and interim losers. Taylor (2003) however shows in a game theoretical setting that interim winners may attempt to lock in their current positions by mimicking the strategy of the losers. There are two reasons why this is unlikely to be true for the tournament among financial analysts. First, by definition, the interim loser's private information is observable to her but not to the interim winner. Given the different information set, it is not possible for the interim winner to follow the interim loser's strategy to retain her lead. Second, strategic interactions are likely to occur if there are only a small number of individuals interacting (Mas-Colell et al., 1995). Only in those settings can the players involved consider the actions of the other players. However, the number of participants is likely to be numerous in analysts' tournaments, reducing the possibility of strategic interactions.

[7] The intuitions behind the hypothesis are as follows. The tournament-like compensation structure provides financial analysts with strong incentives to win the tournament. In order to win, interim losers need to improve their relative performance by a great margin to make up their prior "deficit". They are unlikely to herd with other analysts in the remainder of the tournament period because herding does not differentiate them from their competitors and thereby does not help to improve their relative rankings. On the contrary, they are likely to issue bold forecasts to distinguish their performance in an effort to catch up with interim winners. As for interim winners, they are already in advantageous positions and are less inclined to issue bold forecasts to "rock the boat".

[8] Financial analysts who are interim winners are likely to have different characteristics from those who are interim losers. For example, interim winners may have more experience or have superior predictive abilities than interim losers. However, it does not affect the validity of our analysis because we are interested in changes in the forecast boldness across the mid-year. To the extent that analysts' characteristics stay the same during the entire year, our variable of interest shall be unrelated to analyst characteristics.

In order to test our hypothesis, we need to identify the tournament period and the interim assessment date. We assume that both the "All-star" tournament and the intrafirm tournament are run on a calendar year basis because *Institutional Investor* sends questionnaires in April or May (shortly after analysts' prior-year forecast accuracy is known) and the bonuses to analysts are typically paid shortly before Christmas.[9] We note that the measurement error in identifying the tournament period biases against finding any significant results. As for interim assessment date, mid-year serves as a natural starting point and is used in prior studies (Brown et al., 1996; Kempf and Ruenzi, 2007).[10] Our first hypothesis is thus as follows:

H1: Changes in the forecast boldness from the first half-year to the second half-year are negatively related to analysts' first half-year performance rankings.

In addition to our central hypothesis, we propose four related hypotheses. First, prior literature (Bronars, 1987; Grund et al., 2010) documents that the losing sports teams take greater risks towards the end of the game than they would under less time-constrained circumstances. For example, Grund et al. (2010) analyze the NBA teams' risk taking behavior measured by three-point attempts and show that the fraction of three-point shots by the losing team increases substantially when time is running out: it is 20% for the first three quarters and rises to about 33% when the game has only three minutes left. Drawing on this finding, we hypothesize that the effect of interim ranking on changes in boldness is stronger, when the interim assessment date is closer towards the year end. This constitutes our second hypothesis:

H2: The effect of interim ranking on changes in the forecast boldness is more pronounced when the interim assessment date is closer towards the year end.

[9] The majority of listed firms in the U.S. have December 31 as their fiscal year end and typically announce annual earnings in the first quarter of the next calendar year, shortly before money managers receive the Institutional Investor All-star surveys. These earnings announcements help money managers to evaluate the performance of analysts in forecasting prior year earnings, and cast their votes according to analysts' performance.

[10] We assume that analysts' performance in the first half-year and in the second half-year are equally important for winning the tournament. To the best of our knowledge, there is no evidence suggesting otherwise.

Second, we hypothesize that the effect of interim ranking on changes in the boldness is more pronounced for inexperienced analysts. The tournament outcome has a greater impact on the labor market's assessment of analysts' abilities, and, consequently, their compensations/career prospects, for inexperienced analysts than for seasoned analysts because a shorter track record offers fewer chances for the market to learn of analysts' abilities.[11] Consistent with this notion, Hong et al. (2000) find that the relation between forecast accuracy and career outcomes is more pronounced for inexperienced analysts. Because tournament outcomes matter more for inexperienced analysts, they have greater incentives to reverse mid-tournament losses.[12] Our third hypothesis is thus as follows:

H3: The effect of interim ranking on the changes in the forecast boldness is more pronounced for inexperienced analysts.

Next, we analyze the effect of interim performance ranking on tournament participants' behavior separately for years of low and years of high market activity. Using Baker and Wurgler (2006) market activity index, Groysberg et al. (2011) find that during periods of high market activity, the pay differentials among financial analysts are greater. For example, the ratio of the 90th percentile of analysts' pay to the 10th percentile is 255% in 1990, a year of low market activity, while it is 610% in 2000, a year of high market activity. A bigger pay difference between winning and losing indicates greater rewards for winning. In periods of high market activity when winning the tournaments carries higher rewards, analysts have stronger incentives to win the tournament and they are more likely to change their forecast boldness for this purpose. Therefore, we hypothesize the following:

H4: The effect of interim ranking on the changes in the forecast boldness is more pronounced in years with high market activity.

[11] An analog is that the performance at the recruiting seminar is much more important for rookies than for seasoned scholars.

[12] Hong et al. (2000) find that inexperienced analysts are less likely to deviate from consensus forecasts than experienced analysts. Our finding does not contradict theirs since our focus is on the association between interim performance ranking and changes in boldness.

Finally, we examine the informativeness of changes in forecast boldness separately for interim losers and interim winners. Clement and Tse (2005) show that bold forecasts are more accurate than non-bold forecasts, suggesting that analysts' decisions to issue bold forecasts are in general based on accurate information. Their finding implies that when an analyst becomes bolder in her forecasts, the accuracy of her forecasts shall improve. If the interim loser's decision to become bolder in the remainder of the tournament period is likely determined by her incentives to make up for prior "deficit", instead of high-quality information, we predict that changes in boldness are less informative for interim losers than for interim winners. Using mid-year as the interim assessment date, we state our fifth hypothesis as follows:

H5: The informativeness of changes in boldness from the first half-year to the second half-year is lower for mid-year losers, relative to mid-year winners.

3 Data and variable definitions

We obtain quarterly earnings forecasts from I/B/E/S and our sample period is from 1991 to 2007. We eliminate firm-quarter observations with only one analyst following, because there is no relative ranking on the firm basis.[13] Following Clement and Tse (2005), we include the last forecast an analyst issues in the period no earlier than one quarter ahead and no later than the fiscal quarter end, [14] and define analyst forecasts as bold if they are above or below both the analyst's own prior forecast and the latest consensus forecast prior to the analyst's forecast. All the other forecasts are defined as non-bold.[15]

[13] Requiring at least 3 or 5 analysts following for each firm-quarter observation does not change our results.

[14] Our results remain unchanged if we include all one-quarter-ahead forecasts and define boldness using the proportion of bold forecasts among all forecasts made by the analyst.

[15] We obtain similar results if we use the boldness measure in Hong et al. (2000).

The independent variable of concern is analyst interim performance ranking in tournaments.[16] We measure financial analysts' performance mainly through the accuracy of their forecasts, because it not only is one dimension along which analysts are evaluated but also relates to analysts' performance along other dimensions, such as industry knowledge and stock picking abilities. For example, Loh and Mian (2006) document that analysts who forecast earnings more accurately tend to issue more profitable stock recommendations. Consistent with the important role played by forecast accuracy in the "All-star" tournament, Stickel (1992) and Leone and Wu (2007) report that those chosen as "All-star" on average make more accurate earnings forecasts. Forecast accuracy also matters for analysts' career concerns. Hong and Kubik (2003) and Wu and Zang (2009) show that more accurate forecasters are more likely to move up the brokerage house hierarchy and be promoted to research executive positions, while Mikhail et al. (1999) find that an analyst has a greater likelihood of being fired if her forecast accuracy declines relative to her peers. These papers suggest that forecast accuracy is used by brokerage houses to judge analysts' performance in promotion and turnover decisions. If brokerage houses use the same criteria to evaluate analysts' annual performance, forecast accuracy is likely an important determinant of the allocation of year-end bonuses.

We use industry-level accuracy ranking and brokerage-level accuracy ranking to proxy for "All-star" tournament ranking and intrafirm tournament ranking respectively. Both industry-level ranking and brokerage-level ranking are based on firm-level accuracy ranking, which is the ranking of a specific analyst relative to other analysts following the same firm. The quarterly firm-level ranking computation follows Clement and Tse (2005) and is shown in Equation (1):

$$Firm - level\ accuracy\ ranking_{ijq} = \frac{AFE\ max_{jq} - AFE_{ijq}}{AFE\ max_{jq} - AFE\ min_{jq}} \qquad (1)$$

[16] Analyst interim performance ranking is not empirically observable and we need to estimate it. Measurement errors bias against finding significant results.

where $AFE\ max_{jq}$ and $AFE\ min_{jq}$ are the maximum and minimum absolute forecast errors for analysts following firm j in quarter q. AFE_{ijq} is the absolute forecast error (absolute value of difference between forecasted value and actual value) for analyst i following firm j in quarter q. Higher value of ranking indicates better performance.[17]

We obtain industry-level ranking by value-weighting firm-level ranking and the weight is determined by the market value of the firm relative to the aggregate market value of all firms in the industry. The industry-level accuracy ranking measure for firm j followed by analyst i in industry k in quarter q is thus

$$Industry - level\ accuracy\ ranking_{ijq} = \sum W_{jq} * Firm - level\ accuracy\ ranking_{ijq}, j \in industry\ k \quad (2)$$

where W_{jq} is the weight based on relative market value of equity of firm j in industry k. Industry classification is based on I/B/E/S Sector Industry Group Classification.[18] We argue that analysts' performance related to bigger firms carries more weight in the "All-star" tournament performance assessment because bigger firms are more likely to attract the attention of professional money managers, whose votes determine the tournament outcome.

Similar to industry-level ranking, brokerage-level accuracy ranking is computed by value-weighting firm-level accuracy ranking. The weight is determined by the market value of equity of the firm divided by the aggregate market value of all firms followed by analysts from the brokerage house. Value-weighting seems reasonable because trading of bigger firms' stocks typically generates more commissions for the brokerage house, making analysts covering these firms more valuable. The

[17] An alternative ranking measure is to rank all analysts from 1 to *n*, with *n* being the number of analysts following the firm. The advantage of using our measure is that it considers the magnitude of prior "deficit" that the analyst has to make up while the alternative measure does not. Conceptually, the magnitude of prior "deficit" warrants consideration because it may affect the extent to which the boldness of forecasts is changed. Nevertheless, untabulated results show that we obtain similar findings using this alternative ranking measure.

[18] Our inferences are the same if industry classification is based on Global Industry Classifications Standard (GISC) system.

brokerage-level accuracy ranking measure for firm j followed by analyst i employed by brokerage firm l in quarter q is

$$Brokerage - level\ accuracy\ ranking_{ijq} = \sum V_{jq} * Firm - level\ accuracy\ ranking_{ijq}, j \in brokerage\ l's\ \ coverage \quad (3)$$

where V_{jq} is the weight based on relative market value of equity of firm j to the aggregate market value of all firms followed by analysts employed by brokerage firm l in quarter q.

We include the following variables as control variables because Clement and Tse (2005) show that they are associated with the likelihood of issuing bold forecasts: *Dayelap* (the days elapsed since the last forecast by any analyst following the same firm), *Horizon* (the time from the forecast date to the end of the fiscal period), *Frequency* (the forecasting frequency of the analyst for the firm in the current fiscal period), *Company* (the number of companies the analyst follows), *Industry* (the number of industries the analyst follows) and *Brokerage size* (the number of analysts employed by the brokerage firm). To facilitate comparisons and interpretations of coefficient estimates, following Clement and Tse (2005), we scale all the control variables to range from 0 to 1. The scaled quarterly control variables for analyst i following firm j in quarter q is

$$Characteristics_{ijq} = \frac{Raw\_Characteristic_{ijq} - Raw\_Characteristic\ min_{jq}}{Raw\_Characteristic\ max_{jq} - Raw\_Characteristic\ min_{jq}} \quad (4)$$

where $Raw\_Characteristic\ max_{jq}$ and $Raw\_Characteristic\ min_{jq}$ are the original maximum and minimum values of a characteristic of all analysts following firm j in quarter q.

Our central hypothesis (H1) requires values to be measured on a half-year basis. We compute half-year values by taking the average of the two quarterly values.[19] In addition, since the tournament period is run on a calendar year basis, we convert fiscal half-year to calendar half-year so that the calendar half-

[19] If there is only one quarterly observation in a half-year, then half-year value is equal to the only quarterly value. The underlying assumption is that tournament outcomes are determined by the average of quarterly earnings forecast accuracy rankings in a year. A possible alternative is that the tournament outcomes are determined by annual earnings forecast accuracy ranking. Our conclusion is robust to this alternative because annual earnings equal sum of four quarterly earnings and analysts who issue accurate quarterly earnings forecasts are likely to issue accurate annual earnings forecasts.

year includes most of months in the fiscal half-year. For example, the fiscal half-year ending on July 31 is defined as the first calendar half-year. Our final sample consists of 52,022 analyst-firm-half-year observations, after requiring the following variables to be non-missing: Δ*Bold*, *Industry-level accuracy ranking*, *Brokerage-level accuracy ranking*, Δ*Dayelap*, Δ*Horizon*, Δ*Frequency*, Δ*Company*, Δ*Industry* and Δ*Brokerage size*. Appendix provides detailed variable definitions.

4 Results

4.1 Descriptive statistics

We report descriptive statistics in Table 1. Panel A shows the distribution of several analyst and forecast characteristics in the first half-year before they are scaled to range from 0 to 1. *Dayelap* measures the number of days that have elapsed since the last forecast made by any analyst following the firm. Its mean value is 5.939 and its median is 2. *Horizon* measures the number of calendar days from the forecast date to the end of the fiscal period. Its mean is 38.264 and its median is 37.5, suggesting that on average the forecast is made a little over one month before the fiscal quarter end. The mean value of *Frequency* indicates that on average analysts issue 1.483 forecasts per quarter. *Company* and *Industry* measure the number of different companies and industries an analyst follows respectively. On average, each analyst follows 12.623 firms and 3.098 industries. As indicated by the distribution of *Brokerage size*, about 48.055 analysts are employed by each brokerage house. [20]

Panel B shows the distribution of interim rankings and changes in scaled characteristics. The mean value of the industry-level ranking is 0.151 and the median is 0.095 while the mean and median values of the brokerage-level ranking are 0.050 and 0.017 respectively. The median values are equal to 0 for all change variables. In addition, the mean value is not significant for Δ*Bold*, Δ*Frequency*, and Δ*Industry*.

[20] Untabulated results show that the distributions of the scaled variables are generally comparable to those reported in Clement and Tse (2005).

These results indicate that changes in the scaled characteristics from the first half-year to the second half-year are small.

4.2. Main result

In this section, we examine H1, which posits that changes in the forecast boldness across the mid-year are negatively related to analysts' first half-year performance rankings.

To test H1, our regression model is specified as follows.

$$\Delta Bold_{ijt} = \alpha_0 + \alpha_1 Accuracy\ ranking_{ijt-1} + \alpha_2 Lag\ bold + \alpha_3 \Delta Dayelap_{ijt} + \alpha_4 \Delta Horizon_{ijt} + \alpha_5 \Delta\ Frequency_{ijt} + \alpha_6 \Delta Company_{ijt} + \alpha_7 \Delta Industry_{ijt} + \alpha_8 \Delta Brokerage\ \ size_{ijt} + \varepsilon_{ijt} \quad (5)$$

where changes are defined as the second half-year values minus the first half-year values.[21]

Δ*Bold* is the change in the half-year value of *Bold*. *Bold* is binary on the quarterly level. Since the half-year value is the mean of two quarterly values, Δ*Bold* takes on five possible values (-1,-0.5, 0, 0.5 and 1);

Accuracy ranking is either *Industry-level interim accuracy ranking* or *Brokerage-level interim accuracy ranking* in the first half-year;

Lag Bold is the mean value of two quarterly value of *Bold* in the first half-year;

Δ*Dayelap* is the change in the scaled measure of the days elapsed since the last forecast by any analyst following the firm;

Δ*Horizon* is the change in the scaled measure of the time from the forecast date to the end of the fiscal period;

[21] An alternative way to compute half-year values is to obtain the sum of two quarterly values and then scale it to range from 0 to 1. For example, to compute half-year *Firm-level interim accuracy ranking*, we obtain the sum of the absolute forecast errors of the two quarterly forecasts and then scale it to range from 0 to 1 by using the formula $Firm - level\ accuracy\ ranking_{ijt} = \frac{AFE\ max_{jt} - AFE_{ijt}}{AFE\ max_{jt} - AFE\ min_{jt}}$, t refers to each half-year. Our results are robust to this alternative approach.

Δ*Frequency* is the change in the scaled measure of the forecasting frequency;

Δ*Company* is the change in the scaled measure of the number of companies that the analyst follows;

Δ*Industry* is the change in the scaled measure of the number of industries the analyst follows;

Δ*Brokerage size* is the change in the scaled measure of the number of analysts employed by the brokerage firm.

If H1 is true, we predict that the coefficient on $Accuracy\ ranking_{ijt-1}$ is negative, indicating that interim losers are more likely to increase the boldness of their forecasts, relative to interim winners.

We run an ordered logit regression, since Δ*Bold* is categorical variable. Our results are reported in Table 2. Regression (1) includes all control variables and *Industry-level accuracy ranking*. The coefficient on *Industry-level accuracy ranking* is -0.185, significant at the 1% level, indicating that analysts are more likely to increase forecast boldness in the second half-year if they are mid-year losers. The odds ratio suggests that, when we go from the lowest ranked analyst to the highest ranked analyst, the odds of being in a higher change in boldness category are reduced by close to 17%, holding the values of other variables constant.[22] This finding is consistent with Hypothesis 1.

Turning to control variables, the coefficient on *Lag Bold* is negative and significant, suggesting that analysts are more likely to issue bolder forecasts if they herd in the first half-year. Consistent with Clement and Tse (2005), the coefficient on *ΔDayelap* is negative and significant, suggesting that analyst forecast is more likely to be bold if it is issued shortly after previous forecast. *ΔHorizon* exhibits a significant negative relationship with changes in boldness. Higher value of forecast horizon implies a longer time until the end of the fiscal period and more uncertainty about actual earnings, which likely

[22] We base this inference on the fact that accuracy ranking measures are scaled to range from 0 for lowest level of accuracy ranking among all analysts providing a forecast for a given firm in a particular half-year, to 1 for the highest level of the accuracy ranking among all analysts providing a forecast for a given firm in that half-year.

induce analysts' herding behavior. The coefficient on *ΔFreqency* is positive and significant, indicating that analysts who issue forecasts frequently are more likely to issue bold forecasts.

Regression (2) replaces *Industry-level interim accuracy ranking* with *Brokerage-level interim accuracy ranking*. The coefficient on *Brokerage-level accuracy interim ranking* in regression (2) is -0.322, significant at the 1% level, indicating that mid-year losers in the intrafirm tournament are more likely to increase forecast boldness. The odds ratio estimate suggests that when we go from the lowest ranked analyst to the highest ranked analyst, the odds of being in a higher change in boldness category are reduced by 27%, holding the values of other variables constant. The coefficients on control variables are similar to those in regression (1).

In regression (3), we include both accuracy rankings in one regression. The coefficient on *Industry-level interim accuracy ranking* is -0.159, significant at the 1% level while the coefficient on *Brokerage-level interim accuracy ranking* is -0.285, significant at the 1% level. This finding indicates that analysts are more likely to increase their forecast boldness when they are regarded as interim losers in either the "All-star" tournament or the intrafirm tournament, suggesting that both tournaments are important to financial analysts.

Overall, our findings support our central hypothesis that mid-year losers are more likely to increase forecast boldness in the second half-year than mid-year winners.

4.3 Robustness check

This section subjects our main finding to two robustness tests. Specifically, we test whether it is robust to a continuous measure of boldness and to a more comprehensive performance measure based on forecast accuracy, stock picking abilities, investment banking revenue generating ability and forecast frequency.

4.3.1. A continuous boldness measure

The boldness measure we use is binary on the quarterly level. In this section, we examine whether our results are robust to a continuous measure of forecast boldness.

The definition of the continuous measure follows Clement and Tse (2005). It is computed as the absolute distance of the revised forecast from consensus forecasts for analyst i following firm j in quarter q minus the minimum absolute distance for analysts following firm j in quarter q, with this difference scaled by the range in absolute distances for all analysts who follow firm j in quarter q. The value of the measure ranges from 0 to 1 and a higher value indicates a bolder forecast. Specifically, 1 indicates that the forecast is the boldest while 0 indicates that the forecast is the least bold among all analysts following the firm. Similarly, we obtain half-year values by taking mean value of two quarterly values.

Our model specification is similar to that in Table 2. Now that the dependent variable is continuous, we use OLS regressions and report our results in Table 3.

Regression (1) shows that the coefficient on *Industry-level interim accuracy ranking* is -0.020, significant at the 5% level. Regression (2) shows that the coefficient on *Brokerage-level interim accuracy ranking* is not significant. Regression (3) reveals that *Industry-level interim accuracy ranking* remains negative and significant at the 5% level, when we include both rankings.

Overall, using an alternative continuous measure of boldness, we continue to find evidence that analysts participate in the “All-star” tournament and change their forecasts’ boldness according to the mid-year industry-level ranking. We obtain weaker results in support of analysts’ participation in the intra-firm tournament.

4.3.2 Rankings based on a more comprehensive performance measure

We measure financial analysts' performance through accuracy of their forecasts, despite the possibility that analysts' performance in the tournament is evaluated along several dimensions. Our approach seems justifiable for the following two reasons. First, Loh and Mian (2006) suggest that analysts who forecast earnings accurately tend to do well along other dimensions, such as issuing stock recommendations. If analysts' performance along other dimensions is positively correlated with their performance in forecasting earnings, the measurement error introduced by focusing on forecast accuracy is likely small. Second, if the measurement error problem is severe, we shall be unable to find any significant results. The fact is to the contrary, alleviating the measurement error concern.

To further address this concern, we test whether our results are robust to a more comprehensive measure of analyst performance. For the All-star tournament, we examine the six dimensions along which *Institutional Investors* evaluates analysts: earnings estimates, industry knowledge, written reports, stock picks, timely communication with investors and responsiveness to investor requests (Leone and Wu, 2007; Wu and Zang, 2009). Analysts' performance in earnings estimates is captured by forecast accuracy. Data are available for measuring stock picking abilities. We capture timely communication with investors by the frequency of issuing forecasts. When analysts receive information, they can quickly inform investors by issuing a new forecast. Therefore, analysts who issue their forecasts frequently are likely to score high in the aspect of timely communication with investors. Consistent with this notion, Leone and Wu (2007) show that these analysts enjoy a high likelihood of being elected as an "All-star". In sum, we test whether our main finding is robust to an industry-level composite ranking based on earnings forecast accuracy, earnings forecast frequency and stock picking abilities.

For the intra-firm competition, in addition to forecast accuracy, we consider stock picking ability and the ability to bring in investment banking business as two more dimensions of analysts' performance. Analysts who are able to generate investment banking business are likely regarded highly within the brokerage house. Consistent with this view, Grosberg et al. (2011) show that these analysts receive higher compensations than their colleagues.

We follow the definition of stock picking ability in Leone and Wu (2007) and industry-level and brokerage-level stock picking ability rankings are defined as follows.

$$Industry-level\ stock\ picking\ ranking_{ijt} = \sum W_{jt} \frac{RET_{ijt} - RET\ min_{jt}}{RET\ max_{jt} - RET\ min_{jt}}, j \in industry\ k \quad (6)$$

$$Brokerage-level\ stock\ picking\ ranking_{ijt} = \sum V_{jt} \frac{RET_{ijt} - RET\ min_{jt}}{RET\ max_{jt} - RET\ min_{jt}}, j \in brokerage\ l's\ coverage \quad (7)$$

where $RET\ max_{jt}$ and $RET\ min_{jt}$ are the maximum and minimum 30-day [0, +30] (day 0 is the recommendation announcement date) size-adjusted abnormal return for buy or sell recommendation[23] (returns for sell recommendations are multiplied by -1) for analysts following firm j in half-year t. RET_{ijt} is 30-day [0,+30] size-adjusted abnormal return for buy or sell recommendation for analyst i following firm j in half-year t. W_{jt} is the weight based on relative market value of equity of firm j in industry k while V_{jt} is the weight based on relative market value of equity of firm j in all the firms followed by analysts employed by brokerage firm l. A higher value of the ranking indicates that the analyst has better stock-picking abilities. [24]

Similar to other dimensions of analysts' performance, industry-level forecast frequency is defined as below.

$$Industry-level\ forecast\ frequency\ ranking_{ijq} = \sum W_{jq} \frac{Freqency_{ijq} - Freqency\ min_{jq}}{Freqency\ max_{jq} - Frequency\ min_{jq}}, j \in industry\ k$$

where $\text{Freqency max}_{\text{ijq}}$ and $\text{Freqency min}_{\text{jq}}$ are the maximum and minimum forecast frequency for analysts following firm j in quarter q. $\text{Freqency}_{\text{ijq}}$ is the number of forecasts made by analyst i for firm j in quarter q. W_{jq} is the weight based on relative market value of equity of firm j in industry k. Half-year values are computed by taking the average of the two quarterly values.

[23] Similar to analyst earnings forecast sample, we only keep the last recommendation an analyst issues in each half-year.

[24] Our results are qualitatively similar when we measure stock picking ability by taking the 10-day/ 60-day size-adjusted return starting from the recommendation issuance date.

We measure investment banking revenue generating ability via *Underwriter*. It is a dummy variable which equals one if the investment bank employing the analyst underwrites the initial public offerings or seasoned equity offerings of the firm covered by the analyst in the first half of the year. Since the underwriting relation may stem from the analyst's coverage, *Underwriter* is an indicator of the analyst's investment banking business generating ability. Our approach is similar to Grosberg et al. (2011). Public offering information is obtained from SDC Public Offering database. Our composite rankings are computed by putting equal weights on the dimensions we consider.[25]

Because of additional data requirement, our sample is reduced to 21,017 analyst-firm-half-year observations. We use an ordered logit regression since the dependent variable is the categorical change-in-boldness variable.[26] Our results are reported in Table 4. Regression (1) shows that the coefficient on *Industry-level interim composite ranking* is -0.572, significant at the 1% level. The odds ratio estimate suggests that, when we go from the lowest to the highest ranked analyst, the odds of being in a higher change in boldness category are reduced by close to 44%, holding the values of other variables constant. Regression (2) reveals that the coefficient on *Brokerage-level interim composite ranking* is -0.979, significant at the 1% level. The odds ratio estimate suggests that the odds of being in a higher change in boldness category are reduced by close to 62% when we go from the lowest to the highest ranked analyst. Regression (3) shows that the coefficients on both the industry-level and the brokerage-level rankings are negative and significant at the 1% level.

[25] Our un-tabulated results show that the ability to bring in investment banking business is less important as a performance measure after the Global Research Settlement in 2003. We change its weight to 0 in the brokerage-level composite ranking after 2003 and obtain similar results.

[26] Different from our earlier model, we do not control for Δ*Frequency*. Δ*Frequency* represents the change in the scaled measure of the forecasting frequency and is the same as the change in the interim firm-level frequency ranking. If we include both *Industry-level interim composite ranking* (which is a linear transformation of the interim frequency ranking) and Δ*Frequency* (the change in the interim frequency ranking) in the same regression, there is a severe multicollnearity problem as a result of the high correlation between the two.

In sum, our results suggest that our main finding is robust to a more comprehensive performance measure based on forecast accuracy, stock picking abilities, investment banking revenue generating ability and forecast frequency.

4.4 Different interim performance assessment date

H2 predicts that the effect of interim ranking on changes in boldness is more pronounced when the assessment date is closer to the end of the year. This section tests this hypothesis. Specifically, in addition to the middle of the year, we use two alternative interim performance assessment dates: the end of the first calendar quarter and the end of the third calendar quarter. We convert fiscal quarter to calendar quarter so that the calendar quarter includes most of months in the fiscal quarter. For example, the fiscal quarter ending on February 28 is defined as the first calendar quarter.

Similar to our analysis on a half-year basis, if a period has more than one quarter, its value equals the mean of quarterly values. For example, when the interim period is the first three quarters, the interim period value is the mean of the three quarterly values. This approach ensures that the length of the period does not affect its value. All change variables reflect changes from the assessment period to the rest of the year. Our regression model includes both *Industry-level interim accuracy ranking* and *Brokerage-level interim accuracy ranking*. If the coefficient on the ranking variable becomes more negative when the assessment date is closer to the year end, it is evidence in support of our hypothesis.

Results from ordered logic regressions are reported in Table 5. Regression (1), (2) and (3) report results for the interim period of one quarter, two quarters and three quarters respectively.[27] Regression (1) shows that the coefficient estimate on *Industry-level interim accuracy ranking* is -0.01, insignificant at the

[27] The numbers of observations are different in the three regressions since half-year values could be constructed even if there is only one quarterly observation in that half-year, while quarterly values could only be constructed for each specific quarter. So there are greater number of observations in regression (2), compared with regression (1) and regression (3).

10% level, while the coefficient estimate on *Brokerage-level interim accuracy ranking* is -0.224, significant at the 5% level. Regression (2) shows that when our interim assessment date is the end of the second quarter, the coefficient estimate on *Industry-level interim accuracy ranking* is -0.159, significant at the 1% level while the coefficient estimate on *Brokerage-level interim accuracy ranking* is -0.285, significant at the 1% level. [28] Regression (3) shows that the coefficient estimate on *Industry-level interim accuracy ranking* is -0.289, significant at the 1% level while the coefficient estimate on *Brokerage-level interim accuracy ranking* is -0.303, significant at the 5% level, when our interim assessment date is the end of the third quarter. Our results indicate that the coefficients on both industry-level and brokerage-level ranking variables become more negative when the interim assessment date is closer to the year end, lending support to our hypothesis.

In the lower panel, we report the *p*-value of tests of equal coefficients on *Industry-level interim accuracy ranking*/*Brokerage-level interim accuracy ranking*. Our results suggest that the coefficient on *Industry-level interim accuracy ranking* is significantly lower when we move the interim assessment date from the end of the first quarter to either the mid-year or the end of the third quarter. This finding lends support to our hypothesis.

In general, Table 5 shows that when the interim assessment date gets closer to the end of the year, the effect of interim performance ranking on changes in boldness becomes more pronounced. Our results support H2.

4.5. Sub-sample analysis for the association between interim analyst forecast rankings and change in forecast boldness—analysts' experience

[28] This regression is the same as Regression (3) in Table 2.

This section tests H3, which predicts a more pronounced effect of interim rankings on changes in boldness for inexperienced analysts. Specifically, we split the sample according to analysts' general experience. In subsamples, we regress changes in boldness on *Industry-level interim accuracy ranking*, *Brokerage-level interim accuracy ranking* and control variables. If H3 is true, we expect the coefficients on the rankings to be more negative for less experienced analysts.

Table 6 tabulates regression results for analysts with less (below the median) and more (above the median) general experience. Analysts' general experience is measured as the number of years of forecasting experience for any firm. In the subsample of less experienced analysts, the coefficient on *Industry-level interim accuracy ranking* and the coefficient on *Brokerage-level interim accuracy ranking* are -0.240 and -0.341 respectively, both significant at the 5% level. In the subsample of more experienced analysts, neither of the coefficients is significant at the 10% level. A test of equal coefficients on *Industry-level interim accuracy ranking* yields a *p*-value of 0.07, suggesting that the difference between less experienced analysts and more experienced analysts is statistically significant.

In sum, we find evidence that the effect of interim performance rankings on changes in boldness is more pronounced for inexperienced analysts. This finding is consistent with the view that the incentive to win the tournament is stronger for analysts with no proven records.

4.6. Sub-sample analysis for the association between interim analyst forecast rankings and future change in forecast boldness—market activity

This section tests H4, which posits that the effect of interim performance ranking on changes in boldness is more pronounced in years of high market activity, when the pay discrepancy between winners and losers is greater (Groysberg et al., 2011).

To test H4, we regress changes in boldness on control variables, *Industry-level interim accuracy ranking* and *Brokerage-level interim accuracy ranking*, separately for years of low market activity and years of high market activity. Years are classified according to Baker and Wurgler (2006) index.[29] Specifically, 1994 to 2001, 2006 and 2007 are categorized as years with high market activity and the rest of the years in our sample are categorized as years with low market activity. Our results are reported in Table 7. Regression (1) and Regression (2) report the results for years with low market activity and years with high market activity respectively. Neither of the two coefficients on the ranking variables is significant at the 10% level in years of low market activity. However, both of them are negative and significant at the 1% level in years of high market activity. Furthermore, the difference in the coefficient on *Industry-level interim accuracy ranking* is significant at the 10% level.

Our results support H4 and are consistent with the notion that when rewards to winning the tournament are greater, mid-year losers have greater incentives to win the tournament and therefore are more likely to increase the boldness of their forecasts in an attempt to win.

4.7 The differential informativeness of changes in boldness between mid-year winners and mid-year losers

H5 posits that interim losers' changes in boldness are less informative than interims winners'. To test H5, we follow the methodology in Clement and Tse (2005), who examine the informativeness of bold forecasts. Specifically, they regress forecast accuracy on a binary variable indicating bold forecasts and show that the coefficient on the binary variable is positive and significant. Their finding suggests that on average, bold forecasts are more accurate than herding forecasts. Our model specification is derived by taking changes on both sides of their regression. It is thus as follows:

[29] The Baker and Wurgler (2006) index is originally designed to measure investor sentiment. By construction, it captures a variety of market activity signals including banking-related (e.g., initial public offering volume, first-day IPO returns, and equity share in new issues) and commission-related (e.g., average monthly turnover on NYSE-listed stocks) variables.

$$\Delta Accuracy_{ijt} = \alpha_0 + \alpha_1 \Delta Bold_{ijt} + \alpha_2 \Delta Dayelap_{ijt} + \alpha_3 \Delta Horizon_{ijt} + \alpha_4 \Delta\, Frequency_{ijt} + \alpha_5 \Delta Company_{ijt} + \alpha_6 \Delta Industry_{ijt} + \alpha_7 \Delta Brokerage\ \ size_{ijt} + \varepsilon_{ijt} \tag{8}$$

where all change variables are defined as the value for the second-half minus the value for the first-half of the year. *Accuracy* is defined in the same way as Clement and Tse (2005) and Appendix provides more details. A higher value of *Accuracy* indicates more accurate forecast.

The coefficient, α_1, reflects the informativeness of change in boldness. If changes in boldness are based on information, we expect α_1 to be positive, reflecting a positive association between changes in boldness and changes in accuracy. We run the regression separately for interim losers and interim winners. If interim losers' issuance of bold forecasts is contaminated by the tournament-induced incentive to overcome prior "deficit", we expect that α_1 is less positive for interim losers than for interim winners.

Panel A and B of Table 8 report, under "Main test", the results when interim winners/losers are based on a median split on *Industry-level interim accuracy ranking* and a median split on *Brokerage-level interim accuracy rankin*g respectively. Our results are generally consistent with H5. Specifically, Panel A shows that the coefficient on changes in boldness is 0.012, significant at the 10% level, for interim losers while it is 0.031, significant at the 1% level, for interim winners. The difference between the two coefficients amounts to 0.019, significant at the 5% level. Panel B reveals that the coefficient on changes in boldness is 0.012, not significant at the 10% level, for interim losers while it is 0.028, significant at the 1% level, for interim winners. The difference between the two amounts is 0.016, significant at the 1% level. Consistent with Clement and Tse (2005), the coefficient on changes in forecasting horizon is negative in all regressions, suggesting that an increase in the forecast horizon leads to less accurate forecasts.

Although our results support H5, they are subject to the alternative explanation that interim losers are less capable or less informed than interim winners (Chen and Matsumoto, 2006; Ke and Yu, 2006) and, consequently, changes in boldness are less informative for interim losers regardless of the tournament-induced incentive. To test this alternative explanation, we redefine changes as the value for the first-half of current year minus that for the second-half of prior year. To the extent that tournaments are run annually, the change in boldness from the second half of prior year to the first half of current year should be unaffected by the tournament-related incentives because the second half of prior year is not an interim period of current year's tournament. Our results, reported under the heading "Benchmark test", thus describe the informativeness of changes in boldness, when the tournament-induced incentives are absent.

Results reported under "Benchmark test" show that the difference in the informativeness of changes in boldness between interim winners and interim losers is dramatically reduced, when the tournament-induced incentives are absent. Panel A shows that the coefficient on changes in boldness is 0.030, significant at the 1% level, for interim losers and is 0.033, significant at the 1% level, for interim winners. The difference between the two is statistically insignificant and its magnitude (0.003) is much lower than the corresponding value under "Main test" (0.019). A consistent finding is available from Panel B. The coefficient on changes in boldness is 0.030, significant at the 1% level, for interim losers and 0.031, significant at 1% level, for interim winners, indicating that there is only little difference in the informativeness of changes in boldness when incentives induced by the intrafirm tournament are absent. This compares to a difference of 0.016 when these incentives are present.

Overall, the results in Table 8 suggest that the informativeness of changes in boldness is affected by analysts' incentives. Because interim losers' decisions to become bolder in the remainder of the tournament period are likely determined by their desire to make up for prior "deficit", instead of high quality information, interim losers' changes in boldness are less informative than interim winners'.

This finding implies the following. First, not all bold forecasts are created equal. For bold forecasts issued by interim losers in the remainder of the tournament period, a healthy dose of skepticism is necessary. Second, to the extent that analysts' compensation structure is designed to encourage analysts to issue accurate forecasts, the tournament-like compensation structure seems to have unintended consequences.

5. Conclusions

Although a large body of literature examines analysts' decision making, little is documented as to how the competitive nature of financial analysts' environment affects their decisions. This study attempts to address this gap in prior literature. Specifically, we offer evidence that viewing financial analysts as participants of the "All-star" tournament and the intrafirm tournament provides a useful framework for a better understanding of analysts' behavior.

Our central hypothesis is that, relative to interim winners, interim losers are more likely to increase the boldness of their forecasts in the remainder of the year in an attempt to improve their relative rankings. We find results consistent with this hypothesis. After controlling for current boldness and several known determinants of changes in boldness, we find that the odds of the analyst becoming bolder are lower by 15%-25% for the highest ranked analyst than for the lowest ranked analyst. Our inferences are robust to a continuous measure of forecast boldness and a more comprehensive performance ranking based on forecast accuracy, stock picking abilities, investment banking revenue generating ability and forecast frequency.

We then develop and test several predictions stemming from our central hypothesis. Drawing on the finding that losing sports teams are more likely to take "desperate" (i.e., more risky) moves when they are more time-constrained, we hypothesize and find that the negative association between interim performance ranking and changes in forecast boldness is stronger, when the interim assessment date is closer to the end of the tournament period. In addition, we document that the effect of interim ranking on changes in boldness is more pronounced for inexperienced analysts and in years of high market activity, consistent with the view that the incentive to win the tournament is stronger when analysts have no proven records and when the rewards to winning the tournament are greater.

Finally, we illustrate that the tournament-like compensation structure has unintended consequences. We show that interim losers' changes in boldness are less informative than interim winners'. This finding suggests that interim losers' decisions to issue bold forecasts are determined by the incentive to compensate for prior "deficit", instead of high quality information. To the extent that the purpose of the compensation structure is to motivate analysts to issue accurate earnings forecasts, this finding reveals the unintended effect of the tournament-like compensation structure.

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Table 1

Descriptive statistics

Our sample includes 52,022 analyst-firm-half-year observations from 1991 to 2007. Panel A reports the descriptive statistics for raw forecast and analyst characteristics while Panel B reports the descriptive statistics for the interim rankings and changes in the scaled forecast and analyst characteristics. Appendix provides a detailed description of variable construction.

Panel A: Distribution of raw forecast and analyst characteristics in the first half-year

Variables	N	Mean	Q1	Median	Q3
Dayelap	52,022	5.939	0	2	7
Horizon	52,022	38.264	20.5	37.5	56
Frequency	52,022	1.483	1	1.5	2
Company	52,022	12.623	8.5	12	15.5
Industry	52,022	3.098	2	3	4
Brokerage size	52,022	48.055	19	41.5	76

Panel B: Distribution of interim rankings and changes in the scaled forecast and analyst characteristics

Variables	N	Mean	Q1	Median	Q3	*P*-value of the test of significance (mean)
Industry-level interim accuracy ranking	52,022	0.151	0.028	0.095	0.239	<0.01
Brokerage-level interim accuracy ranking	52,022	0.050	0.007	0.017	0.046	<0.01
ΔBold	52,022	-0.000	0.000	0.000	0.000	0.86
ΔDayelap	52,022	-0.017	-0.214	0.000	0.167	<0.01
ΔHorizon	52,022	0.016	-0.283	0.000	0.325	<0.01
ΔFrequency	52,022	0.002	-0.250	0.000	0.250	0.43
ΔCompany	52,022	-0.004	-0.139	0.000	0.130	<0.01
ΔIndustry	52,022	0.001	-0.104	0.000	0.107	0.30
ΔBrokerage size	52,022	0.002	-0.034	0.000	0.045	<0.01

Table 2

Effect of analyst interim performance rankings on changes in boldness

This table reports the ordered logit regression results. The sample includes 52,022 analyst-firm-half-year observations from 1991 to 2007. The dependent variable is changes in boldness, a categorical variable. Appendix provides a detailed description of variable construction. *P*-values are in parentheses. The symbols *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively.

DV: Change of Boldness	(1)		(2)		(3)	
	Coefficient estimates	Odds ratio	Coefficient estimates	Odds ratio	Coefficient estimates	Odds ratio
Industry-level interim accuracy ranking	-0.185*** (<0.01)	0.831			-0.159*** (0.01)	0.853
Brokerage-level interim accuracy ranking			-0.322*** (<0.01)	0.725	-0.285*** (<0.01)	0.752
Lag Bold	-5.035*** (<0.01)	0.007	-5.038*** (<0.01)	0.006	-5.036*** (<0.01)	0.006
ΔDayelap	-0.069*** (<0.01)	0.933	-0.069*** (<0.01)	0.933	-0.069*** (<0.01)	0.933
ΔHorizon	-0.330*** (<0.01)	0.719	-0.331*** (<0.01)	0.718	-0.330*** (<0.01)	0.719
ΔFrequency	2.145*** (<0.01)	8.542	2.144*** (<0.01)	8.534	2.145*** (<0.01)	8.542
ΔCompany	0.020 (0.62)	1.020	0.022 (0.58)	1.022	0.019 (0.63)	1.019
ΔIndustry	-0.014 (0.70)	0.986	-0.013 (0.73)	0.987	-0.014 (0.71)	0.986
ΔBrokerage size	0.045 (0.46)	1.046	0.042 (0.50)	1.043	0.043 (0.49)	1.044
Number of observation	52,022		52,022		52,022	
Pseudo R^2	0.55		0.55		0.55	

Table 3

Effect of analyst interim performance rankings on change in boldness (a continuous measure)

This table reports OLS regression results. Our sample includes 52,022 analyst-firm-half-year observations from 1991 to 2007. The dependent variable is change in boldness (a continuous measure). Appendix provides a detailed description of variable construction. *P*-values are in parentheses. The symbols *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively.

DV: Change of Boldness (continuous measure)	(1)	(2)	(3)
Intercept	0.454***	0.451***	0.453***
	(<0.01)	(<0.01)	(<0.01)
Industry-level interim accuracy ranking	-0.020**		-0.020**
	(0.03)		(0.03)
Brokerage-level interim accuracy ranking		-0.001	0.004
		(0.98)	(0.76)
Lag Bold (continuous)	-0.913***	-0.913***	-0.913***
	(<0.01)	(<0.01)	(<0.01)
ΔDayelap	-0.006*	-0.006*	-0.006*
	(0.09)	(0.09)	(0.09)
ΔHorizon	-0.014***	-0.014***	-0.014***
	(<0.01)	(<0.01)	(<0.01)
ΔFrequency	0.001	0.001	0.001
	(0.79)	(0.80)	(0.80)
ΔCompany	-0.001	-0.001	-0.001
	(0.89)	(0.93)	(0.89)
ΔIndustry	-0.002	-0.002	-0.002
	(0.73)	(0.75)	(0.73)
ΔBrokerage size	0.010	0.010	0.010
	(0.27)	(0.27)	(0.26)
Number of observation	52,022	52,022	52,022
Adjusted R^2	0.46	0.46	0.46

Table 4

Effect of interim composite performance rankings on change in boldness

This table reports the ordered logit regression results. The sample includes 21,017 analyst-firm-half-year observations from 1991 to 2007. The dependent variable is changes in boldness, a categorical variable. Appendix provides a detailed description of variable construction. *P*-values are in parentheses. The symbols *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively.

DV: Change of Boldness	(1)		(2)		(3)	
	Coefficient estimates	Odds ratio	Coefficient estimates	Odds ratio	Coefficient estimates	Odds ratio
Industry-level interim composite ranking	-0.572***	0.564			-0.507***	0.602
	(<0.01)				(<0.01)	
Brokerage-level interim composite ranking			-0.979***	0.376	-0.858***	0.424
			(<0.01)		(<0.01)	
Lag Bold	-5.324***	0.005	-5.336***	0.005	-5.328***	0.005
	(<0.01)		(<0.01)		(<0.01)	
ΔDayelap	-0.059*	0.943	-0.059*	0.943	-0.059*	0.942
	(0.10)		(0.10)		(0.10)	
ΔHorizon	-1.090***	0.336	-1.092***	0.336	-1.091***	0.336
	(<0.01)		(<0.01)		(<0.01)	
ΔCompany	0.108*	1.114	0.107*	1.113	0.106*	1.112
	(0.06)		(0.06)		(0.06)	
ΔIndustry	0.019	1.019	0.024	1.025	0.022	1.022
	(0.72)		(0.65)		(0.68)	
ΔBrokerage size	0.069	1.072	0.062	1.064	0.065	1.067
	(0.42)		(0.47)		(0.45)	
Number of observation	21,017		21,017		21,017	
Pseudo R^2	0.46		0.46		0.46	

Table 5

Effect of analyst interim performance rankings on change in boldness—different interim performance assessment date

This table reports the ordered logit regression results. The sample includes 52,022 analyst-firm-half-year observations from 1991 to 2007. The dependent variable is changes in boldness, a categorical variable. Appendix provides a detailed description of variable construction. *P*-values are in parentheses. The symbols *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively.

DV: Change of Boldness	Assessment period is the first quarter (1)		Assessment period is the first two quarters (2)		Assessment period is the first three quarters (3)	
	Coefficient estimates	Odds ratio	Coefficient estimates	Odds ratio	Coefficient estimates	Odds ratio
Industry-level interim accuracy ranking	-0.010	0.990	-0.159***	0.853	-0.289***	0.749
	(0.89)		(0.01)		(<0.01)	
Brokerage-level interim accuracy ranking	-0.224**	0.799	-0.285***	0.752	-0.303**	0.738
	(0.03)		(<0.01)		(0.02)	
Lag Bold	-12.623***	0.000	-5.036***	0.006	-4.561***	0.010
	(<0.01)		(<0.01)		(<0.01)	
ΔDayelap	-0.049*	0.952	-0.069***	0.933	-0.087***	0.917
	(0.06)		(<0.01)		(<0.01)	
ΔHorizon	-0.318***	0.728	-0.330***	0.719	-0.287***	0.750
	(<0.01)		(<0.01)		(<0.01)	
ΔFrequency	2.129***	8.407	2.145***	8.539	1.982***	7.260
	(<0.01)		(<0.01)		(<0.01)	
ΔCompany	-0.089**	0.915	0.019	1.019	0.009	1.009
	(0.03)		(0.63)		(0.86)	
ΔIndustry	0.006	1.007	-0.014	0.986	0.052	1.053
	(0.87)		(0.71)		(0.28)	
ΔBrokerage size	-0.060	0.942	0.043	1.044	0.016	1.016
	(0.37)		(0.49)		(0.85)	
Number of observation	43,690		52,022		27,041	
Pseudo R^2	0.64		0.55		0.49	

p-value of test of equal coefficients	between (1) and (2)	between (1) and (3)	between (2) and (3)
Industry-level interim accuracy ranking	0.05	0.04	0.42
Brokerage-level interim accuracy ranking	0.66	0.62	0.91

Table 6

Effect of analyst interim performance rankings on change in boldness—sample split on analysts' track record

This table reports the ordered logit regression results. The sample includes 52,022 analyst-firm-half-year observations from 1991 to 2007. The dependent variable is changes in boldness, a categorical variable. Appendix provides a detailed description of variable construction. "Less experienced"/"More experienced" refer to analysts whose general experience is lower/higher than the sample median. *P*-values are in parentheses. The symbols *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively.

DV: Change of Boldness	Less experienced (1)		More experienced (2)	
	Coefficient estimates	Odds ratio	Coefficient estimates	Odds ratio
Industry-level interim accuracy ranking: a	-0.240***	0.786	-0.047	0.954
	(0.01)		(0.62)	
Brokerage-level interim accuracy ranking: b	-0.341***	0.711	-0.211	0.810
	(0.01)		(0.17)	
Lag Bold	-4.953***	0.007	-5.156***	0.006
	(<0.01)		(<0.01)	
ΔDayelap	-0.063**	0.939	-0.075**	0.928
	(0.05)		(0.04)	
ΔHorizon	-0.291***	0.748	-0.385***	0.681
	(<0.01)		(<0.01)	
ΔFrequency	2.148***	8.570	2.139***	8.493
	(<0.01)		(<0.01)	
ΔCompany	0.060	1.062	-0.031	0.970
	(0.26)		(0.60)	
ΔIndustry	-0.003	0.997	-0.026	0.974
	(0.95)		(0.65)	
ΔBrokerage size	0.030	1.030	0.060	1.062
	(0.72)		(0.52)	
p-value of test of equal coefficients on a between (1) and (2)		0.07		
p-value of test of equal coefficients on b between (1) and (2)		0.51		
Number of observation	26,103		25,919	
Pseudo R^2	0.55		0.55	

Table 7

Effect of analyst interim performance rankings on change in boldness—sample split on market activity

This table reports the ordered logit regression results. The sample includes 52,022 analyst-firm-half-year observations from 1991 to 2007. The dependent variable is changes in boldness, a categorical variable. Appendix provides a detailed description of variable construction. Based on Baker and Wurgler (2006) index, 1994 to 2001, 2006 and 2007 are defined as years with high market activity and the rest of the years are defined as years with low market activity. *P*-values are in parentheses. The symbols *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively.

DV: Change of Boldness	Low market activity (1)		High market activity (2)	
	Coefficient estimates	Odds ratio	Coefficient estimates	Odds ratio
Industry-level interim accuracy ranking: a	-0.089	0.915	-0.266***	0.767
	(0.32)		(<0.01)	
Brokerage-level interim accuracy ranking: b	-0.216	0.805	-0.360***	0.697
	(0.14)		(0.01)	
Lag Bold	-4.804***	0.008	-5.274***	0.005
	(<0.01)		(<0.01)	
ΔDayelap	-0.092***	0.912	-0.046	0.955
	(0.01)		(0.17)	
ΔHorizon	-0.344***	0.709	-0.319***	0.727
	(<0.01)		(<0.01)	
ΔFrequency	2.177***	8.823	2.120***	8.329
	(<0.01)		(<0.01)	
ΔCompany	-0.024	0.977	0.053	1.055
	(0.69)		(0.31)	
ΔIndustry	0.037	1.038	-0.056	0.946
	(0.51)		(0.26	
ΔBrokerage size	0.093	1.097	0.009	1.009
	(0.30)		(0.91	
p-value of test of equal coefficients on a between (1) and (2)	0.08			
p-value of test of equal coefficients on b between (1) and (2)	0.46			
Number of observation	23,819		28,203	
Pseudo R^2	0.54		0.55	

Table 8

Differential informativeness of change in boldness for interim losers and interim winners

This table reports OLS regression results. The sample includes 52,022 analyst-firm-half-year observations from 1991 to 2007. The dependent variable is changes in accuracy. Changes are defined as values for the second-half minus those for the first-half of the year under "Main test" and defined as values for the first-half of current year minus those for the second-half of prior year under "Benchmark test". Appendix provides a detailed description of variable construction. *P*-values are in parentheses. The symbols *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively.

Panel A: Median split on industry-level interim accuracy ranking

DV: Change of Accuracy	Main test		Benchmark test	
	Interim losers (1)	Interim winners (2)	Interim losers (3)	Interim winners (4)
Intercept	0.026***	-0.028***	0.021***	-0.028***
	(<0.01)	(<0.01)	(<0.01)	(<0.01)
ΔBold	0.012*	0.031***	0.030***	0.033***
	(0.09)	(<0.01)	(<0.01)	(<0.01)
ΔDayelap	-0.037***	-0.041***	-0.046***	-0.041***
	(<0.01)	(<0.01)	(<0.01)	(<0.01)
ΔHorizon	-0.119***	-0.117***	-0.122***	-0.103***
	(<0.01)	(<0.01)	(<0.01)	(<0.01)
ΔFrequency	0.003	-0.002	0.008	0.001
	(0.69)	(0.83)	(0.28)	(0.84)
ΔCompany	-0.012	0.003	0.007	-0.008
	(0.30)	(0.80)	(0.54)	(0.46)
ΔIndustry	-0.007	0.005	-0.022**	-0.001
	(0.54)	(0.66)	(0.05)	(0.95)
ΔBrokerage size	-0.008	-0.037*	-0.022	0.015
	(0.65)	(0.06)	(0.22)	(0.38)
Number of observation	25,718	25,868	24,010	24,578
Adjusted R^2	0.02	0.02	0.02	0.02

Panel B: Median split on brokerage-level interim accuracy ranking				
DV: Change of Accuracy	Main test		Benchmark test	
	Interim losers (1)	Interim winners (2)	Interim losers (3)	Interim winners (4)
Intercept	0.033***	-0.014***	0.024***	-0.016***
	(<0.01)	(<0.01)	(<0.01)	(<0.01)
ΔBold	0.012	0.028***	0.030***	0.031***
	(0.20)	(<0.01)	(<0.01)	(<0.01)
ΔDayelap	-0.053***	-0.039***	-0.053***	-0.040***
	(<0.01)	(<0.01)	(<0.01)	(<0.01)
ΔHorizon	-0.123***	-0.116***	-0.126***	-0.106***
	(<0.01)	(<0.01)	(<0.01)	(<0.01)
ΔFrequency	0.008	0.001	0.013	0.001
	(0.39)	(0.96)	(0.18)	(0.81)
ΔCompany	-0.016	-0.007	0.029*	-0.015
	(0.29)	(0.47)	(0.06)	(0.11)
ΔIndustry	-0.012	0.010	-0.043***	0.001
	(0.39)	(0.23)	(<0.01)	(0.90)
ΔBrokerage size	-0.032	-0.008	-0.032	0.006
	(0.16)	(0.60)	(0.13)	(0.68)
Number of observation	25,769	25,817	24,319	24,269
Adjusted R^2	0.02	0.02	0.02	0.02

Appendix (in alphabetical order)

Variable definition

Variable name	Variable definition
Accuracy$_{ijt}$	An accuracy measure of the forecast made by analyst i for firm j in half-year t. It is computed as the average of the two quarterly values in half-year t. The quarterly value is calculated as the maximum absolute forecast error for analysts who follow firm j in the quarter minus the absolute forecast error for the analyst i following firm j in the quarter scaled by the range of absolute forecast error for analysts following firm j in the quarter.
Bold$_{ijt}$	An indicator variable of the boldness of analyst i's forecast for firm j in half-year t. It is computed as the average of two quarterly values in half-year t. The quarterly value equals one if analyst i's forecast is above both the analyst's prior forecast and the consensus forecast immediately before the forecast revision, or else below both, and equals zero otherwise. The consensus forecast is based on forecasts issued for the same quarter prior to analyst's forecast revision.
Bold$_{ijt}$ *(Continuous)*	A continuous measure of forecast boldness of analyst i's forecast for firm j in half-year t. It is computed as the average of two quarterly values in half-year t. The quarterly value is calculated as the absolute distance of the revised forecast from consensus forecast for analyst i following firm j in the quarter minus the minimum absolute distance for analysts who follow firm j in the quarter, with this difference scaled by the range in absolute distances for analysts following firm j in the quarter.
Brokerage-level accuracy ranking$_{ijt}$	A measure of analyst i's forecast accuracy ranking in her brokerage firm in half-year t. It is computed as the average of two quarterly values in half-year t. The quarterly value is calculated as value-weighted firm-level accuracy ranking for firms followed by analyst i in the quarter. The weight is calculated as the market value of equity of firm j deflated by the aggregate market value of all the firms followed by analysts in the brokerage firm.
Brokerage-level composite ranking$_{ijt}$	A measure of analyst i's composite ranking in her brokerage firm in half-year t. It is computed as equally-weighted average of Brokerage-level accuracy ranking, Brokerage-level stock picking ability ranking, and investment banking business generating ability indicator. This indicator is a dummy, which equals 1, if the investment bank employing the analyst underwrites the initial public offerings or seasoned equity offerings of the firm covered by the analyst in the first half of the year, and 0 otherwise.
Brokerage-level stock picking ability ranking$_{ijt}$	A measure of analyst i's stock picking ability ranking in her brokerage firm in half-year t, calculated as value-weighted firm-level stock picking ability ranking for firms followed by analyst i in half-year t. The weight is calculated as the market value of equity of firm j

	deflated by the aggregate market value of all firms followed by analysts in the brokerage firm.
Brokerage size$_{ijt}$	A measure of the number of analysts employed by the brokerage employing analyst i following firm j in half-year t. It is computed as the average of two quarterly values in half-year t. The quarterly value is calculated as the difference between the number of analysts employed by the brokerage employing analyst i following firm j in the quarter and the minimal number of analysts employed by brokerages for analysts following firm j in the quarter deflated by the range of number of analysts employed by the brokerage for analysts following firm j in the quarter.
Company$_{ijt}$	A measure of the number of companies for which analyst i issues forecasts in half-year t. It is computed as the average of two quarterly values in half-year t. The quarterly value is calculated as the difference between the number of companies followed by analyst i following firm j in the quarter and the minimum number of companies followed by analysts who follow firm j in the quarter scaled by the range of number of companies followed by analysts following firm j in the quarter.
Dayelap$_{ijt}$	A measure of the days elapsed since last forecast by analyst following firm j in half-year t. It is computed as the average of two quarterly values in half-year t. The quarterly value is calculated as the difference of the days between analyst i's forecast of firm j's earnings in the quarter and the most recent forecast of firm j's earnings before analyst i's and the minimum number of days between two adjacent forecasts of firm j's earnings by any two analysts in the quarter deflated by the range of days between two adjacent forecasts of firm j's earnings in the quarter.
Firm-level accuracy ranking$_{ijt}$	An accuracy measure of the forecast made by analyst i for firm j in half-year t. It is computed as the average of the two quarterly values in half-year t. The quarterly value is calculated as the maximum absolute forecast error for analysts who follow firm j in the quarter minus the absolute forecast error for the analyst i following firm j in the quarter scaled by the range of absolute forecast error for analysts following firm j in the quarter.
Firm-level stock picking ability ranking$_{ijt}$	A measure of analyst i's profitability of stock recommendation for firm j in half-year t, calculated as the difference between analyst i's 30-day [0,+30] (day 0 is the recommendation announcement date) size-adjusted abnormal return for stock recommendation (return for sell recommendations are multiplied by -1) for firm j in half-year t and minimum 30-day [0,+30] size adjusted abnormal return for stock recommendation for analysts who follow firm j in half-year t scaled by the range of 30-day [0,+30] size-adjusted abnormal return for stock recommendation for analysts following firm j in half-year t.
Frequency$_{ijt}$	A measure of analyst i's forecast frequency for firm j, i.e., the number

	of forecasts made by analyst i for firm j in half-year t. It is computed as the average of two quarterly values in half-year t. The quarterly value is calculated as the difference between the number of forecasts made by analyst i for firm j in the quarter and the minimum number of forecasts made by analysts for firm j in the quarter scaled by the range of the number of forecasts issued by analysts for firm j in the quarter.
Horizon$_{ijt}$	A measure of the number of days from the forecast date to fiscal quarter end for analyst i following firm j in half-year t. It is computed as the average of two quarterly values in half-year t. The quarterly value is calculated as the difference of the number of days from the forecast date to fiscal quarter end for analyst i following firm j in the quarter and the minimum number of days from the forecast date to fiscal quarter end for analysts who follow firm j in the quarter scaled by the range of number of days from the forecast date to fiscal quarter end for analysts following firm j in the quarter.
Industry$_{ijt}$	A measure of the number of industries for which analyst i issues forecasts in half-year t. It is computed as the average of two quarterly values in half-year t. The quarterly value is calculated as the difference between the number of industries (with the same two-digit SIC code) followed by analyst i following firm j in the quarter and the minimum number of industries followed by analysts who follow firm j in the quarter scaled by the range of number of industries followed by analysts following firm j in the quarter.
Industry-level accuracy ranking$_{ikt}$	A measure of analyst i's forecast accuracy for industry k in half-year t. It is computed as the average of two quarterly values in half-year t. The quarterly value is calculated as value-weighted firm-level accuracy rankings for firms followed by analyst i in industry k in the quarter. The weight is calculated as the market value of equity of firm j deflated by the aggregate market value of all the firms in industry k. The industries are classified according to I/B/E/S SIG definitions.
Industry-level composite ranking$_{ikt}$	A measure of analyst i's composite ranking in industry k in half-year t. It is computed as the equally weighted average of Industry-level accuracy ranking, Industry-level stock picking ability ranking and Industry-level frequency ranking.
Industry-level frequency ranking$_{ikt}$	A measure of analyst i's value-weighted forecast frequency for industry k in half-year t, calculated as value-weighted firm-level forecast frequency ranking for firms followed by analyst i in industry k in half-year t. The weight is calculated as the market value of equity of firm j deflated by the aggregate market value of all the firms in industry k. The industries are classified according to I/B/E/S SIG definitions.
Industry-level stock picking ability ranking$_{ikt}$	A measure of analyst i's value-weighted profitability of stock recommendation for industry k in half-year t, calculated as value-weighted firm-level stock picking ability ranking for firms followed

	by analyst i in industry k in half-year t. The weight is calculated as the market value of equity of firm j deflated by the aggregate market value of all the firms in industry k. The industries are classified according to I/B/E/S SIG definitions.