

# 明星分析师的负面外部效应

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**Abstract:** We hypothesize that when the winning odds are eclipsed by the presence of superstars, tournament participants will choose to bow out of the competition. We use the setting of financial analysts to test this hypothesis. We document that non-star analysts avoid direct competition with star analysts through their coverage decisions. Moreover, non-stars' reluctance to compete with stars is more pronounced when star analysts are more highly ranked, when winning the tournament carries higher rewards, when institutional ownership is lower, when the firm faces lower uncertainties, and when non-stars are of average ability. In addition, we show that non-stars who avoid direct competitions with stars are more likely to become an *Institutional Investor* All-star in the future, suggesting that competition avoidance benefits non-stars. Finally, we find that non-star coverage is positively associated with consensus forecast accuracy after controlling for star coverage. Collectively, our results suggest that the presence of superstars discourages others from participating in the tournament.

**Key words:** Competition; Financial analyst coverage.

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## 1 Introduction

While classic economic theory (Lazear and Rosen, 1981) points out that tournament is effective in eliciting efforts from the participating agents, recent development in economic theory (Knoeber and Thurman, 1994; Brown, 2011) shows that the effectiveness of tournament in eliciting efforts depends crucially on whether the participants are relatively equal in their abilities. If participants have unequal abilities, the less talented may optimally give up by either reducing their efforts or even quitting the competition. Using data from PGA Tournaments, Brown (2011) finds that professional golfers' first-round scores are approximately 0.2 strokes worse when Tiger Woods (i.e., the superstar during Brown's (2011) sample period) participates than when he is absent, which is consistent with the notion that the presence of a superstar in a tournament leads to reduced effort from other participants.

In this paper, we aim to offer empirical evidence that highlights the impact of superstars on tournament participation decisions. Specifically, we predict that less talented tournament participants bow out of the competition when their chances of winning are eclipsed by superstars. Our prediction is consistent with Brown (2011), since dropping out of the competition is an unambiguous indicator of zero effort.

In order to test our prediction, ideally, we need a setting where we can clearly identify superstars and track tournament participation decisions. Financial analysts offer such a setting. Every year, financial analysts who perform well are recognized by *Institutional Investor*, an influential magazine, as “All-Stars.” Star analysts are better performers and their superior performance is remarkably consistent (Stickel, 1992; Desai et al., 2000; Gleason and Lee, 2003; Leone and Wu, 2007). In addition, despite the influence of the brokerage house, analysts have certain flexibility in choosing which firms to follow.<sup>1</sup> Once they decide to initiate (terminate) coverage of a firm, they effectively enter (end) a firm-level tournament with other analysts following the same firm. Therefore, their coverage decisions reflect their tournament participation decisions, and these decisions are empirically observable.

The competition among analysts following the same firm can be regarded as a tournament, because the reward to the winner is disproportionately high. The client of sell-side analysts is typically the professional money manager, who has low-cost access to many sell-side analysts’ research. When she has questions on a particular firm, she is likely to consult the top analyst covering the firm. Therefore, being the top analyst means high attention from the

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<sup>1</sup> Our results do not depend on the assumption that analysts have flexibility in choosing firms to follow. To the extent that the analyst’s winning the firm-level competition is important to the brokerage house that employs the analyst, the brokerage house may allocate analysts to avoid competing with stars.

money manager, which helps analysts enormously to gain name recognition in the buy-side community. The name recognition increases analysts' chances of being (re)elected as an All-star.<sup>2</sup> In addition, being the top analyst offers bargaining powers with the management of the firm being covered and increases the analyst's abilities to bring the firm's investment banking business to her brokerage house, offering her considerable leverage in negotiating with her employer on remuneration and career advancement opportunities. In fact, one of the rewards of winning the firm-level competition is documented in Mikhail et al. (1999) and Hong and Kubik (2003), who show that those analysts who outperform others are likely to move to a more prestigious brokerage house, representing higher status and better pay.

Our discussions above suggest that analysts are motivated to win the firm-level tournament, i.e., the competition among analysts covering the same firm. Since star analysts are strong and seemingly superior competitors, we hypothesize that non-star analysts avoid a direct competition with the stars.<sup>3</sup> We label this as "competition avoidance effect". Our hypothesis however is not without tension, since Brown et al. (2015) report that financial analysts being surveyed indicate that competition is not of first-order importance to them in their coverage decisions. Therefore, empirically how competition affects analyst coverage remains an open question.

In addition to our central hypothesis, we propose the following related hypotheses. These hypotheses not only are interesting by themselves but also offer further evidence that

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<sup>2</sup> As a matter of fact, the analyst's excellent work with one or two firms she covers is typically cited by Institutional Investor's All-star Ranking Report as justifications for her being selected as an "All-star" (see, e.g., Appendix 2 for an excerpt from the 2008 *Institutional Investor* All-star Ranking Report).

<sup>3</sup> We mainly use *Institutional Investor*'s All-star designation to identify strong competitors. Later we show that our conclusion continues to hold when we use other ways to identify them.

non-stars' reluctance to cover the same firm as stars is driven by competition-induced incentives. The first hypothesis is related to the definition of star analysts. Empirically, we consider all analysts ranked by *Institutional Investor* in its All-star election (runners-up and members of first-, second-, and third-team) as star analysts. However, differences exist among these analysts. Clearly, being recognized as team members (first-, second- or third-team members) is more prestigious than being recognized as runners-up.<sup>4</sup> Non-star analysts are likely to go to greater length to avoid competing with team members because team members are even tougher competitors than runners-up. We thus hypothesize that the competition avoidance effect is more pronounced, when we define star analysts as the team members than when we define star analysts as runners-up.

Second, tournament participants are more incentivized to win when there is greater discrepancy in rewards between losers and winners (i.e., the opportunity cost of losing is greater). Using Baker and Wurgler (2006) investor sentiment index, Groysberg et al. (2011) find that the pay differentials among financial analysts are greater during periods of high investor sentiment. For example, the ratio of the 90<sup>th</sup> percentile of analysts' pay to the 10th percentile is 255% in 1990, a year of low investor sentiment, while it is 610% in 2000, a year of high investor sentiment. A greater difference in pay between winning and losing indicates greater rewards for winning. In periods of high investor sentiment, winning the firm-level competition carries higher rewards and analysts have stronger incentives to avoid competing with the stars. We therefore

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<sup>4</sup> There is a substantial difference between team members and runners-up. As we can see from the *Institutional Investor's* All-star Ranking Report in Appendix 2, while all team members receive positive coverage in the report, only names of runners-up are mentioned and there is zero discussion of their presumably excellent performance.

hypothesize that the competition avoidance effect is more pronounced in years of high investor sentiment.<sup>5</sup>

Third, our discussions are based on the assumption that financial analysts are able to adjust their coverage decisions based on who else is covering the firm.<sup>6</sup> Since institutional investors are the main consumer of analysts' research (O'Brien and Bhushan, 1990), analysts' coverage discretions are likely to be more limited for firms with high institutional ownership, where analysts' research is in greater demand. We thus hypothesize that the competition avoidance effect is more (less) pronounced for firms with lower (higher) institutional ownership.

We next consider the impact of firms' uncertainty on the competition avoidance effect. The advantage of star analysts over non-star analysts lies partially in better access to insiders. However, for firms with great uncertainties, insiders' information is likely to be noisy and the advantage of star analysts over non-stars is small. Since star analysts are less formidable competitors, non-star analysts' incentives to avoid a direct competition with them are weaker. We therefore hypothesize that the competition avoidance effect is less pronounced for firms with greater uncertainties.

Our argument is based on the notion that it's optimal for non-star analysts to avoid competing with stars. However, this notion may be untrue for non-star analysts with

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<sup>5</sup> One might expect that when investor sentiment is high, non-star analysts are more engaged in competing against star analysts because of the high pay difference. This, however, is not consistent with our empirical analysis.

<sup>6</sup> This assumption is supported by the survey results in Brown et al. (2015) since many analysts indicate that "Other sell-side analysts cover the company" is "very important" in their coverage decision. Anecdotal evidence also lends support. For example, Barron's reported on January 13, 2016 that Rudolf Hokanson, a financial analyst, discontinued coverage of the entire energy sector, which included house-hold names, such as British Petroleum. (<http://blogs.barrons.com/stockstowatchtoday/2016/01/13/this-energy-analyst-just-suspended-coverage-of-all-his-oil-stocks/>)

exceptionally high or low abilities. Non-stars with high abilities may have a reasonable chance against stars and it may be rational for them to compete directly with stars. The incentives of low-ability non-star analysts to avoid competing with stars are low, because they can't win the firm-level competition even if they switch to other firms. This discussion yields the prediction that the competition avoidance effect is more pronounced for non-stars with average abilities.

Next, we examine the consequence of avoiding direct competition with star analysts. Our prior discussions suggest that winning the firm-level competition helps non-stars to gain recognition in the buy-side community and paves the way for non-stars to be recognized as stars. Since non-star analysts who avoid direct competition with star analysts face lower hurdles to win the firm-level tournament, we expect them to have higher odds of winning the competition and, ultimately, experience higher likelihood of being recognized as stars. We thus predict that the likelihood of non-star analysts becoming a star analyst is higher for those who avoid direct competitions with star analysts.

We test our main hypothesis, using a sample of 39,047 firm-year observations from 1993 to 2010. Specifically, we examine the association between the change in star coverage and the change in non-star coverage. If our central hypothesis is true, we expect the association to be negative.<sup>7</sup> This change model research design is important because it alleviates alternative explanations related to non-time-varying firm characteristics. One such explanation is

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<sup>7</sup> Another way to test our hypothesis is to examine analysts' decisions to terminate or initiate coverage of firms. However, we note that some analysts may choose to initiate coverage of a firm while some other analysts may choose to terminate the coverage of the firm simultaneously. Since studying either the termination or the initiation of coverage *alone* offers an incomplete picture of analyst coverage, we need to consider both decisions in our analyses, which implies running two regressions rather than one. We feel that this approach is unnecessarily complicated without adding new insights. Having said this, our results remain qualitatively the same if we use this alternative research design.

that star analysts and non-star analysts have different incentives and they self-select to cover different types of firms. To the extent that firm characteristics that attract analysts' coverage remain constant over time, our research design provides a robust defense against this alternative explanation.

Our descriptive statistics offer strong evidence that non-star analysts avoid competing with star analysts. Using firms with no change in star analyst coverage as a benchmark, we find that on average, the number of non-star analysts following drops by 1.07 for firms with an increase in star coverage, while it increases by 0.94 for firms with a decrease in star coverage.

We next use multivariate ordered logistic regressions to control for changes in known determinants of analyst coverage (firm size, book-to-market ratio, leverage, institutional ownership, R&D expenses, advertising expenses, CAPM beta and ROA).<sup>8</sup> We find that the odds of observing an increase in the non-star coverage are lower (higher) by 58% (125%) for firms with an increase (a decrease) in star analyst coverage than for firms with no change in star analyst coverage. Our results are consistent with the notion that non-star analysts avoid direct competitions with star analysts.

Our results related to other hypotheses are generally supportive. We find that the odds of observing an increase in non-star coverage are higher by an additional 12% when there is a decrease in the number of team members (All-star First-team, Second-team or Third-team members) than when there is a decrease in the number of runners-up following the firm. This

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<sup>8</sup> Using multinomial logistic regressions yields qualitatively similar results.

finding suggests that non-star analysts deem the team members as tougher competitors than runners-up and go to greater lengths to avoid competing with them directly.<sup>9</sup>

Turning to our hypothesis related to pay differentials, we find that when there is an increase in star coverage, the odds of observing an increase in non-star coverage are reduced by an additional 14% in years of higher investor sentiment. This finding is consistent with our hypothesis that the higher pay differentials among analysts during these years provide extra incentives for non-star analysts to win the firm-level tournament and these analysts choose to avoid competing with stars to maximize their winning odds.

To test our hypothesis that the competition avoidance effect is more (less) pronounced if analysts have more (less) discretion in determining their coverage, we split our sample by the median of institutional ownership. Our results indicate that the competition avoidance effect is reduced by about 13% for firms with larger institutional ownership, lending support to our hypothesis.

We then examine our hypothesis that the competition avoidance effect is less pronounced for firms with greater uncertainties. We measure uncertainties using both stock return volatility and cash flow volatility. We find that non-star analysts' avoidance of competing with star analysts is reduced by between 8% and 54% for firms with high uncertainties than for firms with low uncertainties, consistent with the view that the competition avoidance effect is less pronounced for firms with high uncertainties.<sup>10</sup>

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<sup>9</sup> Similarly, in untabulated tests, we find that non-star analysts are more reluctant to compete with current stars than with "were-stars", i.e., financial analysts who were previously selected as star analysts but not so in the current year.

<sup>10</sup> We obtain similar results when we use forecast dispersion to measure uncertainty.



To test the hypothesis that the competition avoidance effect is more pronounced for analysts with average abilities, we regress the likelihood of avoiding competition on an indicator of the analyst's ability, which equals 1, if the analyst's forecast accuracy is between the 10<sup>th</sup> and 90<sup>th</sup> percentile of its distribution, and 0 otherwise. The coefficient on the dummy is positive and significant, suggesting that analysts of average abilities are more likely to avoid competition than analysts of exceptionally low or high abilities.

Next, we test our hypothesis that the likelihood of becoming star analysts is greater for non-star analysts who avoid direct competition with star analysts. For each non-star, we compute her likelihood of dropping (initiating) the coverage of the firm when the star coverage of the firm increases (declines). This likelihood indicates her tendency to avoid direct competitions with star analysts. We find that non-stars' likelihood of becoming stars is higher for those who refrain from competing directly with stars. Specifically, the odds of becoming stars are higher by 98% for analysts who always avoid than for analysts who never avoid direct competitions with stars.

If indeed non-star analysts avoid competing with star analysts, we expect that these analysts will move to firms with lower star coverage. We investigate non-star analysts who change their coverage. Using analyst-firm-year level data, we find results in support of our expectation.

Furthermore, we assess how the competition avoidance effect influences the accuracy of consensus analysts' forecasts. Our multivariate regression results indicate that an increase in non-star analyst coverage is significantly associated with more accurate consensus forecasts, after controlling for the change in star analyst coverage. This finding indicates that, by reducing

the number of non-star analysts following and therefore diminishing the resources for information acquisition and processing, the competition avoidance effect mitigates the positive impact of increasing star coverage on the accuracy of consensus forecasts.

We subject our findings to a battery of robustness checks. We first test whether our results are driven by changes in analysts' status, from non-star to star or from star to non-star, which induce simultaneous changes in the opposite direction in the number of stars and in the number of non-stars. We identify these changes and adjust the number of analysts following accordingly. Our results continue to hold after these adjustments.<sup>11</sup> Second, we use an alternative window to measure analyst coverage. The new window starts from the announcement of current year's earnings and ends before the announcement of next year's earnings. We count the number of analysts who issue at least one one-year ahead EPS forecast for the firm in this longer window to measure analyst coverage. Our findings are robust towards this new measure. Third, we are able to replicate our main finding, using a sample of firms where the change in star-analyst coverage is not due to firm characteristics, but due to exogenous events, such as retirement or sudden death. This alleviates the concern that our findings are driven by unobservable firm characteristics, whose correlations with star coverage and non-star coverage take on different signs. Fourth, we consider an alternative industry-blind definition of star analysts, which defines a star analyst irrespective of the industry for which she

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<sup>11</sup> Another possibility is that brokerage firms assign a fixed number of analysts to cover one firm. If this is true, when a brokerage firm replaces a star (non-star) analyst with a non-star (star) analyst, the change in the star coverage is in the opposite direction of the change in the non-star coverage, suggesting ostensibly the competition avoidance effect. We address this concern by adjusting the number of analysts following. Specifically, if a star analyst replaces a non-star analyst from the same brokerage firm, the adjustment to the number of star (non-star) analyst following is -1(+1) in the year of change, and vice versa. Our inferences remain unchanged when we use the adjusted numbers, indicating that this possibility does not drive our findings.

is chosen. This definition yields similar results. Fifth, in un-tabulated tests, we examine whether the Reg FD and Global Research Analyst Settlement drive our results. Specifically, we remove the year of the event and the subsequent year from our sample. Our conclusions continue to hold, suggesting that our results are not completely explained by the changes in analyst coverage as a result of either the Reg FD or the Global Research Analyst Settlement.<sup>12</sup>

Our results are generally supportive of the idea that analysts bow out of the competition with superstars, identified through the “All-star” ranking. However, since analysts’ performance is publicly observable, there may be other ways to define stars. As an alternative, we choose stars based on their forecast accuracy and stock picking abilities, which are considered useful and important analysts’ performance measures in the literature (Hong and Kubik, 2003; Wu and Zang, 2009; Mikhail et al., 1999; Groysberg et al., 2011). We find that the competition avoidance effect is robust to these alternative ways to define strong players: analysts tend to avoid covering the same firm as accurate forecasters and excellent stock-pickers. These results suggest that the competition avoidance effect is not limited to the all-star designation.

Our study contributes to the literature in the following ways. First, our study extends prior research on the effectiveness of tournament-type competitions. Kale et al. (2009) document that firms with larger tournament incentives tend to perform better and have higher firm value. Kini and Williams (2012) show that tournament-based incentives motivate managers to choose risky firm policies. Francis et al. (2016) find that firms with higher relative peer quality experience higher stock returns and profitability performance. Taken together, these three studies indicate

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<sup>12</sup> In untabulated test, we also examine whether non-star analysts put in less effort in their work when competing with star analysts. We use forecast accuracy as a measure of analysts’ efforts and our results are generally confirmative.

that internal tournaments are an effective way to elicit efforts from senior executives. We show that the effectiveness of tournaments falters in the presence of a superstar, specifically, participants tend to “give up” and exert no effort, when a superior competitor enters the arena.

Ammann et al. (2016) document that after a CEO receives a prestigious media award, the competitors to her firm experience significant positive stock market performances, suggesting that the award motivates rivalry CEOs to perform better. Aharoni et al. (2016) demonstrate that when a firm is covered by more than one star analysts, these star analysts tend to provide more accurate forecasts for this firm than for other firms under their coverage. Both papers are seemingly consistent with the idea that star analysts encourage competition. A crucial distinction, however, exists between our paper and these two studies. In our paper, the tournament participants are unequal: star analysts are clearly favored than non-stars; while in the other two, the competition represents a fair game. In Aharoni et al. (2016), the competition is among stars, who have equal status, while the CEO receiving the media award is not necessarily deemed superior by her peers. In fact, Ammann et al. (2016) shows that the effect of the media recognition on peer firms is less pronounced when the award is determined by merits rather than luck, evidence consistent with our argument that the incentive effect of tournaments is weaker when tournament participants exhibit distinctive talents.

Second, our study extends prior research on analysts’ coverage decisions. Prior research documents that analyst coverage influences price informativeness, earnings manipulations, financing activities, firm valuation and cost of capital.<sup>13</sup> Kirk (2011) shows that firms are willing to pay for analyst coverage. All these findings highlight the importance of

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<sup>13</sup> For example, Brennan et al. (1993), Irvine (2003), Best et al.(2003), Roulstone (2003), Lang et al. (2004), Chang et al.(2006), and Yu (2008).

analyst coverage to listing firms. In fact, a long line of literature examines determinants of analyst coverage, and existing findings typically attribute the coverage decision to the characteristics of the analyst and the covered firm.<sup>14</sup> We contribute to this line literature by showing that analyst coverage decision is also affected by who else is following the firm.

Third, our study has implications for the literature on star analysts (Stickel 1992; Gleason and Lee 2003; Leone and Wu, 2007; Loh and Stulz, 2011). A common finding in this line of literature is that star analysts are superior to other analysts. Unsurprisingly, firms favor star analyst coverage and some firms even condition their choice of underwriters on the prospects of receiving the coverage (Krigman et al., 2001). Our results show that star analyst coverage leads to the consequence of driving away non-stars.<sup>15</sup>

Finally, our paper is related to the recent literature examining the impact of competition on analysts. Hong and Kacperczyk (2010) show that competition reduces analysts' bias while Yin and Zhang (2014) find that interim losers are more likely to issue bolder forecasts, suggesting that analysts are participants of tournaments. Similar to these two studies, we examine the effect of competition on analysts. Different from them, we focus on how the expected competition affects analysts' coverage decisions.

The rest of the paper proceeds as follows. Section 2 covers sample formation, variable measurement and descriptive statistics. Section 3 tests our central hypothesis. Section 4

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<sup>14</sup> Existing empirical research has found that analyst coverage is affected by the size and the growth of the firm (Bhushan, 1989), institutional ownership (O'Brien and Bhushan, 1990), R&D and advertising expenditure (Barth et al. 2001), analysts' underlying expectations (McNichols and O'Brien, 1997; Das et al., 2006), firm risks (Hong et al., 2000), and investors' demand for analyst research (Brown et al. 2015).

<sup>15</sup> Non-star analysts' competition avoidance reduces analyst coverage for firms that experience an increase in star coverage but it improves information environment of firms that non-star analysts switch their coverage to.

examines how the competition avoidance effect is affected by the star analyst ranking, investor sentiment, uncertainties and non-star's abilities. Section 5 investigates whether analysts who avoid competing directly with stars are more likely to be voted as // All-stars. Section 6 tests our main research question by using analyst-level data. Section 7 examines whether competition avoidance effect affects consensus forecast accuracy. Section 8 conducts robustness tests. Section 9 considers whether the competition avoidance effect is limited to the "All-star" setting. Section 10 concludes.

## **2 Sample formation, variable measurement and descriptive statistics**

### ***2.1 Sample formation and variable measurement***

We obtain the initial sample by merging COMPUSTAT with I/B/E/S. We require firms to be covered by financial analysts. The number of analysts following in year  $t$  is the number of distinct analysts who issue at least one one-year-ahead EPS forecast in the three months around the announcement date of earnings of fiscal year  $t$ . For example, if a firm reports the earnings of fiscal year 2000 in February 2001, we examine analyst forecasts in the I/B/E/S detail file from January 2001 to March 2001. If there are five analysts issuing one-year-ahead earnings forecasts for the firm during that period, the number of analysts following is five for fiscal year 2000. This measurement window provides reasonable assurance to identify analyst coverage, since analysts are likely to issue forecasts around earnings announcements (Ivković and Jegadeesh, 2004). In addition, it allows us to observe and control firm performance as of

year  $t$ , which may affect analysts' coverage. We test whether our results are sensitive to the choice of measurement window in Section 8.2.

We manually collect all-star analysts' information from *Institutional Investor*. *Institutional Investor* publishes its annual analyst rankings in October, and we consider all the analysts ranked (first-team, second-team, third-team and runners-up) as star analysts. Since "All-star" analysts are associated with industries, a firm is identified as with all-star analyst following only if the firm is in the industry for which this analyst is chosen as an "All-star". To identify industry expertise, we obtain Sector/Industry/Group (SIG) codes from I/B/E/S for every firm-year observation, and manually match these SIG codes with industry classifications assigned by *Institutional Investor*. We exclude "All-star" analysts in the "multi-industry," "small growth companies," and "government sponsored enterprise" categories because it is impossible to determine the analyst's specific industry expertise. To avoid look-forward bias, we determine whether an analyst is an "All-star" according to the last available *Institutional Investor* ranking prior to the earnings announcement date. For example, if Firm A announces year 2000's earnings in February 2001, we use the "All-star" ranking as of October 2000 to determine the "All-star" status.

We require the following variables to be non-missing: total assets, book-to-market ratio, leverage, institutional ownership, R&D expenses, advertising expenses, beta and ROA. These variables are from CRSP, COMPUSTAT or Thomson-Reuters Institutional Holdings (13F) database. All the variables are defined in the Appendix 1. Our final sample consists of 39,047 firm-year observations between 1993 and 2010.

## **2.2 Descriptive statistics**

Panel A of Table 1 reports the mean, 1<sup>st</sup> quartile, median, 3<sup>rd</sup> quartile and standard deviation for several variables. Our results show that on average, our sample firms are followed by 8.574 analysts, among whom 0.662 are star analysts and 7.912 are non-star analysts. The mean value of total assets is 10.642 billions. The mean value of the book-to-market ratio, computed as the book value of equity divided by market value of equity, is 0.537. The mean value of leverage, computed as book value of long-term debt and short-term debt divided by total assets, is 0.219, and the median value is 0.183. On average, institutional investors hold 58.6% of the ownership of our sample firms. R&D expenses and advertising expenses average 4.2% and 1.1% of total assets respectively. The mean value of beta (estimated by using the 36 monthly returns before the beginning of current fiscal year) is 1.004 and the mean value of ROA, computed as earnings before extraordinary items divided by total assets, is 1.4%.

Panel B reports the correlation coefficients. We document a strong positive correlation between the number of star analysts and the number of non-star analysts following the firm. This result indicates that firms followed by many non-stars are likely followed by many stars, suggesting that star analysts and non-star analysts are attracted by the same set of firm characteristics. Consistent with prior literature (Bhushan 1989; O'Brien and Bhushan, 1990; McNichols and O'Brien, 1997; Das et al., 2006), we find that the total number of analysts following is positively related to total assets, institutional ownership and ROA while it is negatively related to the book-to-market ratio (an inverse measure of growth).

### **3 Test of main hypothesis: the competition avoidance effect**



### *3.1 Univariate analysis*

In our univariate analysis, we compare changes in the number/percentage of non-star analysts following for three types of firms: firms with a decrease, firms with an increase and firms with no change in the number of star analysts following. If our main hypothesis is true, we expect that the number and the percentage of non-star analysts following will increase (decrease) for firms with a decline (an increase) in star coverage, relative to firms with no change in star coverage. This difference-in-difference design controls for both general time-series trends and firm characteristics that are time-invariant. For example, firms with a drop in star coverage must be followed by star analysts prior to the change and may be different from other firms in size and/or industry membership. To the extent that these characteristics do not vary across time, our approach controls for the differences.

Panel A of Table 2 reports the number and the proportion of non-star analysts following, together with the total number of analysts, for three types of firms: firms with an increase, firms with no change and firms with a decrease in star coverage from year  $t-1$  to year  $t$ . For firms with an increase in star coverage, we observe that on average the number of non-star analysts following drops by 0.847 and its proportion drops by 13.1%. Both changes are significant at the 1% level. The total number of analysts increases by 0.549, significant at the 1% level. For firms with no change in star coverage, we observe that the number of non-star analysts increases by 0.218 and the percentage of non-star analysts increases by 0.1%. The total number of analysts increases by 0.218, significant at the 1% level. For firms with a drop in star coverage, we find that the number of non-star analysts increases by 1.157 and its proportion increases by 13.8%.

Both changes are significant at the 1% level. The total number of analysts decreases by 0.239, significant at the 1% level.

Relative to firms with no change, on average, the number of non-star analysts following drops by 1.065, the proportion of non-star analysts drops by 13.2% and the total number of analysts increases by 0.331, for firms with an increase in star coverage. We observe the opposite for firms with a decrease in star coverage. For those firms, the number of non-star analysts following increases by 0.939, the percentage of non-star analysts following increases by 13.7% and the total number of analysts decreases by 0.457.

In sum, our results in Panel A suggest that there is a significant decrease (increase) in the number of non-star analysts following for firms with an increase (decrease) in the number of star analysts following. Our results support our main hypothesis and are consistent with the view that non-star analysts avoid competing with stars. In addition, we find that the total number of analyst following is not constant over time.

### *3.2 Multivariate regression analysis*

Prior literature has shown that analyst coverage is affected by the size and the growth of the firm (Bhushan, 1989), institutional ownership (O'Brien and Bhushan, 1990), R&D and advertising expenditure (Barth et al. 2001), firm performance (McNichols and O'Brien, 1997; Das et al., 2006) and firm risks (Hong et al., 2000). To alleviate the concern that the univariate approach ignores known determinants of analyst coverage, we next use a multivariate ordered logistic regression, whose specification is as follows:

$$Non - star Change_{jt} = \alpha_0 + \alpha_1 Star Increase_{jt} + \alpha_2 Star Decrease_{jt} + \alpha_3 \Delta Total Assets_{jt} + \alpha_4 \Delta B/M_{jt} + \alpha_5 \Delta Leverage_{jt} + \alpha_6 \Delta Institutional Ownership_{jt} + \alpha_7 \Delta R\&D_{jt} + \alpha_8 \Delta Advertising Expense_{jt} + \alpha_9 \Delta Beta_{jt} + \alpha_{10} \Delta ROA_{jt} + Year fixed effects + \epsilon_t ,$$

where

- $Non - star Change_{jt}$  equals 1 if the number of firm j's non-star analysts following increases, 0 if the number remains the same, and -1 if the number decreases;
- $Star Increase_{jt}$  is a dummy variable, which equals 1 if there is an increase in the number of firm j's star analysts following from year t-1 to year t and 0 otherwise;
- $Star Decrease_{jt}$  is a dummy variable, which equals 1 if there is a decrease in the number of firm j's star analysts following from year t-1 to year t and 0 otherwise;
- $\Delta Total Assets_{jt}$  is the change in logarithm of firm j's total assets from year t-1 to year t.
- $\Delta B/M_{jt}$  is the change in firm j's B/M ratio (book value of equity divided by market value of equity) from year t-1 to year t.
- $\Delta Leverage_{jt}$  is the change in firm j's leverage (book value of long-term debt and short-term debt divided by total assets) from year t-1 to year t;
- $\Delta Institutional Ownership_{jt}$  is the change in firm j's percentage of outstanding shares owned by institutions from year t-1 to year t;
- $\Delta R\&D_{jt}$  is the change in firm j's R&D expenses deflated by total assets from year t-1 to year t;
- $\Delta Advertising Expense_{jt}$  is the change in firm j's advertising expenses deflated by total assets from year t-1 to year t;

- $\Delta Beta_{jt}$  is the change in firm j's beta (estimated by using the 30 monthly returns before the beginning of the fiscal year) from year t-1 to year t;
- $\Delta ROA_{jt}$  is the change in firm j's ROA (earnings before extraordinary items to total assets) from year t-1 to year t.

We include both *Star Increase* and *Star Decrease* in our regression so that the benchmark case is when the star coverage remains the same. If our main hypothesis is true, we expect the coefficient on the *Star Increase* (*Star Decrease*) dummy to be negative (positive) and significant, indicating that the likelihood of an increase in the non-star analyst coverage is lower (higher) when the star coverage increases (decreases), than when the star coverage remains the same.<sup>16</sup>

Our regression results are reported in Panel B of Table 2. Model 1 does not control for firm characteristics, while Model 2 does. Since the results from both models are similar, we focus on the results when control variables are included. Consistent with our prediction, the coefficient estimate on *Star Increase* dummy is -0.874, significant at the 1% level. The related odds ratio is 0.417, suggesting that the odds of being in a higher non-star coverage change category are lower by close to 58% for firms with an increase in star analyst coverage than for firms with no change in star coverage. The coefficient estimate on *Star Decrease* dummy is 0.809, significant at the 1% level. The related odds ratio is 2.246, suggesting that the odds of being in a higher non-star coverage change category are higher by close to 125% for firms with a decrease in star analyst coverage than for firms with no change in star coverage. Our results

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<sup>16</sup> A change in the star status of the analyst may explain the negative coefficient on the *Star Increase* dummy. We discuss this possibility in the robustness check section.

clearly demonstrate that the change in the non-star analyst coverage is in the opposite direction of the change in the star analyst coverage.<sup>17</sup>

The coefficients on other variables take on signs suggested by prior studies. Consistent with Bhushan (1989), the coefficient on the change in total assets is positive and the coefficient on the change in book-to-market ratio (which is an inverse measure of growth) is negative, suggesting that large firms and growth firms are followed by more analysts. Similar to the finding in Knyazeva (2007), the coefficient on the change in leverage is negative, indicating that lower leverage is associated with more analysts following. O'Brien and Bhushan (1990) document that institutional ownership leads to more analysts following, and the positive coefficient on the change in institutional ownership is consistent with their finding. The positive coefficients on R&D and advertising expenditures suggest that, as documented in Barth et al. (2001), analyst following increases with the two expenditures. The negative coefficient on the change in beta shows that analyst following decreases when the firm's beta risk increases. Finally, the coefficient on the change in ROA is positive and significant, indicating that firms with better performance are followed by more analysts. This result is consistent with McNichols and O'Brien (1997) and Das et al. (2006).

In sum, the results in Table 2 show that non-star analysts avoid covering firms covered by stars, providing support to our main hypothesis.

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<sup>17</sup> An alternative explanation is that star analysts choose to follow firms with lower non-star analyst following. It is unlikely to be true because star analysts' concerns about competing with non-star analysts are likely to be less severe than non-star analysts' concerns about competing with all-star analysts. This is because all-star analysts may be more talented than non-star analysts (Leone and Wu, 2007) and the talented are probably less worried about competitions than the non-so-talented.

We also evaluate whether the competition avoidance effect is affected by the percentage change in the number of all-star analysts following the firm. The idea is that the withdrawal/addition of one star analyst matters more to a firm followed by two star analysts than to a firm followed by ten star analysts. While this idea has its conceptual appeals, its influence on our results is limited, because the majority of firms in our sample are not covered by star analysts and the percentage change can't be computed for them. For the firm-year observations where we are able to compute this percentage change, our untabulated test results show that indeed the competition avoidance effect is more pronounced for firms with a larger percentage change in the star coverage.

#### **4 The impact of star analyst ranking, investor sentiment, analysts' discretion, and uncertainties on the competition avoidance effect**

##### ***4.1 The impact of the star analyst ranking***

Our central hypothesis is based on the premise that non-star analysts avoid competing with star analysts. We call this the competition avoidance effect. We also posit that the competition avoidance effect is more pronounced when the star analyst is a member of the first-team, second-team and third-team than when the star analyst is a runner-up. This section tests this hypothesis.

While the division between team members and runners-up is arbitrary, this division is based on our reading of *Institutional Investor's* All-star Ranking Report. Appendix 2 provides an exact copy of the text of the report for the Gaming and Lodging Industry in 2008. As we can see, while all team members receive positive coverage in the report, only names of runners-up are

mentioned and there is zero discussion of their presumably excellent performance, indicating a substantial difference between team members and runners-up.

Empirically, we use a multivariate ordered logistic regression approach to conduct our test. The dependent variable is *Non-star Change*. The main independent variables are *FST Increase/Decrease* and *Runner-up Increase/Decrease*, four dummy variables. *FST Increase/Decrease* equals one, if the number of “All-star” first-team, second-team or third-team analysts following the firm increases/decreases, and zero otherwise. *Runner-up Increase/Decrease* equals one, if the number of “All-star” runners-up following the firm increases/decreases, and zero otherwise. Because all dummies are included in the regression, the coefficient on one dummy represents the effect incremental to the other dummies. If our hypothesis is true, we expect the coefficient on *FST Increase/Decrease* to be more negative/positive than the coefficient on *Runner-up Increase/Decrease*.

Our results are reported in Table 3. Model 2 controls for firm characteristics while Model 1 does not. Because the results from Model 1 and Model 2 are similar, we focus on the multivariate regression results to avoid unnecessary repetition. The coefficient on *FST Increase* is -0.813 and the coefficient on *Runner-up Increase* is -0.718.<sup>18</sup> The two are not significantly different. The coefficient on *FST Decrease* is 0.743 and the coefficient on *Runner-up Increase* is 0.685. The difference between the two is significant at the 5% level. Examining the odds ratios (2.101 vs. 1.983) reveal that the odds of observing an increase in the non-star coverage are

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<sup>18</sup> These results indicate that when the coverage from members of the First-, Second- or Third-Team increases, the odds of having an increase in non-star coverage are reduced by 56%. If the coverage from members of the runner-up list also increases, the odds of having an increase in non-star coverage will be further reduced by 51%.

higher by an additional 12% when there is a decrease in the number of team members following than when there is a decrease in the number of runners-up following.

In sum, Table 3 shows that a decrease in star coverage results in more pronounced competition avoidance effect when star analysts are more highly ranked.

#### **4.2 The impact of investor sentiment**

We predict that the competition avoidance effect is more pronounced in years with high investor sentiment. This section tests this prediction.

We use ordered logistic regression approach. The dependent variable is *Non-star Change*. Our main independent variables are *Star Increase/Decrease*, *High investor sentiment* and their interaction terms. *High investor sentiment* is a dummy, which equals 1 for years of high investor sentiment, and equals zero for other years. According to Baker and Wurgler (2006) investor sentiment index, 1994, 1995, 1996, 1997, 1999, 2000, 2001, 2006 and 2007 are classified as high investor sentiment years and other years in our sample are classified as low investor sentiment years. If our prediction is true, we expect the coefficient on *Star Increase \* High investor sentiment* to be negative and significant, and the coefficient on *Star Decrease \* High investor sentiment* to be positive and significant.

Our results are reported in Table 4. Model 2 includes control variables while Model 1 does not. Because the results from both models are similar, we focus on the multivariate regressions results (Model 2). The coefficient on *Star Increase \* High investor sentiment* is -



0.157, significant at the 5% level. The related odds ratio (0.86) suggests that when there is an increase in the star coverage, the odds of being in a higher non-star coverage change category are reduced by an additional 14% in years of high investor sentiment than in other years. The coefficient on *Star Decrease \* High investor sentiment* is positive is 0.087, not significant at the 10% level.

In sum, our results in Table 4 indicate that the competition avoidance effect is more pronounced in years with high investor sentiment.

#### **4.3 The impact of analysts' discretion**

This section tests the hypothesis that the competition avoidance effect is more (less) pronounced for firms with low (high) institutional ownership, where analysts have more (less) discretion in their coverage decisions.

Our indicator of high institutional ownership is *High Inst* (dummy). It equals 1 if institutional ownership in year t-1 is above the sample median, and 0 otherwise. We use the regression approach. The dependent variable is *Non-star Change*. Our main independent variables are *Star Increase/Decrease*, *High Inst*, and their interaction terms.

Our regression results are reported in Table 5. Model 1 reports results where we don't include control variables and Model 2 reports results where control variables are added. In Model 1 the coefficients on interaction terms are not significant. In Model 2, the coefficient on *Star Increase* is -0.927, significant at the 1% level. The coefficient on *Star Increase \* High Inst* is 0.126, significant at the 5% level, suggesting that the effect of competition avoidance is more

(less) pronounced for firms with low (high) institutional ownership. This finding lends support to our hypothesis.

#### **4.4 The impact of uncertainties**

We hypothesize that the competition avoidance effect is affected by firms' uncertainties. This section tests it.

We use two indicators of high uncertainty. The first is based on the return volatility. It's a dummy variable, which equals one if the return volatility is greater than the sample median and equals zero otherwise. Return volatility is computed as the standard deviation of the 24 monthly returns before the beginning of the fiscal year. The second is a dummy based on the cash flow volatility. It equals one if the cash flow volatility is greater than the sample median and equals zero otherwise. Cash flow volatility is computed as the standard deviation of 8 quarterly cash flow ratios (cash flow from operations deflated by total assets) prior to current fiscal year.<sup>19</sup>

Similar to prior analyses, we use a regression approach. The dependent variable is *Non-star Change*. Our main independent variables are *Star Increase/Decrease*, our indicator of high uncertainty, and their interaction terms.

Our regression results are reported in Table 6. Panel A reports the results where uncertainty is measured by return volatility. When we control for firm characteristics, the coefficient on *Star Increase* is -1.038 and the coefficient on *Star Increase \* High uncertainty* is

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<sup>19</sup> We also tried to use forecast dispersion as an alternative way to measure firm uncertainty. Our results are similar.

0.429, both significant at the 1% level. The related odds ratios suggest that in response to an increase in star coverage, the odds of observing an increase in the non-star coverage change category are reduced by 65% for firms with low uncertainty. However, this reduction is weakened by 54% for firms with high uncertainty. Turning to the cases of a decrease in star coverage, the coefficient on *Star Decrease* is 0.841, significant at 1% level and the coefficient on *Star Decrease \* High uncertainty* is -0.082, significant at the 10% level. The related odds ratios suggest that the odds of observing an increase in the non-star coverage change category are higher by 132% for firms with low uncertainty. However, this reduction is weakened by 8% for firms with high uncertainty.

Panel B reports results where uncertainty is measured by cash flow volatility. Model 2 shows that the coefficient on *Star Increase* is -0.949 and the coefficient on *Star Increase \* High uncertainty* is 0.164, both significant at the 1% level. The related odds ratios suggest that in response to an increase in star coverage, the odds of observing an increase in the non-star coverage change category are reduced by 61% for firms with low uncertainty. However, this reduction is weakened by 18% for firms with high uncertainty. In the case of a decrease in star coverage, the coefficient on *Star Decrease* is 0.846, significant at 1% and the coefficient on *Star Decrease \* High uncertainty* is -0.083, significant at the 10% level. The related odds ratios suggest that the odds of observing an increase in the non-star coverage change category are higher by 133% for firms with low uncertainty. However, this reduction is weakened by 8% for firms with high uncertainty.

Overall, our results in Table 6 show that the competition avoidance effect is weakened by between 8% and 54% for firms with high uncertainties than for firms with low uncertainties.

#### 4.5 The impact of non-star analysts' abilities

To test whether the competition avoidance effect is more pronounced for analysts with average abilities, we regress the likelihood of avoiding the competition on an indicator of analysts' abilities. The dependent variable is a dummy variable which equals one if the analyst avoids competition in the current year, and zero otherwise. An analyst is deemed avoiding competition if she drops/initiates the coverage of the firm when the star coverage of the firm increases/declines. The main independent variable is *Average ability*, a dummy variable which equals one if  $Accuracy_{it}$  is between the 10th and 90th percentile of its distribution, and zero otherwise. We run logit regressions and base our inferences on standard errors clustered by analyst.

$Accuracy_{it}$  is a measure of forecast accuracy of analyst  $i$  in year  $t$ . It's based on  $Accuracy_{ijt}$ .  $Accuracy_{ijt} = \frac{AFE_{max_{jt}} - AFE_{ijt}}{AFE_{max_{jt}} - AFE_{min_{jt}}}$ , where  $AFE_{max_{jt}}$  and  $AFE_{min_{jt}}$  are the maximum and minimum absolute forecast errors for analysts following firm  $j$  in year  $t$ .  $AFE_{ijt}$  is the absolute forecast error (absolute value of difference between forecasted value and actual value) for analyst  $i$  following firm  $j$  in year  $t$ . The forecast error is based on the last one-year-ahead EPS forecast an analyst issues before the fiscal year-end.  $Accuracy_{ijt}$  takes on values between 0 and 1. A higher value of  $Accuracy_{ijt}$  indicates that this analyst is more accurate among analysts following the same firm in the same year. As we can see, when  $AFE_{ijt} = AFE_{min_{jt}}$ , i.e., when the analyst's forecast error is the lowest, the value of  $Accuracy_{ijt}$  equals 1. We average across all firms followed by analyst  $i$  in year  $t$  to compute  $Accuracy_{it}$ .

We follow Leone and Wu (2007) and control the following variables: *Stock picking<sub>it</sub>*, *Boldness<sub>it</sub>*, *Optimism<sub>it</sub>*, *Frequency<sub>it</sub>*, *Brokerage size<sub>it</sub>*, *Following<sub>it</sub>* and *Experience<sub>it</sub>*. We offer more explanations on these control variables below. Detailed variable definitions are also provided in the Appendix 1.

*Stock picking<sub>it</sub>* is a measure of the stock picking ability of analyst i in year t. It's based on *Stock picking<sub>ijt</sub>*.  $Stock\ picking_{ijt} = \frac{Ret_{ijt} - Ret\ min_{jt}}{Ret\ max_{jt} - Ret\ min_{jt}}$ , where  $Ret\ max_{jt}$  and  $Ret\ min_{jt}$  are the maximum and minimum four-day [0,+3] (day 0 is the stock recommendation announcement date) size-adjusted returns for buy and sell recommendations (returns for sell recommendations are multiplied by -1);  $Ret_{ijt}$  is the four-day [0,+3] size-adjusted returns for buy and sell recommendations for analyst i following firm j in year t.<sup>20</sup> *Stock picking<sub>ijt</sub>* is then averaged across all firms followed by analyst i in year t to reach *Stock picking<sub>it</sub>*. A higher value of *Stock picking<sub>it</sub>* indicates better stock-picking ability.

*Boldness<sub>it</sub>* is a measure of the relative boldness in earnings forecasts issued by analyst i in year t.  $Boldness_{ijt} = \frac{Dev_{ijt} - Dev\ min_{jt}}{Dev\ max_{jt} - Dev\ min_{jt}}$ .  $Dev\ max_{jt}$  and  $Dev\ min_{jt}$  are the maximum and minimum deviation from the consensus forecast for analysts following firm j in year t.  $Dev_{ijt}$  is the deviation from the consensus forecast for analyst i following firm j in year t. The consensus forecast is the average of all forecasts made in the prior three months. Forecast deviation is computed as the absolute value of the difference between the analyst's forecast (the last one-year-ahead EPS forecast an analyst issues before the fiscal year-end) and the consensus

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<sup>20</sup> If analysts have higher stock picking ability, their buy/sell recommendation shall be validated by a more positive/negative subsequent return. This idea stands behind the relative stock picking ability ranking.

forecast. These relative rankings are then averaged across the firms followed by analyst i in year t.

*Optimism<sub>it</sub>* is a measure of the relative optimism of forecasts issued by analyst i in year t.

$Optimism_{ijt} = \frac{Bias_{ijt} - Bias_{min_{jt}}}{Bias_{max_{jt}} - Bias_{min_{jt}}}$ . *Bias<sub>max<sub>jt</sub></sub>* and *Bias<sub>min<sub>jt</sub></sub>* are the maximum and minimum forecast bias for analysts following firm j in year t. *Bias<sub>ijt</sub>* is the forecast bias for analyst i following firm j in year t. Bias is computed as the analyst forecast (the last one-year-ahead EPS forecast an analyst issues before the fiscal year-end) minus the actual earnings. These relative rankings are then averaged across the firms followed by analyst i in year t.

*Frequency<sub>it</sub>* is a measure of the relative frequency at which analyst i issues forecasts one-year-ahead forecast in year t.  $Frequency_{ijt} = \frac{freq_{ijt} - freq_{min_{jt}}}{freq_{max_{jt}} - freq_{min_{jt}}}$ . *freq<sub>max<sub>jt</sub></sub>* and *freq<sub>min<sub>jt</sub></sub>* are the maximum and minimum forecast frequency for analysts following firm j in year t. *freq<sub>ijt</sub>* is forecast frequency for analyst i following firm j in year t. Forecast frequency refers to the number of times the analyst issues an one-year-ahead EPS forecast. These relative rankings are then averaged across the firms followed by analyst i in year t.

*Brokerage size<sub>it</sub>* is a measure of the relative size of the brokerage house employing analyst i in year t.  $Brokerage\ size_{it} = \frac{Broker_{it} - Broker_{min_t}}{Broker_{max_t} - Broker_{min_t}}$ . *Broker<sub>max<sub>t</sub></sub>* and *Broker<sub>min<sub>t</sub></sub>* are the maximum and minimum number of analysts employed by a brokerage firm in year t. *Broker<sub>it</sub>* is the number of analysts employed by the brokerage house with which analyst i is affiliated in year t.

$Following_{it}$  is a measure of the relative following by analyst  $i$  in year  $t$ .  $Following_{it} = \frac{follow_{it} - follow_{min_t}}{follow_{max_t} - follow_{min_t}}$ .  $follow_{max_t}$  and  $follow_{min_t}$  are the maximum and minimum number of firms an analyst follows in year  $t$ .  $follow_{it}$  is the number of firms analyst  $i$  follows in year  $t$ .

$Experience_{it}$  is a measure of the relative experience of analyst  $i$  in year  $t$ .  $Experience_{it} = \frac{Years_{it} - Years_{min_t}}{Years_{max_t} - Years_{min_t}}$ .  $Years_{max_t}$  and  $Years_{min_t}$  are the maximum and minimum experience of all analysts in year  $t$ .  $Years_{it}$  is the experience of analyst  $i$  in year  $t$ . Experience refers to the number of the years the analyst has appeared in I/B/E/S.

Our results are reported in Table 7. As we can see, the coefficient on *Average ability* is 0.397, significant at the 1% level. The related odds ratio indicates that the odds of avoiding competition are higher by 49% for analysts of average ability than for analysts of exceptionally high or low ability.

## 5 The likelihood of becoming a star

We posit that the likelihood of non-star analysts becoming a star analyst is higher for those who avoid direct competition with star analysts. This section tests it.

We restrict our sample to non-star analysts and use a regression approach. The dependent variable is  $Star_{i,t+1}$ , which equals 1, if a non-star analyst becomes a star analyst in year  $t+1$ , and 0 otherwise. The main independent variable is  $Comp-avoid_{it}$ , an analyst-year variable. It represents the likelihood that a non-star analyst  $i$  avoids direct competition with star analysts in year  $t$ . Specifically, for each non-star-and-firm pair in year  $t$ , we use a dummy to

indicate whether the analyst exhibits competition avoidance behaviors (i.e., dropping/initiating the coverage of the firm when the star coverage of the firm increases/declines). We take the average of the dummy across all firms followed by the non-star to obtain *Comp-avoid*. A higher value for *Comp-avoid* indicates a higher likelihood that the non-star analyst avoids direct competitions with stars.

Prior literature shows that other analyst characteristics also affect the likelihood of her being chosen as a star analyst. We control the following variables: *Accuracy<sub>it</sub>*, *Stock recommendation profitability<sub>it</sub>*, *Boldness<sub>it</sub>*, *Optimism<sub>it</sub>*, *Frequency<sub>it</sub>*, *Brokerage size<sub>it</sub>*, *Following<sub>it</sub>* and *Experience<sub>it</sub>*. These control variables are discussed in Section 4.5.

Our logistic regression results are reported in Table 8. Not surprisingly, the coefficient on *Accuracy* is positive and significant at 1% level, indicating that accurate forecasters are more likely to be selected as “All-star” analysts. Stickel (1992) shows that “All-star” analysts forecast more frequently. Consistent with his finding, the coefficient on *Frequency* is positive and significant. Prior studies document that larger brokerage firms employ better analysts (Clement, 1999). Besides, *Brokerage size* is positively related with the likelihood of being selected as “All-star”. The coefficient on *Following* is positive and significant, suggesting that analysts following many firms are more likely to be chosen as “All-star”. Our focus is on *Comp-avoid*. Its coefficient is 0.685, significant at the 1% level. The related odds ratio is 1.983, suggesting that the odds of becoming a star are higher by 98% for analysts who always avoid than for analysts who never avoid direct competitions with stars.



In sum, after controlling for several known analyst characteristics, we find that non-stars who avoid direct competitions with stars are much more likely to be chosen as a star. This finding suggests the benefit of avoiding competitions to non-stars.

## **6. The competition avoidance effect—analyst-level evidence**

To provide more direct evidence on competition avoidance effect, we examine our research question by using firm-analyst-year level observations. Specifically, we first identify all analysts who switch their coverage. Let's say that an analyst switches from A and B to C and D (That is, this analyst drops the coverage of A and B and initiates the coverage of C and D). We then compare the star coverage of each firm initiated by the analyst (i.e., C and D) with the average star coverage of firms dropped by the analyst (i.e., the average star coverage of A and B). The comparison outcome can be "Increase", "Decrease" or "The same". We use a categorical variable, *Decrease\_Cov<sub>ijt</sub>*, to indicate the three possibilities. *Decrease\_Cov<sub>ijt</sub>* equals 1/0/-1 if analyst j initiates coverage for firm i and firm i's star coverage is lower than/the same as/higher than the average star coverage of firms dropped by analyst j in year t. We conduct empirical analyses and report our results in Table 9.

Panel A shows that when the dropped firms experience an increase in star coverage, the star coverage of initiated firms on average is lower than the star coverage of dropped firms (the mean value of *Decrease\_Cov* is 0.110). However, when the dropped firms do not experience an increase in star coverage, the star coverage of initiated firms on average is higher than the star coverage of dropped firms (the mean value of *Decrease\_Cov* is -0.12). The difference in *Decrease\_Cov* between the two scenarios is significant at the 1% level. This result clearly

indicates that when firms currently covered by non-star analysts experience an increase in star coverage, non-stars move to firms with lower star coverage.

Panel B reports detailed distribution of *Decrease\_Cov*. We find that when dropped firms experience an increase in star coverage, close to 50% of newly covered firms have lower star coverage than dropped firms. However, only 27% of newly covered firms have lower star coverage than dropped firms, when dropped firms do not experience an increase in star coverage. The results in this panel add further support to the notion that non-stars tend to avoid competing with stars.

Panel C reports the results when we regress *Decrease\_Cov* on *Dropped Star Increase*, a dummy which takes the value of 1, if the dropped firms experience an increase in star coverage, and 0 otherwise, and control variables. The coefficient on *Dropped Star Increase* is positive and significant, suggesting that, when the dropped firms experience an increase in star coverage, we are likely to observe non-stars moving to cover firms with lower star coverage.

Panel D investigates the relation between the likelihood of the non-star dropping out of IBES and the increase in star coverage of firms currently covered by the non-star. Our dependent variable is a dummy, which equals 1 if the analyst drops out, and 0 otherwise. We regress it on *Dropped Star Increase*, and other analyst characteristics. The coefficient on *Dropped Star Increase* is insignificant. This result is inconsistent with the notion that our main results are due to non-stars dropping out of IBES.

Taken together, Table 9 shows that when firms currently covered by non-star analysts experience an increase in star coverage, non-stars move to firms with lower star coverage. In

addition, the likelihood of non-stars dropping out of IBES is unrelated to the increase in current firms' star coverage. Overall, these findings lend support to our claim that non-stars avoid competing with stars.

## **7. Does non-star coverage influence consensus forecast accuracy?**

Our results indicate that when the star coverage increases, non-star coverage is likely to decrease, implying that star analysts potentially thwart the competition among analysts. We now analyze the economic consequence of this finding. Specifically, we examine the impact of non-star analyst coverage on consensus forecast accuracy after controlling for star analyst coverage. We choose to focus on consensus forecast accuracy because it matters to investors and because it is an observable outcome which reflects the collective performance of all analysts following the firm.

Ex ante, it is difficult to predict whether non-star coverage has explanatory power incremental to star coverage. On one hand, we can argue that non-star coverage represents additional resources and efforts devoted to researching the firm and therefore it increases the consensus forecast accuracy; on the other hand, arguments can be made that star analysts dominate in information gathering and processing, relegating non-star analysts to a negligible role. We take our queries to the data.

Specifically, we use OLS regressions to regress the change in consensus forecast accuracy on *Star Increase/Decrease* dummies and *Non-star Increase/Decrease* dummies, controlling for changes in several firm characteristics. We report our results in Table 10.

Table 10 shows that the coefficient on the *Star Increase* dummy is 0.007, significant at the 1% level, while the coefficient on the *Non-star Increase* dummy 0.005, also significant at the 1% level. Our results suggest that non-star coverage, especially its increase, has incremental explanatory power for the consensus forecast accuracy.

To somewhat quantify the impact of the competition avoidance effect, we assume that star analyst coverage is not correlated to non-star analyst coverage, when the effect is absent. This is likely an understatement of the competition avoidance effect, because prior literature and our prior results indicate that star analysts and non-star analysts seem to be attracted by the same set of firm characteristics. Therefore, when the effect is absent, the correlation between the two types of coverage is likely positive. We nevertheless choose this assumption for simplicity.

Under the assumption above, absent the competition avoidance effect, an increase in star analyst coverage improves the accuracy of the consensus forecasts by 0.7%, and it does not alter non-star analyst coverage. The impact of the competition avoidance effect is reported in Table 3 (Panel B Model 2), which shows that increasing star coverage reduces the likelihood of increasing non-star-coverage by close to 19% (the odds ratio is reduced by 58%). Since increasing non-star coverage improves the consensus forecast accuracy by 0.5% (Table 10 Model 1), our results indicate that close to 14% of the benefits brought by increasing star coverage is offset by the competition avoidance effect<sup>21</sup>.

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<sup>21</sup> An increase in star coverage leads to an improvement of 0.7% in the consensus forecast accuracy. The competition avoidance effect however results in a 19% chance that the non-star coverage will decrease, which reduces the forecast accuracy by 0.5%. 14% is computed by dividing the expected value of the drop in forecast

Overall, we find consistent evidence that an increase in non-star coverage is associated with more accurate consensus forecasts, after controlling for the changes in star coverage. This is consistent with the notion that this increase implies greater resources devoted to collecting and processing information, which results in more precise consensus prediction of future earnings. Our results suggest that the existence of competition avoidance effect negatively influences the accuracy of consensus forecasts by discouraging non-star analysts from following firms with an increase in star coverage.

## **8. Robustness Tests**

### ***8.1 Rule out mechanical reasons***

#### *8.1.1 Methodology*

We have shown so far that the number of non-star analysts following increases (decreases) when the number of star analysts following decreases (increases). We attribute this finding to non-star analysts avoiding competition with stars. However, a change in the status of an analyst, from non-star to star or from star to non-star, can potentially explain our finding, because it induces simultaneous changes in the opposite direction in the number of stars and in the number of non-stars. For example, when the analyst becomes a star and retains her coverage, the firms she covers will see a simultaneous increase in the number of star analysts following and a drop in the number of non-star analysts following, leading to an ostensible

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accuracy (0.5%\*0.14) due to competition avoidance by the improvement in forecast accuracy (0.7%) due to the increase in star coverage.

manifestation of the competition avoidance effect.<sup>22</sup> This section discusses our empirical analysis conducted to investigate this possibility.

Specifically, we first identify a change in the analyst status and compute the necessary adjustment in the year of change. For example, if an analyst becomes a star, the adjustment to be made to the number of stars (non-star) is -1 (+1) in the year of change. Then, starting from the first year in which the firm appears in our sample, we cumulate the adjustment to be applied in each year, and our actual adjustment is based on the cumulated number. We use an example to demonstrate this adjustment process and explain why it is necessary to use the cumulated number.

Suppose analysts A, B and C follow the same firm for three years, starting from the first year the firm appears in our sample. In the second year, analyst B becomes a star and in the third year, analyst C becomes a star and analyst B remains a star. Analyst A is a non-star for the entire three years. As there is no change in the analyst following, there is no competition avoidance effect and the changes in star analysts and non-star analysts following are entirely due to the mechanical reason. If we are successful in adjusting for the mechanical reason, we shall observe that the adjusted numbers are identical in all three years.

The unadjusted number for stars (non-stars) is 0 (3), 1 (2) and 2 (1), respectively for the first, second and third year. If we ignore the adjustments of prior years, the adjustment to be made to the number of stars (non-stars) is -1 (+1) for both the second and the third years. As a result, the adjusted number for stars (non-stars) is 0 (3), 0 (3) and 1 (2) respectively for the first,

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<sup>22</sup> Conceptually, the alternative explanation is unlikely to be true because our results are based on a broad cross-section of data, and the limited occurrences of changes in status are unlikely to have a material effect on the results.

second and third year. This adjustment is not successful, because the adjusted numbers are not identical across the three years.

Using the cumulated number solves this problem. Under this approach, the adjusted number is 0 and 3 respectively for stars and non-stars in the second year. In the third year, the cumulated adjustment is -2 for the number of star analysts and +2 for the number of non-star analysts. Therefore the adjusted number is 0 and 3, respectively for stars and non-stars. The adjusted numbers are identical across all three years, accurately reflecting the absence of the competition avoidance effect. This example shows the importance of using the cumulated adjustment.

#### *8.1.2 Results*

After we adjust the number of analysts following, we conduct tests similar to those in Table 2. Our results are reported in Table 11 Panel A.

The model specification is the same as in Panel B of Table 2. Model 2 reports the results after controlling for firm characteristics. The coefficient on *Star Increase* is -0.704, significant at the 1% level. The related odds ratio is 0.495, suggesting that the odds of being in a higher non-star coverage change category is lower by 50% for firms with an increase in star analyst coverage than for firms with no change in star coverage. The coefficient on *Star Decrease* is 0.745, significant at the 1% level. The related odds ratio is 2.107, suggesting that the odds of being in a higher non-star coverage change category are higher by 111% for firms with a decrease in star analyst coverage than for firms with no change in star coverage.

In sum, Table 11 Panel A shows that the competition avoidance effect is robust towards considering the mechanical reason related to the change in the status of an analyst.

## ***8.2 Using an alternative window to measure analyst coverage***

Our prior results are based on the number of analysts following during the three months around the annual earnings announcement date. As we explained earlier, we choose this window to ensure a reasonable chance of detecting analyst coverage. However, an analyst who makes a forecast for the firm during the three months may terminate her coverage, and an analyst who fails to make a forecast during the period may initiate coverage in the later months. As analyst coverage is not based on contracts, this measurement error concern applies to all possible measurement windows.

Conceptually, it is not clear how this concern systematically affects our results related to the competition avoidance effect. Nonetheless, we test whether our results are robust to analyst coverage based on a longer one-year measurement window. This window starts after the announcement of earning of fiscal year  $t$  and ends before the announcement of earning of fiscal year  $t+1$ . From the I/B/E/S detailed file, we count the number of analysts who issue at least one one-year ahead EPS forecast for the firm in this alternative measurement window. We use hand-collected data to determine the number of star analysts among them. We repeat our prior analyses to examine whether the competition avoidance effect is robust towards the alternative way of defining analyst coverage.



Table 11 Panel B reports the results. The dependent variable is *Non-star Change*. Model 1 does not control for firm characteristics while Model 2 does. In Model 2, the coefficient on *Star Increase* dummy is -0.942 and the coefficient on *Star Decrease* dummy is 1.005, both significant at the 1% level. The related odds ratios suggesting that the odds of being in a higher non-star coverage change category are lower (higher) by 61% (173%) for firms with an increase (a decrease) in star analyst coverage than for firms with no change.

In sum, the results in Panel B indicate that our findings are robust towards using a longer measurement window to identify analyst coverage.

### **8.3 Using an exogenous sample**

Our prior results are subject to the concern that we fail to control for firm characteristics whose correlations with star analyst coverage and non-star analyst coverage take on different signs. It is difficult to pinpoint these factors, since prior literature and our correlation matrix indicate that firm characteristics have a similar impact on both stars and non-stars.

To address this concern, we try to replicate our main finding using a sample of firms where the decrease in star-analyst coverage is not due to firm characteristics, but due to exogenous events, such as retirement or sudden death. To construct the sample, we first identify star analysts who stop providing forecasts for all firms in I/B/E/S. Then we search FACTIVEA for articles containing either the name of the analyst or the name of the brokerage house employing her, in the year when she leaves I/B/E/S. We read articles to identify reasons for the disappearance. If the disappearance is due to a change in career, e.g. becoming a buy-

side analyst, promotion, health issues, sudden death and retirement, we treat this disappearance as exogenous. Our sample consists of firms that experience no change in star coverage (as control firms) and firms whose decrease in star coverage is entirely due to exogenous reasons (as treatment firms). The treatment sample consists of 119 firm-year observations.

We replicate our ordered logistic regression analyses on this sample. Specifically, we regress *Non-star Change* on *Star Decrease* dummy. *Star Decrease* dummy equals one, if the number of star analysts decreases for exogenous reasons, and zero if the number of star analysts remains the same. Our results are reported in Table 11 Panel C.

Model 1 shows the regression results without controlling for firm characteristics. The coefficient on *Star Decrease* is 0.338, significant at 5% level. Model 2 shows the regression results after controlling for firm characteristics. The coefficient on *Star Decrease* is 0.518 and the odds ratio is 1.171, indicating that the odds of having an increase in non-star coverage are higher by close to 17% for firms experiencing an exogenous decrease in star coverage than for firms with no change in star coverage.

In sum, Table 11 Panel C indicates that when there is an exogenous decrease in star coverage, the non-star coverage is much more likely to increase. This result shows that our results are unlikely explained by unobservable firm characteristics that are correlated with star coverage and non-star coverage in different ways.

#### ***8.4 Using an industry-blind definition of star analyst***

Our definition of star analyst is associated with industries. An analyst who is chosen as a star for Industry A but not for Industry B is deemed a star for Industry A firms but not for Industry B firms. In this section, we test whether our results are robust if we define star analysts regardless of the specific industry. That is, as long as an analyst is a star for one industry, she is deemed a star for all firms she covers.

Our results are reported in Table 11 Panel D. Model 1 does not control for firm characteristics while Model 2 does. In Model 2, the coefficient on *Star Increase* dummy is -0.882 and the coefficient on *Star Decrease* dummy is 0.819, both significant at the 1% level. The related odds ratios suggesting that the odds of being in a higher non-star coverage change category are lower (higher) by 59% (127%) for firms with an increase (a decrease) in star analyst coverage than for firms with no change.

In sum, our conclusion continues to hold if we use an industry-blind definition of star analysts.

## **9. General Competition**

The competition avoidance effect is based on the understanding that analysts have strong incentives to win the firm-level competition and their odds of winning are enhanced by avoiding strong competitors. Our prior results based on the “All-star” setting can be deemed a special case in which we identify strong players through the “All-star” designation. In this section, we consider other measures of strong competitors and test whether the competition avoidance effect continues to hold. If we obtain affirmative results, they serve as evidence that our central

message speaks to the general competition among analysts and is not limited to the “All-star” setting.

Specifically, we use the forecast accuracy and stock-picking abilities as a basis to re-define star analysts. Both are considered useful and important analysts’ performance measures in the literature (Hong and Kubik, 2003; Wu and Zang, 2009; Mikhail et al., 1999; Groyberg et al., 2011). The forecast accuracy and stock picking ability of analyst  $i$  in year  $t$  is measured by  $Accuracy_{it}$  and  $Stock\ picking_{it}$  respectively. Both variables are defined in Section 4.5. If  $Accuracy_{it} / Stock\ picking_{it}$  is among the top ten percentile of all analysts in year  $t$ , analyst  $i$  is deemed an accuracy based star/stock-picking-ability based star.

Our results based on the new definitions of star analysts are reported in Table 12. Since we further require  $Accuracy_{it}$  and  $Stock\ picking_{it}$  to be non-missing, our sample size decreases from 39,047 to 37,494. Column (1) reports results for accuracy-based stars. As we can see, the coefficient on *Star Increase* dummy is negative and significant and the coefficient on *Star Decrease* dummy is positive and significant, regardless whether we include control variables. Specifically, when control variables are included, the coefficient on *Star Increase* dummy is -0.715, significant at the 1% level. The related odds ratio is 0.489, indicating that the odds of being in a higher non-star coverage change category are reduced by about 51% for firms that experience a star coverage increase than for firms with no change in star coverage. The coefficient estimate on *Star Decrease* dummy is 0.977, significant at the 1% level. The related odds ratio is 2.656, indicating that the odds of being in a higher non-star coverage change category are increased by close to 166% for firms that experience a star coverage decrease than for firms with no change in star coverage.

Column (2) reports results for stock-picking-ability based stars. After controlling for firm characteristics, the coefficient estimate on *Star Increase* dummy is -0.779, significant at the 1% level. The related odds ratio is 0.459, indicating that the odds of being in a higher non-star coverage change category are reduced by about 54% for firms that experience a star coverage increase than for firms with no change in star coverage. The coefficient estimate on *Star Decrease* dummy is 0.920, significant at the 1% level. The related odds ratio is 2.510, indicating that the odds of being in a higher non-star coverage change category are increased by close to 151% for firms that experience a star coverage decrease than for firms with no change in star coverage.

In sum, using different measures of performance, Table 12 shows that analysts are reluctant to compete with strong competitors. These results not only are interesting by themselves but also suggest that our finding helps to address the broad research question how competition affects analyst coverage decisions.

## **10 Conclusions**

While prior literature offers evidence that tournament incentives are capable of eliciting efforts from tournament participants (Kale et al., 2009; Kini and Williams, 2012), we show that the effectiveness of tournament incentives crucially hinges on the assumption that the chances of winning the tournament are similar among participants. We predict that when the winning odds are reduced by the presence of superstars, tournament participants will choose to leave

the competition. We test this prediction, using the setting of financial analysts, because this setting allows us to identify superstars and track the tournament participation decisions.

Using a sample of 39,047 firm-year observations from 1993 to 2010, we empirically test our prediction. Star analysts are defined as all the analysts included in *Institutional Investor* “All-star” analyst rankings (first-team, second-team, third-team and runners-up). We find strong evidence that non-star analysts avoid competing with star analysts. Using firms with no change in star analyst coverage as a benchmark, we show that on average, the number of non-star analysts following drops by 1.065 for firms with an increase in star coverage, while it increases by 0.939 for firms with a decrease in star coverage. After controlling for known determinants of analyst coverage, we find that the odds of observing an increase in the non-star coverage are lower (higher) by 58% (125%) for firms with an increase (a decrease) in star analyst coverage than for firms with no change in star coverage.

In addition to our central hypothesis, we find that the competition avoidance effect is more pronounced for more highly-ranked star analysts, in years with higher investor sentiment, for firms with lower institutional ownership, for firms with lower uncertainties, and for analysts of average ability. These results not only are informative by themselves but also support our central hypothesis that the incentive to win the firm-level tournament discourages non-star analysts from covering the same firm as star analysts.

We next examine whether avoiding competition enhances non-star analysts’ chances of being recognized as stars. Our results suggest that the answer is affirmative. Specifically, the odds of becoming a star are higher by 98% for analysts who always avoid than for analysts who never avoid direct competitions with stars.

If indeed non-star analysts avoid competing with star analysts, we expect that non-stars will move to firms with lower star coverage. We empirically examine the sample of non-star analysts who experience changes in their coverage. Using analyst-firm-year level data, we obtain results in support of our expectation.

We investigate how competition avoidance effect shapes information environment by examining the impact on the accuracy of consensus analysts' forecasts. Our results show that increase in non-star analyst coverage is significantly associated with more accurate consensus forecasts, consistent with the view that by reducing the number of non-star analysts following and therefore diminishing the resources for information acquisition and processing, the competition avoidance effect mitigates the positive impact of increasing star coverage on the accuracy of consensus forecasts.

Our further analyses show that our findings are robust towards an alternative measurement window to determine analyst coverage, they are not driven by changes in analysts' status (from non-star to star or from star to non-star), they continue to hold in a sample where star analysts' departure is due to exogenous reasons, such as a career change or retirement, and they are robust to star analyst definition regardless of specific industry.

Lastly, we use the forecast accuracy and stock-picking ability as a basis to re-define star analysts. Our results are consistent with our hypothesis that analysts are reluctant to compete with strong competitors. This finding suggests that the competition avoidance effect is not limited to the "All-star" setting and addresses the effect of competition on coverage decisions in a broad sense.

In sum, we show that tournament participants will leave the competition when their winning chances are squeezed by the presence of superstars. Our results have implications for the design and implementation of internal competition and corporate governance. However, our research design prevents us from making definitive statements on the causal relationship between the change in star coverage and the change in non-star coverage.



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**Table 1 Descriptive statistics**

The sample consists of 39,047 firm-year observations with analyst coverage between 1993 and 2010. The number of analysts following in year  $t$  is the number of analysts who issue at least one one-year-ahead EPS forecast in the three months around the earnings announcement date of year  $t$ . Panel A presents the summary statistics and Panel B reports correlation matrix where coefficients significant at the 5% level are in bold. Appendix 1 provides a detailed description of the construction of the variables.

Panel A Summary statistics					
Variables	Mean	Q1	Median	Q3	Standard deviation
<i>Total number of analysts</i>	8.574	4	6	12	6.910
<i>Number of star analysts</i>	0.662	0	0	1	1.216
<i>Number of non-star analysts</i>	7.912	3	6	11	6.238
<i>Total Assets in billion</i>	10.642	0.247	0.871	3.250	74.951
<i>B/M</i>	0.537	0.279	0.463	0.700	1.776
<i>Leverage</i>	0.219	0.038	0.183	0.337	0.212
<i>Institutional Ownership</i>	0.586	0.378	0.607	0.797	0.278
<i>R&amp;D</i>	0.042	0	0	0.042	0.122
<i>Advertising Expense</i>	0.011	0	0	0.002	0.038
<i>Beta</i>	1.004	0.563	0.928	1.360	0.625
<i>ROA</i>	0.014	0.006	0.036	0.077	0.369

Panel B Correlation Matrix

Variables	Total number of analysts	Number of star analysts	Number of non-star analysts	Total Assets in billion	B/M	Leverage	Institutional Ownership	R&D	Advertising Expense	Beta	ROA
Total number of analysts	1										
Number of star analysts	<b>0.614</b>	1									
Number of non-star analysts	<b>0.991</b>	<b>0.499</b>	1								
Total Assets in billion	<b>0.529</b>	<b>0.460</b>	<b>0.549</b>	1							
B/M	<b>-0.050</b>	<b>-0.021</b>	<b>-0.194</b>	-0.002	1						
Leverage	<b>0.016</b>	<b>0.105</b>	<b>0.025</b>	<b>0.247</b>	<b>-0.066</b>	1					
Institutional Ownership	<b>0.293</b>	<b>0.227</b>	<b>0.292</b>	<b>0.237</b>	<b>-0.021</b>	<b>0.064</b>	1				
R&D	<b>-0.055</b>	<b>-0.092</b>	<b>-0.100</b>	<b>-0.325</b>	<b>-0.038</b>	<b>-0.092</b>	<b>-0.122</b>	1			
Advertising Expense	<b>-0.051</b>	0.003	-0.011	<b>-0.112</b>	<b>-0.020</b>	<b>-0.036</b>	<b>-0.029</b>	<b>-0.034</b>	1		
Beta	<b>0.138</b>	<b>0.076</b>	<b>0.138</b>	-0.0003	<b>-0.182</b>	<b>-0.126</b>	<b>0.229</b>	<b>0.200</b>	<b>-0.158</b>	1	
ROA	<b>0.058</b>	<b>0.039</b>	<b>0.123</b>	<b>0.078</b>	0.002	<b>-0.060</b>	<b>0.042</b>	<b>-0.391</b>	<b>0.015</b>	<b>-0.087</b>	1

**Table 2 Competition avoidance effect**

The sample consists of 39,047 firm-year observations between 1993 and 2010. The number of analysts following in year  $t$  is the number of analysts who issue at least one one-year-ahead EPS forecast in the three months around the earnings announcement date of year  $t$ . Panel A reports the univariate test and Panel B reports multivariate regression results. The dependent variable in Panel B equals 1 if the number of non-star analysts following increases, equals 0 if the number of non-star analysts remains the same and equals -1 if the number of non-star analysts following decreases. Inferences are based on standard errors clustered by firm. Appendix 1 provides a detailed description of the construction of the variables. The symbols \*, \*\* and \*\*\* denote significance at the 10%, 5% and 1% levels, respectively.

## Panel A Univariate test

		Number of star analysts following increases (N=5,746)	Number of star analysts following remains the same (N=27,955)	Number of star analysts following decreases (N=5,346)	Test of difference (Increase- Same)	Test of difference (Decrease- Same)
<i>Number of non-star analysts</i>	Year t-1	12.400	6.069	11.342		
	Year t	11.554	6.287	12.499		
	Year t-Year t-1	-0.847***	0.218***	1.157***	-1.065***	0.939***
<i>Proportion of non-star analysts</i>	Year t-1	0.803	0.974	0.796		
	Year t	0.934	0.975	0.934		
	Year t-Year t-1	-0.131***	0.001***	0.138***	-0.132***	0.137***
<i>Total number of analyst following</i>	Year t-1	13.349	6.326	13.708		
	Year t	13.898	6.544	13.469		
	Year t-Year t-1	0.549***	0.218***	-0.239***	0.331***	-0.457***

Panel B Ordered logistic regression estimates of the likelihood of a change in the number of non-star analysts following

Variable	Model 1		Model 2	
		Odds ratio		Odds ratio
<i>Star Increase (dummy)</i>	-0.812*** ( $<0.01$ )	0.444	-0.874*** ( $<0.01$ )	0.417
<i>Star Decrease (dummy)</i>	0.721*** ( $<0.01$ )	2.056	0.809*** ( $<0.01$ )	2.246
$\Delta$ Total Assets			1.924*** ( $<0.01$ )	6.849
$\Delta$ B/M			-0.361*** ( $<0.01$ )	0.697
$\Delta$ Leverage			-1.915*** ( $<0.01$ )	0.147
$\Delta$ Institutional ownership			1.570*** ( $<0.01$ )	4.804
$\Delta$ R&D			2.443*** ( $<0.01$ )	11.508
$\Delta$ Advertising expense			10.730*** ( $<0.01$ )	>1,000
$\Delta$ Beta			-0.101*** ( $<0.01$ )	0.904
$\Delta$ ROA			0.322*** ( $<0.01$ )	1.380
Year fixed effects	YES		YES	
Pseudo $R^2$	0.06		0.12	
No of obs	39,047		39,047	

**Table 3**

**Competition avoidance effect of first-team, second-team and third-team v.s. runner-up**

The sample consists of 39,047 firm-year observations between 1993 and 2010. The number of analysts following in year  $t$  is the number of analysts who issue at least one one-year ahead EPS forecast in the three months around the earnings announcement date of year  $t$ . The dependent variable equals 1 if the number of non-star analysts following increases, equals 0 if the number of non-star analysts remains the same and equals -1 if number of non-star analysts following decreases. We run ordered logit regressions. Inferences are based on standard errors clustered by firm. Appendix 1 provides a detailed description of the construction of the variables. The symbols \*, \*\* and \*\*\* denote significance at the 10%, 5% and 1% levels, respectively.

Variable	Model 1		Model 2	
		Odds ratio		Odds ratio
<i>FST Increase (dummy):a</i>	-0.748*** ( $<0.01$ )	0.473	-0.813*** ( $<0.01$ )	0.443
<i>Runner-up Increase (dummy):b</i>	-0.689*** ( $<0.01$ )	0.502	-0.718*** ( $<0.01$ )	0.488
<i>FST Decrease (dummy):c</i>	0.656*** ( $<0.01$ )	1.927	0.743*** ( $<0.01$ )	2.101
<i>Runner-up Decrease (dummy):d</i>	0.617*** ( $<0.01$ )	1.853	0.685*** ( $<0.01$ )	1.983
$\Delta$ Total Assets			1.917*** ( $<0.01$ )	6.800
$\Delta$ B/M			-0.371*** ( $<0.01$ )	0.690
$\Delta$ Leverage			-1.936*** ( $<0.01$ )	0.144
$\Delta$ Institutional ownership			1.571*** ( $<0.01$ )	4.811
$\Delta$ R&D			2.407*** ( $<0.01$ )	11.101
$\Delta$ Advertising expense			11.380*** ( $<0.01$ )	>1,000
$\Delta$ Beta			-0.100*** ( $<0.01$ )	0.905
$\Delta$ ROA			0.318*** ( $<0.01$ )	1.374
Year fixed effects	YES		YES	
<i>p-value of Chi-square test:a=b</i>	0.23		0.94	
<i>p-value of Chi-square test:c=d</i>	0.44		0.05	
Pseudo $R^2$	0.07		0.26	
No of obs	39,047		39,047	



**Table 4 Competition avoidance effect—investor sentiment**

The sample consists of 39,047 firm-year observations between 1993 and 2010. The number of analysts following in year  $t$  is the number of analysts who issue at least one one-year ahead EPS forecast in the three months around the earnings announcement date of year  $t$ . The dependent variable equals 1 if the number of non-star analysts following increases, equals 0 if the number of non-star analysts remains the same and equals -1 if number of non-star analysts following decreases. We run ordered logit regressions. Year 1994, 1995, 1996, 1997, 1999, 2000, 2001, 2006 and 2007 are classified as high investor sentiment years and other years in our sample are classified as low investor sentiment years. Inferences are based on standard errors clustered by firm. Appendix 1 provides a detailed description of the construction of the variables. The symbols \*, \*\* and \*\*\* denote significance at the 10%, 5% and 1% levels, respectively.

Variable	Model 1	Model 2
	Odds ratio	Odds ratio
<i>Star Increase (dummy)</i>	-0.735*** ( $<0.01$ )	0.476
<i>Star Increase (dummy)* High investor sentiment (dummy)</i>	-0.165*** ( $<0.01$ )	-0.800*** ( $<0.01$ )
<i>Star Decrease (dummy)</i>	0.684*** ( $<0.01$ )	0.449
<i>Star decrease (dummy)* High investor sentiment (dummy)</i>	1.850	-0.157** (0.03)
<i>High investor sentiment (dummy)</i>	0.071 (0.23)	0.763*** ( $<0.01$ )
$\Delta$ Total Assets	-0.080 (0.11)	0.087 (0.14)
$\Delta$ B/M		-0.290*** ( $<0.01$ )
$\Delta$ Leverage		1.924*** ( $<0.01$ )
$\Delta$ Institutional ownership		-0.361*** ( $<0.01$ )
$\Delta$ R&D		-1.915*** ( $<0.01$ )
$\Delta$ Advertising expense		1.570*** ( $<0.01$ )
$\Delta$ Beta		2.434*** ( $<0.01$ )
$\Delta$ ROA		10.714*** ( $<0.01$ )
Year fixed effects	YES	YES
Pseudo $R^2$	0.06	0.12
No of obs	39,047	39,047

**Table 5 Competition avoidance effect—analysts' discretion**

The sample consists of 39,047 firm-year observations between 1993 and 2010. The number of analysts following in year  $t$  is the number of analysts who issue at least one one-year ahead EPS forecast in the three months around the earnings announcement date of year  $t$ . The dependent variable equals 1 if the number of non-star analysts following increases, equals 0 if the number of non-star analysts remains the same and equals -1 if number of non-star analysts following decreases. We run ordered logit regressions. *High Inst* equals 1 if institutional ownership in year  $t-1$  is above the sample median and equals 0 otherwise. Inferences are based on standard errors clustered by firm. Appendix 1 provides a detailed description of the construction of the variables. The symbols \*, \*\* and \*\*\* denote significance at the 10%, 5% and 1% levels, respectively.

Variable	Model 1		Model 2	
		Odds ratio		Odds ratio
<i>Star Increase (dummy)</i>	-0.864*** ( $<0.01$ )	0.421	-0.927*** ( $<0.01$ )	0.396
<i>Star Increase (dummy) *</i> <i>High Inst (dummy)</i>	0.087 (0.13)	1.090	0.126** (0.03)	1.134
<i>Star Decrease (dummy)</i>	0.724*** ( $<0.01$ )	2.062	0.827*** ( $<0.01$ )	2.285
<i>Star Decrease (dummy)*</i> <i>High Inst (dummy)</i>	-0.037 (0.53)	0.963	-0.038 (0.53)	0.962
<i>High Inst (dummy)</i>	0.081*** ( $<0.01$ )	1.085	-0.007 (0.77)	0.993
$\Delta$ Total Assets			1.925*** ( $<0.01$ )	6.854
$\Delta B/M$			-0.362*** ( $<0.01$ )	0.696
$\Delta$ Leverage			-1.914*** ( $<0.01$ )	0.147
$\Delta$ Institutional ownership			1.567*** ( $<0.01$ )	4.794
$\Delta R\&D$			2.439*** ( $<0.01$ )	11.463
$\Delta$ Advertising expense			10.705*** ( $<0.01$ )	>1,000
$\Delta$ Beta			-0.101*** ( $<0.01$ )	0.904
$\Delta$ ROA			0.321*** (0.01)	1.378
Year fixed effects	YES		YES	
Pseudo $R^2$	0.06		0.12	
No of obs	39,047		39,047	

**Table 6 Competition avoidance effect—uncertainty**

The sample consists of 39,047 firm-year observations between 1993 and 2010. The number of analysts following in year  $t$  is the number of analysts who issue at least one one-year ahead EPS forecast in the three months around the earnings announcement date of year  $t$ . The dependent variable equals 1 if the number of non-star analysts following increases, equals 0 if the number of non-star analysts remains the same and equals -1 if number of non-star analysts following decreases. We run ordered logit regressions. In Panel A (B), *High uncertainty* equals 1 if return volatility (cash flow volatility) is greater than the sample median, and equals 0 otherwise. Inferences are based on standard errors clustered by firm. Appendix 1 provides a detailed description of the construction of the variables. The symbols \*, \*\* and \*\*\* denote significance at the 10%, 5% and 1% levels, respectively.

Panel A: Uncertainty measured by return volatility

Variable	Model 1		Model 2	
		Odds ratio		Odds ratio
	-0.984*** ( $<0.01$ )	0.374	-1.038*** ( $<0.01$ )	0.354
<i>Star Increase (dummy)</i>				
<i>Star Increase (dummy) *</i>	0.468*** ( $<0.01$ )	1.596	0.429*** ( $<0.01$ )	1.536
<i>High uncertainty (dummy)</i>				
<i>Star Decrease (dummy)</i>	0.780*** ( $<0.01$ )	2.180	0.841*** ( $<0.01$ )	2.318
<i>Star Decrease (dummy) *</i>	-0.128*** ( $<0.01$ )	0.880	-0.082* (0.09)	0.921
<i>High uncertainty (dummy)</i>				
<i>High uncertainty (dummy)</i>	0.084*** ( $<0.01$ )	1.088	0.016 (0.49)	1.016
$\Delta$ Total Assets			1.911*** ( $<0.01$ )	6.757
$\Delta$ B/M			-0.359*** ( $<0.01$ )	0.698
$\Delta$ Leverage			-1.917*** ( $<0.01$ )	0.147
$\Delta$ Institutional ownership			1.545*** ( $<0.01$ )	4.690
$\Delta$ R&D			2.431*** ( $<0.01$ )	11.375
$\Delta$ Advertising expense			10.521*** ( $<0.01$ )	>1,000
$\Delta$ Beta			-0.098*** ( $<0.01$ )	0.906
$\Delta$ ROA			0.315***	1.370

		( $<0.01$ )	
<i>Year fixed effects</i>	YES		YES
<i>Pseudo R<sup>2</sup></i>	0.03		0.12
<i>No of obs</i>	39,047		39,047

Panel B: Uncertainty measured by cash flow volatility

Variable	Model 1		Model 2	
		Odds ratio		Odds ratio
<i>Star Increase (dummy)</i>	-0.885*** ( $<0.01$ )	0.413	-0.949*** ( $<0.01$ )	0.387
<i>Star Increase (dummy) * High uncertainty (dummy)</i>	0.158*** ( $<0.01$ )	1.171	0.164*** ( $<0.01$ )	1.178
<i>Star Decrease (dummy)</i>	0.766*** ( $<0.01$ )	2.151	0.846*** ( $<0.01$ )	2.331
<i>Star Decrease (dummy) * High uncertainty (dummy)</i>	-0.097* (0.09)	0.908	-0.083* (0.08)	0.921
<i>High uncertainty (dummy)</i>	0.058*** ( $<0.01$ )	1.060	0.008 (0.73)	1.008
<i>ΔTotal Assets</i>			1.921*** ( $<0.01$ )	6.831
<i>ΔB/M</i>			-0.361*** ( $<0.01$ )	0.697
<i>ΔLeverage</i>			-1.915*** ( $<0.01$ )	0.147
<i>ΔInstitutional ownership</i>			1.567*** ( $<0.01$ )	4.794
<i>ΔR&amp;D</i>			2.452*** ( $<0.01$ )	11.608
<i>ΔAdvertising expense</i>			10.817*** ( $<0.01$ )	>1,000
<i>ΔBeta</i>			-0.100*** ( $<0.01$ )	0.904
<i>ΔROA</i>			0.325*** ( $<0.01$ )	1.384
<i>Year fixed effects</i>	YES		YES	
<i>Pseudo R<sup>2</sup></i>	0.06		0.12	
<i>No of obs</i>	39,047		39,047	

**Table 7 The likelihood of avoiding competition and non-star analysts' abilities**

The sample consists of 29,694 analyst-year observations between 1993 and 2010. The dependent variable is a dummy variable which equals one if the analyst avoids competition in the current year, and equals zero otherwise. An analyst is deemed avoiding competition if she drops/initiates the coverage of the firm when the star coverage of the firm increases/declines. *Average ability* is a dummy variable which equals one if *Accuracy* is between the 10<sup>th</sup> and 90<sup>th</sup> percentile of its distribution, and equals zero otherwise. We run logit regressions. Inferences are based on standard errors clustered by firm. Appendix 1 provides a detailed description of the construction of the variables. The symbols \*, \*\* and \*\*\* denote significance at the 10%, 5% and 1% levels, respectively.

Variable		Odds ratio
<i>Average ability</i>	0.397*** (<0.01)	1.487
<i>Stock picking</i>	0.005 (0.94)	1.005
<i>Boldness</i>	-0.180 (0.69)	0.835
<i>Optimism</i>	0.351 (0.43)	1.421
<i>Frequency</i>	-0.248*** (<0.01)	0.780
<i>Brokerage size</i>	0.367*** (<0.01)	1.443
<i>Following</i>	1.274*** (<0.01)	3.574
<i>Experience</i>	-0.166*** (<0.01)	0.847
<i>Pseudo R<sup>2</sup></i>		0.01
<i>No of obs</i>		29,694

**Table 8 The likelihood of becoming a star and the competition avoidance**

The sample consists of 29,694 analyst-year observations between 1993 and 2010. The dependent variable equals 1 if a non-star analyst becomes a star analyst in year  $t+1$ , and equals 0 otherwise. *Comp-avoid* is an analyst-year variable. It represents the likelihood that a non-star analyst avoids direct competition with star analysts in year  $t$ . Specifically, for each analyst-firm pair in year  $t$ , we use a dummy to indicate whether the analyst exhibits competition avoidance behaviors (i.e., dropping/initiating the coverage of the firm when the star coverage of the firm increases/declines). We take the average of the dummy across all firms followed by the non-star to obtain *Comp-avoid*. A higher value for *Comp-avoid* indicates a higher likelihood that the non-star analyst avoids direct competitions with stars. We run logit regressions. Inferences are based on standard errors clustered by firm. Appendix 1 provides a detailed description of the construction of the variables. The symbols \*, \*\* and \*\*\* denote significance at the 10%, 5% and 1% levels, respectively.

Variable		Odds ratio
<i>Comp-avoid</i>	0.685*** ( $<0.01$ )	1.983
<i>Accuracy</i>	0.967*** ( $<0.01$ )	2.630
<i>Stock picking</i>	0.176 (0.46)	1.193
<i>Boldness</i>	-1.899 (0.21)	0.150
<i>Optimism</i>	1.805 (0.22)	6.082
<i>Frequency</i>	0.845*** ( $<0.01$ )	2.328
<i>Brokerage size</i>	3.369*** ( $<0.01$ )	29.054
<i>Following</i>	1.927*** ( $<0.01$ )	6.866
<i>Experience</i>	0.183 (0.28)	1.201
<i>Pseudo <math>R^2</math></i>		0.02
<i>No of obs</i>		29,694

**Table 9 Competition avoidance effect—analyst-level evidence**

Our sample in Panel A and B includes 269,661 analyst-firm-year observations for analysts changing their coverage. The number of analysts following in year  $t$  is the number of analysts who issue at least one one-year-ahead EPS forecast in the three months around the earnings announcement date of year  $t$ . *Decrease\_Cov* equals 1 if an analyst moves to a firm with lower star analyst coverage, 0 if an analysts moves to a firm with the same level of star analyst coverage, and -1 if an analyst moves to a firm with greater star analyst coverage. It is also the dependent variable in Panel C. *Dropped Star Increase (dummy)* equals one if average number of star analysts increases for firms dropped by the analyst, and equals zero otherwise. Control variables are constructed by taking difference of firm characteristics between initiated firms and dropped firms. Our sample in Panel D includes 4,197 analyst-year observations. The dependent variable in this panel equals one if an analyst disappears in the I/B/E/S database in year  $t$ , and equals zero otherwise. Inferences are based on standard errors clustered by analyst. Appendix provides a detailed description of the construction of the variables. The symbols \*, \*\*, and \*\*\* denote significance at the 10%, 5% and 1% levels, respectively.

Panel A Univariate test

	Dropped firms experience an increase in star coverage (N=80,424)	Dropped firms do not experience an increase in star coverage (N=189,237)	Test of difference (Increase-No Increase)
<i>Decrease_Cov</i>	0.110	-0.120	0.249***
Change in the number of star analysts following (Dropped firms- Initiated firms)	0.139	-0.340	0.479***

Panel B Distribution of *Decreases\_Cov*

	<i>Decrease_Cov</i> =-1	<i>Decrease_Cov</i> =0	<i>Decrease_Cov</i> =1	Total
Dropped firms experience an increase in star coverage	36%	16%	48%	100%
Dropped firms do not experience an increase in star coverage	38%	35%	27%	100%

Panel C Ordered logistic regression estimates. The dependent variable is *Decrease\_Cov*

Variable	Model 1		Model 2	
	Odds ratio		Odds ratio	
<i>Dropped Star Increase (dummy)</i>	0.476*** ( $<0.01$ )	1.609	0.417*** ( $<0.01$ )	1.517
$\Delta$ Total Assets			-0.498*** ( $<0.01$ )	0.608
$\Delta$ B/M			0.391*** ( $<0.01$ )	1.478
$\Delta$ Leverage			-0.001*** ( $<0.01$ )	0.999
$\Delta$ Institutional ownership			-0.353*** ( $<0.01$ )	0.703
$\Delta$ R&D			-1.468*** ( $<0.01$ )	0.230
$\Delta$ Advertising expense			1.178*** ( $<0.01$ )	3.248
$\Delta$ Beta			-0.214*** ( $<0.01$ )	0.807
$\Delta$ ROA			1.035*** ( $<0.01$ )	0.355
Year fixed effects	YES		YES	
Pseudo $R^2$	0.03		0.21	
No of obs	269,661		269,661	

Panel D Logistic regression estimates of the likelihood of dropping out of IBES

Variable	Odds ratio	
<i>Dropped Star Increase (dummy)</i>	0.725 (0.18)	2.065
Accuracy	-1.130 (0.34)	0.323
Stock picking	2.594 (0.13)	13.379
Boldness	-0.622 (0.95)	0.537
Optimism	0.992 (0.93)	2.696



<i>Frequency</i>	-7.040*** ( $<0.01$ )	$<0.01$
<i>Brokerage size</i>	2.422*** ( $<0.01$ )	11.265
<i>Following</i>	-0.203 (0.98)	0.816
<i>Experience</i>	0.559 (0.47)	1.750
<i>Pseudo <math>R^2</math></i>		0.01
<i>No of obs</i>		4,197

**Table 10 Non-star coverage and the consensus forecast accuracy**

The sample consists of 35,001 firm-year observations between 1994 and 2010. The number of analysts following in year  $t$  is the number of analysts who issue at least one one-year-ahead EPS forecast in the three months around the earnings announcement date of year  $t$ . The consensus forecast accuracy is minus one times the consensus forecast error, defined as the absolute value of the difference between consensus forecast before earnings announcement and actual EPS deflated by stock price two days before the actual earnings announcement date. Inferences are based on standard errors clustered by firm. Appendix provides a detailed description of the construction of the variables. The symbols \*, \*\* and \*\*\* denote significance at the 10%, 5% and 1% levels, respectively. The values in the parentheses are p-values.

Variable	// All-star Model (1)
<i>Star Increase (dummy)</i>	0.007*** ( $<0.01$ )
<i>Non-star Increase (dummy)</i>	0.005*** ( $<0.01$ )
<i>Star Decrease (dummy)</i>	-0.001 (0.50)
<i>Non-star Decrease (dummy)</i>	-0.001 (0.16)
$\Delta$ Total Assets	0.009*** ( $<0.01$ )
$\Delta$ B/M	-0.039*** ( $<0.01$ )
$\Delta$ Leverage	-0.033*** ( $<0.01$ )
$\Delta$ Institutional ownership	0.007*** (0.01)
$\Delta$ R&D	0.005 (0.69)
$\Delta$ Advertising expense	-0.111 (0.12)
$\Delta$ Beta	-0.001 (0.33)
$\Delta$ ROA	0.025*** ( $<0.01$ )
Year fixed effects	YES
$R^2$	0.08
No of obs	35,001

**Table 11 Robustness checks**

The sample consists of 39,047 firm-year observations between 1993 and 2010. The dependent variable in all panels equals 1 if the number of non-star analysts following increases, equals 0 if the number of non-star analysts remains the same and equals -1 if number of non-star analysts following decreases. We run ordered logit models. In Panel A, the number of analysts following in year  $t$  is the adjusted number of analysts who issue at least one one-year ahead EPS forecast in the three months around the earnings announcement date of year  $t$ . The adjustment is done as follows. We first identify a change in the analyst status and compute the necessary adjustment in the year of change. For example, if an analyst becomes a star, the adjustment to be made to the number of stars (non-star) is -1 (+1) in the year of change. Then, starting from the first year in which the firm appears in our sample, we cumulate the adjustment to be applied in each year, and our actual adjustment is based on the cumulated number. In Panel B, the number of analysts following in year  $t$  is the number of analysts who issue at least one one-year ahead EPS forecast after the announcement of earning of fiscal year  $t$  and before the announcement of earning of fiscal year  $t+1$ . In Panel C, *Star Decrease (exogenous)* is a dummy variable which equals one for firms whose number of star analysts following decreases entirely for exogenous reasons, and zero for firms whose number of star analysts following remains the same. To identify analysts whose departure is due to exogenous reasons, we first identify analysts who stop providing forecasts for all firms in I/B/E/S. Then we search FACTIVE using name of the analyst and brokerage house for articles in the disappearing year. We read articles to identify reasons for the disappearance. If the disappearance is due to change in career, promotion, health problem, sudden death and retirement, we treat this disappearance as exogenous. In Panel D, Star analysts are defined as analysts ranked by *Institutional Investor* as all-star irrespective of the industry for which they are selected. Inferences are based on standard errors clustered by firm. Appendix 1 provides a detailed description of the construction of the variables. The symbols \*, \*\*, and \*\*\* denote significance at the 10%, 5% and 1% levels, respectively.

Panel A Competition avoidance effect--excluding mechanical explanation

Variable	Model 1		Model 2	
	Odds ratio		Odds ratio	
<i>Star Increase (dummy)</i>	-0.623*** ( $<0.01$ )	0.537	-0.704*** ( $<0.01$ )	0.495
<i>Star Decrease (dummy)</i>	0.666*** ( $<0.01$ )	1.946	0.745*** ( $<0.01$ )	2.107
$\Delta$ Total assets			1.883*** ( $<0.01$ )	6.571
$\Delta$ B/M			-0.351*** ( $<0.01$ )	0.704
$\Delta$ Leverage			-1.932*** ( $<0.01$ )	0.145
$\Delta$ Institutional ownership			1.549*** ( $<0.01$ )	4.705
$\Delta$ R&D			2.034*** ( $<0.01$ )	7.641
$\Delta$ Advertising expense			10.485*** ( $<0.01$ )	>1,000
$\Delta$ Beta			-0.096***	0.909

$\Delta$ ROA		( $<0.01$ ) 0.175 (0.14)	1.191
Year fixed effects	YES		YES
Pseudo $R^2$	0.02		0.10
No of obs	39,047		39,047

Panel B Competition avoidance effect—using the whole forecasting year

Variable	Model 1		Model 2	
		Odds ratio		Odds ratio
<i>Star Increase (dummy)</i>	-0.871*** ( $<0.01$ )	0.418	-0.942*** ( $<0.01$ )	0.390
<i>Star Decrease (dummy)</i>	0.927*** ( $<0.01$ )	2.526	1.005*** ( $<0.01$ )	2.733
$\Delta$ Total Assets			1.710*** ( $<0.01$ )	5.530
$\Delta$ B/M			-0.724*** ( $<0.01$ )	0.485
$\Delta$ Leverage			-1.924*** ( $<0.01$ )	0.146
$\Delta$ Institutional ownership			1.247*** ( $<0.01$ )	3.479
$\Delta$ R&D			3.397*** (0.01)	29.873
$\Delta$ Advertising expense			8.173*** ( $<0.01$ )	>1,000
$\Delta$ Beta			0.035* (0.07)	1.035
$\Delta$ ROA			0.999*** ( $<0.01$ )	2.718
Year fixed effects	YES		YES	
Pseudo $R^2$	0.08		0.14	
No of obs	39,047		39,047	

Panel C Competition avoidance effect—exogenous event

Variable	Model 1		Model 2	
		Odds ratio		Odds ratio
<i>Star Decrease (exogenous)</i>	0.338*** (0.05)	1.402	0.518*** ( $<0.01$ )	1.171
$\Delta$ Total Assets			1.964*** ( $<0.01$ )	7.126
$\Delta$ B/M			-0.409*** ( $<0.01$ )	0.665
$\Delta$ Leverage			-2.111*** ( $<0.01$ )	0.121

<i>ΔInstitutional ownership</i>		1.576*** ( $<0.01$ )	4.833
<i>ΔR&amp;D</i>		2.146*** ( $<0.01$ )	8.553
<i>ΔAdvertising expense</i>		11.123*** ( $<0.01$ )	>1,000
<i>ΔBeta</i>		-0.075*** ( $<0.01$ )	0.928
<i>ΔROA</i>		0.314** (0.02)	1.369
<i>Year fixed effects</i>	YES		YES
<i>Pseudo R<sup>2</sup></i>	0.02		0.09
<i>No of obs</i>	28,074		28,074

Panel D Competition avoidance effect: using an industry-blind definition of star analyst

Variable		Odds ratio		Odds ratio
<i>Star Increase (dummy)</i>	-0.817*** ( $<0.01$ )	0.442	-0.882*** ( $<0.01$ )	0.414
<i>Star Decrease (dummy)</i>	0.733*** ( $<0.01$ )	2.081	0.819*** ( $<0.01$ )	2.268
<i>ΔTotal Assets</i>			1.927*** ( $<0.01$ )	6.866
<i>ΔB/M</i>			-0.362*** ( $<0.01$ )	0.697
<i>ΔLeverage</i>			-1.953*** ( $<0.01$ )	0.142
<i>ΔInstitutional ownership</i>			1.567*** ( $<0.01$ )	4.791
<i>ΔR&amp;D</i>			2.396*** ( $<0.01$ )	10.973
<i>ΔAdvertising expense</i>			10.621*** ( $<0.01$ )	>1,000
<i>ΔBeta</i>			-0.105*** ( $<0.01$ )	0.901
<i>ΔROA</i>			0.316*** ( $<0.01$ )	1.372
<i>Year fixed effects</i>	YES		YES	
<i>Pseudo R<sup>2</sup></i>	0.06		0.13	
<i>No of obs</i>	39,047		39,047	

**Table 12 Competition avoidance effect: alternative measures of strong competitors**

The sample consists of 37,494 firm-year observations between 1993 and 2010. The number of analysts following in year  $t$  is the number of analysts who issue at least one one-year-ahead EPS forecast in the three months around the earnings announcement date of year  $t$ . The dependent variable in equals 1 if the number of non-star analysts following increases, equals 0 if the number of non-star analysts remains the same and equals -1 if number of non-star analysts following decreases. In column (1), the star analyst is defined as analysts ranked within the top 10 percentile in forecast accuracy. In column (2), the star analyst is defined as analysts ranked within the top 10 percentile in stock picking ability. Inferences are based on standard errors clustered by firm. Appendix 1 provides a detailed description of the construction of the variables. The symbols \*, \*\* and \*\*\* denote significance at the 10%, 5% and 1% levels, respectively.

Variable		Star measured by forecast accuracy (1)				Star measured by stock picking ability (2)			
			Odds ratio		Odds ratio		Odds ratio		Odds ratio
<i>Star</i>	<i>Increase</i>	-0.627*** ( $<0.01$ )	0.534	-0.715*** ( $<0.01$ )	0.489	-0.716*** ( $<0.01$ )	0.489	-0.779*** ( $<0.01$ )	0.459
<i>Star</i>	<i>Decrease</i>	0.938*** ( $<0.01$ )	2.556	0.977*** ( $<0.01$ )	2.656	0.876*** ( $<0.01$ )	2.401	0.920*** ( $<0.01$ )	2.510
$\Delta$ Total Assets				1.963*** ( $<0.01$ )	7.121			1.927*** ( $<0.01$ )	6.872
$\Delta$ B/M				-0.353*** ( $<0.01$ )	0.703			-0.367*** ( $<0.01$ )	0.693
$\Delta$ Leverage				-2.061*** ( $<0.01$ )	0.127			-1.964*** ( $<0.01$ )	0.140
$\Delta$ Institutional ownership				1.561*** ( $<0.01$ )	4.764			1.606*** ( $<0.01$ )	4.980
$\Delta$ R&D				2.452*** ( $<0.01$ )	11.611			2.338*** ( $<0.01$ )	10.357
$\Delta$ Advertising expense				10.130*** ( $<0.01$ )	>1,000			10.481*** ( $<0.01$ )	>1,000
$\Delta$ Beta				-0.099*** ( $<0.01$ )	0.906			-0.091*** ( $<0.01$ )	0.913
$\Delta$ ROA				0.225* (0.07)	1.252			0.262** (0.03)	1.300
Year fixed effects		YES		YES		YES		YES	
Pseudo $R^2$		0.06		0.12		0.07		0.13	
No of obs		37,494		37,494		37,494		37,494	

## Appendix 1 Variable definition

Variable name	Variable definition
<i>Non-star Change<sub>jt</sub></i>	A variable used to measure the change in non-star analyst coverage. It equals 1 if the number of non-star analysts following increases, 0 if the number of non-star analysts remains the same, and -1 if number of non-star analysts following decreases.
<i>Star Increase/Decrease<sub>jt</sub></i>	It equals 1 in year t if the number of star analysts increases/decreases from year t-1 to year t, and 0 otherwise.
<i>ROA<sub>jt</sub></i>	Earnings before extraordinary items divided by total assets
<i>Total assets<sub>jt</sub></i>	Log transformation of total assets
<i>B/M<sub>jt</sub></i>	Book value of equity divided by market value of equity
<i>Leverage<sub>jt</sub></i>	Book value of long-term debt and short-term debt divided by total assets
<i>R&amp;D<sub>jt</sub></i>	R&D expenses deflated by total assets
<i>Beta<sub>jt</sub></i>	Beta estimated by market model by using 30 month returns before beginning of fiscal year. CRSP value-weighted return is used as a proxy for the market return.
<i>Advertising expense<sub>jt</sub></i>	Advertising expenses deflated by total assets
<i>Institutional ownership<sub>jt</sub></i>	Percentage of outstanding shares owned by institutions
<i>FST Increase/Decrease<sub>jt</sub></i>	It equals 1 in year t if the number of first-team, second-team or third-team analysts increases/decreases from year t-1 to year t, and 0 otherwise.
<i>Runner-up Increase/Decrease<sub>jt</sub></i>	It equals 1 in year t if the number of runner-up analysts increases/decreases from year t-1 to year t, and 0 otherwise.
<i>High investor sentiment<sub>jt</sub> (dummy)</i>	A dummy variable which equals one for 1994, 1995, 1996, 1997, 1999, 2000, 2001, 2006 and 2007, and equals zero for other years.
<i>High Inst<sub>jt</sub> (dummy)</i>	It equals 1 in year t if institutional ownership of the firm in year t-1 is greater than the sample median, and equals 0 otherwise.

*High uncertainty dummy<sub>jt</sub> (return volatility)*

A dummy variable which equals one if return volatility is greater than the sample median and equals zero otherwise. Return volatility is computed as the standard deviation of the 24 monthly returns before current fiscal year.

*High uncertainty dummy<sub>jt</sub> (cash flow volatility)*

A dummy variable which equals one if the cash flow volatility is greater than the sample median and equals zero otherwise. Cash flow volatility is computed as the standard deviation of 8 quarterly cash flow ratios (cash flow from operations deflated by total assets) prior to current fiscal year.

*Star Decrease<sub>jt</sub> (exogenous)*

A dummy variable which equals one if the number of star analyst decreases exogenously, and zero if the number of star analyst remains the same.

*Average ability<sub>it</sub>*

A dummy variable which equals one if *Accuracy* is between the 10th and 90th percentile of its distribution, and equals zero otherwise.

*Comp-avoid<sub>it</sub>*

It represents the likelihood that a non-star analyst avoids direct competition with star analysts in year *t*. Specifically, for each non-star-and-firm pair in year *t*, we use a dummy to indicate whether the analyst exhibits competition avoidance behaviors (i.e., dropping/initiating the coverage of the firm when the star coverage of the firm increases/declines). We take the average of the dummy across all firms followed by the non-star to obtain *Comp-avoid*.

*Accuracy<sub>it</sub>*

A measure of forecast accuracy of analyst *i* in year *t*. Specifically,  $Accuracy_{ijt} = \frac{AFE_{maxjt} - AFE_{ijt}}{AFE_{maxjt} - AFE_{minjt}}$ , where  $AFE_{maxjt}$  and  $AFE_{minjt}$  are the maximum and minimum absolute forecast errors for analysts following firm *j* in year *t*.  $AFE_{ijt}$  is the absolute forecast error (absolute value of difference between forecasted value and actual value) for analyst *i* following firm *j* in year *t*. The forecast error is based on the last one-year-ahead EPS forecast an analyst issues before the fiscal year-end. We average across all firms followed by analyst *i* in year *t* to compute *Accuracy<sub>it</sub>*. A higher value of *Accuracy* indicates that this analyst is more accurate in the current year.

*Stock picking<sub>it</sub>*

A measure of stock picking ability of analyst *i* in year *t*.  $Stock\ picking_{ijt} = \frac{Ret_{ijt} - Ret_{minjt}}{Ret_{maxjt} - Ret_{minjt}}$ , where  $Ret_{maxjt}$  and  $Ret_{minjt}$  are the maximum and minimum abnormal return for analysts following firm *j* in year *t*;  $Ret_{ijt}$  is abnormal return for analyst *i* following firm *j* in year *t*. Abnormal return is defined as the four-day [0,+3] size-adjusted abnormal returns for buy and sell



recommendations (returns for sell recommendations are multiplied by -1). Day 0 is the announcement date of analyst investment recommendations. We average across all firms followed by analyst i in year t to compute *Stock picking<sub>it</sub>*.

*Boldness<sub>it</sub>*

A measure of the relative boldness in earnings forecasts issued by analyst i in year t.  $Boldness_{ijt} = \frac{Dev_{ijt} - Dev\ min_{jt}}{Dev\ max_{jt} - Dev\ min_{jt}}$ .  $Dev\ max_{jt}$  and  $Dev\ min_{jt}$  are the maximum and minimum deviation from the consensus forecast for analysts following firm j in year t.  $Dev_{ijt}$  is the deviation from the consensus forecast for analyst i following firm j in year t. The consensus forecast is the average of all forecasts made in the prior three months. Forecast deviation is computed as the absolute value of the difference between the analyst's forecast (the last one-year-ahead EPS forecast an analyst issues before the fiscal year-end) and the consensus forecast. These relative rankings are then averaged across the firms followed by analyst i in year t.

*Optimism<sub>it</sub>*

A measure of the relative optimism of forecasts issued by analyst i in year t.  $Optimism_{ijt} = \frac{Bias_{ijt} - Bias\ min_{jt}}{Bias\ max_{jt} - Bias\ min_{jt}}$ .  $Bias\ max_{jt}$  and  $Bias\ min_{jt}$  are the maximum and minimum forecast bias for analysts following firm j in year t.  $Bias_{ijt}$  is the forecast bias for analyst i following firm j in year t. Bias is computed as the analyst forecast (the last one-year-ahead EPS forecast an analyst issues before the fiscal year-end) minus the actual earnings. These relative rankings are then averaged across the firms followed by analyst i in year t.

*Frequency<sub>it</sub>*

A measure of the relative frequency at which analyst i issues forecasts one-year-ahead forecast in year t.  $Frequency_{ijt} = \frac{freq_{ijt} - freq\ min_{jt}}{freq\ max_{jt} - freq\ min_{jt}}$ .  $freq\ max_{jt}$  and  $freq\ min_{jt}$  are the maximum and minimum forecast frequency for analysts following firm j in year t.  $freq_{ijt}$  is forecast frequency for analyst i following firm j in year t. Forecast frequency refers to the number of times the analyst issues an one-year-ahead EPS forecast. These relative rankings are then averaged across the firms followed by analyst i in year t.

*Brokerage size<sub>it</sub>*

A measure of the relative size of the brokerage house employing analyst i in year t.  $Brokerage\ size_{it} = \frac{Broker_{it} - Broker\ min_t}{Broker\ max_t - Broker\ min_t}$ .  $Broker\ max_t$  and  $Broker\ min_t$  are the maximum and minimum

number of analysts employed by a brokerage firm in year t.  $Broker_{it}$  is the number of analysts employed by the brokerage house with which analyst i is affiliated in year t.

*Following<sub>it</sub>*

A measure of the relative following by analyst i in year t.

$Following_{it} = \frac{follow_{it} - follow_{min_t}}{follow_{max_t} - follow_{min_t}}$ .  $follow_{max_t}$  and  $follow_{min_t}$  are the maximum and minimum number of firms an analyst follows in year t.  $follow_{it}$  is number of firms analyst i follows in year t.

*Experience<sub>it</sub>*

A measure of the relative experience of analyst i in year t.

$Experience_{it} = \frac{Years_{it} - Years_{min_t}}{Years_{max_t} - Years_{min_t}}$ .  $Years_{max_t}$  and  $Years_{min_t}$  are the maximum and minimum experience of all analysts in year t.  $Years_{it}$  is the experience of analyst i in year t. Experience refers to the number of the years the analyst has appeared in I/B/E/S.

*Decrease\_Cov<sub>ijt</sub>*

It equals 1/0/-1 if analyst i initiates coverage for firm j and firm j' star coverage is lower than/the same as/higher than the average star coverage of firms dropped by analyst i in year t. t.

*Dropped Star Increase<sub>it</sub>*

It equals 1, if the firms dropped by analyst i experience an increase in star coverage in year t, and 0, otherwise.

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## **Appendix 2 An excerpt from the 2008 *Institutional Investor* All-star Ranking Report**

### GAMING & LODGING

#### **Joseph Greff JPMorgan**

#### SECOND TEAM

**Celeste Mellet Brown** Morgan Stanley

#### THIRD TEAM

**Steven Kent** Goldman Sachs

#### RUNNERS-UP

**Robin Farley** UBS;

**William Lemer** Deutsche

In the top spot for a third consecutive year is Joseph Greff, who, according to one money manager, "has conviction and communicates it clearly." Greff, 38, joined JPMorgan Securities in June, when it absorbed Bear, Stearns & Co., and among his first calls was a recommendation to sell Las Vegas Sands Corp., at \$50.19, on concerns about earnings at the Nevada-based casino operator's holdings in the U.S. and China. The stock had plunged 24.9 percent, to \$37.71, from the downgrade through mid-September. During the same period the sector gained 6.0 percent. Also in June, Greff downgraded MGM Mirage to neutral, at \$38.90, following a disappointing second-quarter earnings report. By mid-September shares of the Las Vegas-based resort operator had fallen to \$31.72. "His downgrade hit that stock right at the top," marvels one investor. Celeste Mellet Brown of Morgan Stanley leaps from runner-up to second place. Clients hail her as much for her deep understanding of fundamentals as for the speed of her calls. Brown downgraded Scientific Games Corp., a New York-based lottery ticket manufacturer, to underweight in January, at \$28.15, citing increased competition. Two weeks later, after the stock had fallen 26.8 percent, to \$20.61, she upgraded it to equal weight, on valuation. In mid-September the share price was back up to \$26.72. "She's been all over that stock," cheers one backer. Repeating at No. 3 is Steven Kent, who "really explains the gaming industry," says one buy-side fan. In January the Goldman, Sachs & Co. analyst reiterated his sell rating on Shuffle Master, on declining demand. Shares of the Las Vegas-based gaming equipment manufacturer had plunged 52.3 percent by mid-September.