https://pubsonline.informs.org/journal/mnsc

MANAGEMENT SCIENCE
Articles in Advance, pp. 1–21
ISSN 0025-1909 (print), ISSN 1526-5501 (online)

Do Professional Rankings Affect Analyst Behavior? Evidence From a Regression Discontinuity Design

Michael J. Jung,[a] Yiqing Lü,[b] Hong Wu,[c] Yuhai Xuan[d,*]

[a] Department of Accounting and Information Systems, University of Delaware, Newark, Delaware 19716; [b] Business, New York University Shanghai, Shanghai 200124, China; [c] Department of Accountancy, City University of Hong Kong, Hong Kong, China; [d] The Paul Merage School of Business, University of California, Irvine, Irvine, California 92697

*Corresponding author

Contact: mjung@udel.edu, https://orcid.org/0000-0003-1058-3847 (MJJ); yiqing.lu@nyu.edu, https://orcid.org/0000-0002-9047-1652 (YL); hong.wu@cityu.edu.hk, https://orcid.org/0009-0000-9926-3289 (HW); yuhai.xuan@uci.edu, https://orcid.org/0000-0001-6095-0452 (YX)

Received: December 23, 2023
Revised: October 4, 2024
Accepted: December 6, 2024
Published Online in Articles in Advance: August 20, 2025

https://doi.org/10.1287/mnsc.2023.04249

Abstract. This study examines how winning a significant industry award affects the behavior of finance professionals. Focusing on sell-side equity analysts and utilizing a novel data set from *Institutional Investor* on analyst rankings, we employ a regression discontinuity design that compares the postaward research outputs and behavior of third-place, all-star analysts with those of first runner-up analysts who barely miss the distinction. Our results show that third-place all-star winners are more optimistic in their forecasts and recommendations compared with first runner-up analysts after winning the award, and market reactions to their forecast revisions are stronger. The third-place winners also receive higher priority during earnings conference calls and experience better career outcomes. Our evidence is consistent with award-winning analysts leveraging their increased reputation and market influence to generate more trading commissions and career benefits. The broader inference of our findings is that finance professionals who win a significant award are likely to become more, rather than less, strategic.

History: Accepted by Kay Giesecke, finance.
Supplemental Material: The online appendix and data files are available at https://doi.org/10.1287/mnsc.2023.04249.

Keywords: analysts • industry rankings • forecast optimism • trading commissions • regression discontinuity

1. Introduction

Winning a significant professional award typically provides the recipient with recognition, visibility, respect, opportunity, and influence, among other things. From an ex-ante perspective, the tournament for professional awards could attract the most talented employees, encourage their best effort, and reward superior performance (Holmström 1982). However, from an ex-post perspective, it is not entirely clear how winning the award might affect the recipient's subsequent actions. They may wish to maintain the status quo after winning the award, or they may change their behavior to focus on alternative incentives. For example, Olympic athletes train for competition, but for the few who earn a medal, some engage more in activities with financial incentives (e.g., endorsements, professional tours, speaking engagements, etc.). Because of this uncertainty, researchers have been interested in examining the effect of awards in the corporate sector (Malmendier and Tate 2009, Gallus and Frey 2016, Shi et al. 2017, Jensen et al. 2022), among researchers (Borjas and Doran 2015), and in field and laboratory experiments (Kirchler et al. 2018), but they have found mixed evidence.[1]

The question, however, has been underexplored in the setting of finance professionals such as sell-side equity analysts. Analysts play vital roles in society's allocation of capital, firms' information environments, and overall functioning of capital markets (e.g., Chen et al. 2015, Li and You 2015). As financial market intermediaries, they bridge the information gap between corporate issuers of equity securities and investors who trade in such securities, which makes the study of their postaward behavior important and unique.

To examine this question, we use the annual "all-star" rankings from the publication *Institutional Investor (II)*, which are arguably the most significant industry recognition in the sell-side analyst profession (Groysberg et al. 2011). A large literature has considered the rankings merely as a proxy for skill rather than exploring a potential treatment effect of the award itself. This is because it is difficult to infer the effect of the rankings by comparing the behaviors of all top-ranked analysts with all nonranked analysts due to numerous correlated and unobservable confounding factors such as analysts' innate skills and talents. To overcome these issues, we use detailed voting data directly from *II* and a regression discontinuity (RD) design to compare the behavior of specific pairs of analysts who are adjacent in their ranking.

From 2001 to 2014, which is our sample period, the amount of recognition that *II* provided to analysts ranked in the top three positions within each industry was significant. Their names were listed in the print magazine and on the *II* website, short profiles were often provided, select quotes from institutional investors praising the analysts were included, and even elaborate photoshoots were organized (Peltz 2011). The next group of analysts who were dubbed "runners-up" received less recognition.[2] Their names were listed (without profiles, quotes, or photoshoots) in the print magazine up until 2008 and only online in subsequent years. While runners-up were still considered very good and were often up-and-coming analysts, there was significantly less fanfare from *II* and the profession. Essentially, the top three were treated like "all-stars" while the rest were not. For this reason, we compare third-place analysts and first runner-up analysts (i.e., fourth-place analysts) as the adjacently ranked pair of analysts in our RD design to test the treatment effect of the award itself. Furthermore, we utilize the weighted-scores from their votes to narrow down to a subset of the analyst-pairs whose difference in scores was very small. This RD research design enables us to isolate the effect of the award from other confounding factors.[3]

In our examination of postaward behavior, we focus on analyst incentives to make "actionable stock calls" (Lee and Manochin 2021) that generate trading commissions for their brokerage firm, as we believe such incentives likely give rise to strategic behavior. Jackson (2005) and Juergens and Lindsey (2009) document that institutional investors tend to direct their trades toward the brokerage firms whose analysts published the stock calls that prompted the trading decisions. While analyst research can be positive or negative about a firm and its stock, we focus on positive (i.e., optimistic) research because positive stock calls tend to induce more trades than negative stock calls, and the former also leads to better career outcomes (Jackson 2005, Lehmer et al. 2022). However, as discussed in Jackson (2005), analysts face a possible loss of reputation when they produce overly optimistic research outputs that do not come to fruition. For instance, Lee and Lo (2016) show that analysts who were positive (negative) on firms that later revealed misstated earnings experienced a loss (gain) in reputation. Lee et al. (2023) document that analysts who "throw in the towel" and capitulate on a failing stock recommendation can experience an erosion of reputation and confidence. In our setting of all-star awards, we expect the select subset of award-winners to gain significant reputation and influence compared with nonwinners, and this in turn increases the potential benefits from being correct and decreases the potential costs from being incorrect in their stock calls. Therefore, winning the award should enable them to focus on generating trading commissions with much less worry that an overly optimistic forecast will tarnish their reputation. Consistent with this notion, Lee and Lo (2016) show that the loss of reputation is smaller for all-star analysts than nonstar analysts. A counter argument is that winning the award may strengthen analysts' incentives to maintain their reputation as it becomes a more valuable asset.[4] Therefore, we expect the effect of the award on the subsequent publishing behavior of analysts to be an empirical question, and our prediction is that the *II* ranking enables a top-ranked analyst to publish more positive research than the next closest analyst who did not receive a top-three ranking.

We use forecast optimism as our main proxy for analysts' optimistic research for two reasons.[5] First, analyst stock calls that are intended to generate actionable trading ideas tend to be accompanied by above-consensus forecasts or revisions of forecasts, as prior studies have shown the relation between optimistic forecasts and trades for the analyst's brokerage firm (e.g., Jackson 2005, Lehmer et al. 2022). Second, while individual investors tend to react more to analyst recommendations, institutional investors tend to react more to earnings forecasts (Mikhail et al. 1999; Malmendier and Shanthikumar 2007, 2014).[6] From our conversations with sell-side analysts, and based on our own institutional knowledge, we know that analysts spend most of their time and effort trying to provide their largest institutional clients (e.g., Blackrock, Fidelity, State Street, Wellington, T. Rowe Price, etc.) with actionable trading ideas, expert industry knowledge, access to management, and the marketing of certain firms and stocks. Therefore, to the extent that each of these actions are correlated with an analyst's optimism about their covered firms, we believe that focusing on forecast optimism sufficiently captures analysts' incentives to make positive stock calls and publish optimistic research to induce trading commissions from institutional investors.

We use detailed *II* voting data from 2001 to 2014 and focus on pairs of third-place and first runner-up analysts whose composite scores (i.e., votes weighted by voters' assets under management) are very close. We document three sets of findings. First, in the year following the publication of the rankings, third-place analysts (i.e., the award winners) are more optimistic than first runner-up analysts in their earnings forecasts. They are also more optimistic in their forecasts of price targets and revisions of stock recommendations, as well as more reluctant to downgrade stocks after bad news has occurred for the firm. Moreover, the results are more pronounced for analysts who cover firms with higher ownership by transient institutional investors, which are the clients who trade most often and generate more commissions for the analysts' brokerages. These results are consistent with a postaward effect that enables the winners to focus more on their incentives to generate trading commissions relative to before winning the award and compared with nonwinners. Importantly, our RD design gives us confidence to attribute a causal effect to the all-star rankings, which has been a challenge in the prior literature.

Second, we find that stock market reactions to the forecast revisions by third-place analysts are significantly greater than those by first runner-up analysts, even for the same amount of forecast revision. This result indicates another postaward effect—a third-place analyst can move a firm's stock price up more than a first runner-up analyst can.

Third, with respect to the career benefits associated with winning an all-star award, we find that third-place analysts receive higher priority in quarterly earnings conference calls and cover new firms that are larger and have more growth opportunities, compared with first runner-up analysts. They are also more likely to get promoted in the years subsequent to receiving the all-star award. These results confirm that the *II* rankings are a significant industry award in the sell-side analyst profession, and the winners receive career benefits.

In addition, we also examine alternative properties of analyst research, namely, earnings forecast boldness, frequency, and accuracy. We find that third-place analysts, relative to first runner-up analysts, make bolder forecasts and update them more frequently. The result on greater frequency is consistent with analyst incentives to generate more trading commissions. We find that third-place analysts tend to be more optimistic than first runner-up analysts both when actual EPS exceed forecasts and when they fall short of forecasts. This leads to the finding that there is no significant difference in *absolute* forecast bias between the third-place analysts and first runner-up analysts, but the downside for third-place analysts is that they tend to be less accurate than first runner-up analysts when actual EPS falls short of forecasts.

Our baseline results are reinforced by two placebo tests. In the first test comparing second-place and third-place analysts, since both are considered all-stars, we predict and find that earnings forecasts made by second-place analysts are *not* significantly more optimistic than those made by third-place analysts. In the second test, we compare the first runner-up analysts with all other lower-ranked runner-up analysts (e.g., 5th place, 6th place, etc.). Since none are considered all-stars, we predict and find that earnings forecasts made by first runner-up analysts are *not* significantly more optimistic than those made by other lower-ranked runner-up analysts. These placebo tests underscore our main finding that differences in optimistic forecasts are found between third-place analysts and first runner-up analysts and provide further support for our identification strategy.

Finally, in examining next-year effects (untabulated), we find that the strategic behavior of third-place analysts after winning all-star awards does not appear to impact their future rankings. For third-place analysts in year t, there is an almost equal probability of remaining an all-star (51%) versus not remaining an all-star (49%) in year $t + 1$. Moreover, when comparing the likelihood of winning an all-star award one and two years after the ranking year between third-place and first runner-up analysts, none of the forecast characteristics (including optimism) affect the future all-star rank differently for third-place versus first runner-up analysts. Additionally, market reaction tests show that, in the second year after the rankings, market reactions to third-place analysts' revisions are not significantly different from those to first runner-up analysts' revisions. This result suggests that the market reaction effect associated with all-star awards may "reset" each year due to the annual nature of the rankings.

Our study makes several contributions to the literature on professional awards and finance professionals. First, we use the empirical setting of sell-side equity analysts to answer a broad research question about whether and how industry and professional awards can causally affect the behavior of capital market professionals. Prior studies have illustrated two roles of reputation and professional awards. On one hand, there can be a disciplining effect, as Jiang et al. (2016) find that reputation concerns motivate independent directors to dissent with managers. On the other hand, there can be rent-seeking or strategic behavior. Malmendier and Tate (2009) find that award-winning CEOs underperform relative to their industry peers, receive personal perks, and waste shareholders' wealth. Shi et al. (2017) find that superstar CEOs' *competitors* undertake more intensive acquisition activities after winning their own award and that these acquisitions are also associated with lower announcement returns. Our paper contributes to this literature by showing that analyst rankings could induce strategic behavior and also complements recent work that highlights how important it is for sell-side equity analysts to generate trading commissions (e.g., Lehmer et al. 2022), as opposed to earlier literature that highlights forecast accuracy as a primary objective of sell-side analysts (e.g., Mikhail et al. 1999).

Second, our paper contributes to the literature on the dynamics of sell-side analyst incentives. While prior studies document the incentives for analysts to issue optimistic and bold forecasts, as well as the associated career outcomes, our paper focuses on a mechanism that *enables* analysts to be more optimistic in the first place, which has not been previously highlighted. We show that, although sell-side analysts face the tradeoff between producing optimistic research outputs to generate trading commissions and the cost of losing reputation if these outputs are too optimistic from time to time, such a tradeoff is altered by the all-star ranking. Specifically, the boost in reputation and influence gained from winning the award increases the benefits of being correct on bold calls while reducing the cost of being wrong, enabling the analyst to focus more on generating trades and less on the potential reputational risks of over-optimism.

Third, our paper extends two streams of the analyst literature that focuses on all-star rankings. Prior studies on analyst rankings in general find that these rankings reward superior performance, including superior ability and "innate talent" (Leone and Wu 2007). Other determinants for the rankings include brokerage firm status (Emery and Li 2009), and industry expertise (Bradley et al. 2017). Another stream of literature examines the associated contemporaneous benefits, such as higher compensation (Groysberg et al. 2011), increased access to management (Soltes 2014), and investment banking business (Krigman et al. 2001, Clarke et al. 2007). Our research complements these studies by showing that postranking benefits that analysts receive could come from the ranking itself, rather than their superior ability. Moreover, our RD design allows us to cleanly identify and isolate the effect of all-star rankings on the postaward behavior of analysts. This is important because ex-ante correlations between analyst characteristics (such as ability) and rankings could confound changes in analyst incentives and behaviors, as well as the associated benefits, making it difficult to render clear causal interpretations in prior studies.

Finally, our study provides insights for policymakers and investors. Since the Global Settlement of 2002, which prohibited analysts from being compensated based on investment banking deals, equity research operations have increasingly relied on revenue from commissions. Thus, while analysts no longer have incentives to promote the stocks of investment banking clients, they may now have greater incentives to promote stocks that generate the most trades, which U.S. policymakers should consider in future regulation (similar to how the European Union updated the Markets in Financial Instruments Directive (MiFID II)[7] in 2018). In addition, institutional investors should be cognizant that the incentives of an all-star analyst may have changed from before the award to after it. For example, after winning the award, the analyst may be more motivated to promote stocks in anticipation of large market reactions.

2. Institutional Background and Analyst Incentives

2.1. Background on Institutional Investor Rankings

Institutional Investor (*II*) is a trade publication for the asset management industry.[8] Each October, it publishes a survey of institutional investors, including portfolio managers and buy-side analysts, who vote for the best sell-side equity analysts. The analysts are grouped into roughly 55 to 65 industries (the number varies over the years), the votes are weighted by assets under management to produce composite scores, and rankings are created. The sell-side analyst with the highest score in each industry-year is named "First-Place All-American," followed by the "Second-Place" and "Third-Place" analysts. Collectively, the literature refers to these analysts as "all-stars" or "all-Americans" (e.g., Hong and Kubik 2003, Liu and Ritter 2011).[9] Other analysts whose composite scores are within 35% of the third-place score are named "runners-up," and we use the "first runner-up" analyst in this study to compare with the third-place analyst. We discuss additional details about the voting process in Appendix A of our Internet Appendix.

Buy-side voters consistently cite industry knowledge, professionalism, accessibility, access to management, and special services as the most important reasons for voting for a particular analyst (Bradshaw 2011). However, these attributes are generally unobservable to researchers. Bradley et al. (2017) proxy for industry knowledge using an analyst's work experience prior to becoming a sell-side analyst. They find that previous work experience incrementally increases the likelihood of becoming an *II* all-star, but only when the analyst covers stocks related to their preanalyst industry work experience. Leone and Wu (2007) find that first-time winners have less experience than analysts who have never been ranked, which highlights "innate talent" as a determinant. Emery and Li (2009) find that name recognition, as proxied by brokerage house size and a prior all-star ranking, is a more significant determinant than forecasting performance. Green et al. (2014) examine brokerage-hosted investor conferences and Bradley et al. (2022) examine nondeal road shows, both of which can proxy for analysts' access to management and special services for the buy-side. Corroborating the importance of this aspect, in the 2021 edition of the *II* rankings, the head of North American equity research at JP Morgan Chase stated that the most successful analysts have "a laser focus on interacting with and impacting clients."[10] Collectively, these studies indicate that newer lead analysts with deep industry knowledge and who work for the largest brokerage firms that host exclusive events for institutional investors to meet with firm management have the highest likelihood of becoming *II*-ranked.

Academic research shows that the rankings serve as an important industry recognition. Early research shows a positive association between all-star analyst rankings and forecast frequency, accuracy, and market reaction to forecast revisions (Stickel 1992), although no definitive conclusion was made about causality. Firm managers appear to respond favorably to all-star analysts. Soltes (2014) finds that such analysts are associated with a higher tendency to meet with management, and Mayew (2008) finds that all-star analysts are less likely to be shut out of earnings conference calls even if they have a negative rating on the firm. This level of access to management is consistent with the attributes of sell-side analysts that institutional investors value (Bradshaw 2011). The employing brokerage firms also view the distinction positively, as all-star analysts contribute to performance by generating higher trading commissions (Jackson 2005) and attracting investment banking clients (Dunbar 2000, Krigman et al. 2001, Clarke et al. 2007). Brown et al. (2015) interview sell-side analysts on their views about all-star rankings. One analyst describes the award as an "external stamp of approval" and says that *II* rankings greatly increase access to management because of the rankings' visibility. Another analyst remarks that *II* rankings give analysts significant leverage within their own firms because all-star analysts can easily find employment elsewhere. In summary, *II* rankings are viewed by institutional investors, firm managers, and the sell-side analysts themselves as an important industry recognition.

2.2. Analyst Incentives

2.2.1. Trading Commission. The Global Settlement of 2002 mandated that Wall Street firms separate their equity research and investment banking operations. As a result, equity research analysts could no longer be compensated directly or indirectly through investment banking deals. While the settlement did not dictate how analysts should be paid, what has evolved is that equity research operations have been funded (and their analysts been compensated) primarily based on commissions paid by institutional investors. Institutional investors pay commissions for trade executions (often referred to as "hard dollars"), as well as for analyst research and services (often called "soft dollars"). Greenwich Associates LLC, for many years, provided data to the financial services industry related to soft and hard-dollar commissions.[11] In 2015, the firm published a survey titled "Broker Vote Mechanics: Valuing Sell-side Research and Compensating Brokers." The key takeaway from the survey was that commissions were becoming increasingly important for both equity research providers (as a source of revenue) and institutional investors (as an allocated expense for sell-side research).

Existing studies in accounting and finance have highlighted trading commissions as an important incentive for sell-side equity analysts and their employing brokerage firms. These studies include Hayes (1998), Irvine (2004), Jackson (2005), Cowen et al. (2006), Beyer and Guttman (2011), Firth et al. (2013), Gu et al. (2013), Groysberg and Healy (2013), Maber et al. (2014), and Harford et al. (2019), among others. More recently, Lehmer et al. (2022) conclude that sell-side equity analysts drive higher brokerage trading volumes through more optimistic earnings forecasts and are rewarded for this behavior.

2.2.2. The Need to Make Actionable Trading Calls. Prior studies have examined how the employment incentives and career concerns of sell-side analysts affect their research outputs (e.g., Michaely and Womack 1999). As discussed in the prior subsection, most relevant to our purposes are studies that focus on incentives to generate trading commissions for their employer. All else equal, analysts who make positive, actionable trading calls (with buy recommendations and above-consensus forecasts) generate higher trading commissions (Lee and Manochin 2021, Lehmer et al. 2022). One reason is that, with or without short-sale constraints, investors are typically limited in the number of shares they can sell of a particular stock when analysts are negative, relative to the number of shares they can buy when analysts are positive. Lee et al. (2023) interview analysts and document one who initiated coverage of a firm with a Sell rating and remarked:

> I went with a sell-rating on the company. This was a significant call, especially given the popularity of the company with a range of blue-chip income funds in Europe. The initial call was met with confusion as the sales force did not really know what to do with a negative recommendation on a stock that was widely held by the long-only investment community. It was not a stock that hedge funds typically got involved with. Clients were generally indifferent to the recommendation despite what I considered to be a compelling negative thesis.

However, analysts who repeatedly make positive stock calls can face negative repercussions to their reputation among institutional investors and their internal equity salesforce if their stock call is wrong (Jackson 2005, Lee and Lo 2016, Lee et al. 2023). This concern could exist among reputable analysts due to their incentives to maintain their reputation as a valuable asset (Diamond 1989, Jiang et al. 2016). For example, Lee et al. (2023) quote an analyst as saying:

> …[I] had maintained and reiterated my buy-rating. However, a few months later the company profit warned out of the blue…. That profit warning was followed by two others. It was hellish. I maintained my "buy into the downgrade" stance throughout. After the second downgrade I started to have twinges about whether I was right, but I had an emotional bias with so much of my reputation invested in the company. When I eventually downgraded to a hold, I got lots of negative reaction, flak from sales—"too little, too late."

Thus, an analyst must consider the trade-off between promoting too many positive stocks calls to generate trading commissions and refraining from such calls that may backfire.

Our conversations with sell-side analysts provide insights into how this trade-off evolves during their careers. Most sell-side analysts start their careers as assistants or associates under a lead analyst, focusing on accumulating their industry knowledge, as well as honing their financial analysis, writing, and stock pitching skills. Fang and Hope (2021) provide empirical evidence for some of these career dynamics. One can say that accuracy is one of the most important elements of their work as an assistant or associate. If successful after several years, then they begin to initiate coverage of stocks on their own, develop actionable trading ideas (Bozanic et al. 2019), and build their client relationships with the buy-side, as well as with their own brokerage's equity sales team (Lee and Manochin 2021).

2.2.3. All-Star vs. Non-All-Star Status. For the sell-side analysts who achieve a top-three ranking in their respective industry, the increase in status alters the trade-off in favor of enabling the analyst to publish more positive, actionable research that generates trading commissions than for non-all-stars. First, the all-star analyst can become known as the foremost authority on a particular stock. Lee et al. (2023) and Lee and Manochin (2021) refer to analysts having a "franchise stock" or being the "oracle" on a particular company. Second, the coverage universe of all-star analysts tends to expand in size and scope. That is, the all-star analyst will likely oversee coverage of a broad sector, comprising multiple industries and analyst coverage teams. For example, an all-star analyst in the Consumer Products Leisure industry (e.g., stocks in the toys, outdoor living, and vacation stocks), recently remarked, "My team now covers all of consumer [e.g., restaurants, retail, etc.] versus just a single sector—this mirrors the buy side and also gives us a differentiated perspective into each of our covered sectors." Third, all-star analysts also can become the figurehead of the sector for the brokerage firm, which entails speaking with more current and prospective clients. A ranked analyst for the automotive industry remarked, "We have many more clients to service now … ", while another said, "We also try to speak regularly with the most successful and brightest private company leaders within each sector, which provides great insight into their respective industries." These tangible changes that come with the all-star status bring greater benefits to the analyst when making stock calls because they tend to generate greater reactions and levels of interest from clients. In contrast, non-all-star analysts with lower visibility and reputation who make similar stock calls may elicit muted reactions.

All-star status also should, on average, lower the potential cost of being wrong on stock calls. This is because the all-star analysts' internal and external audiences know that the analyst is trying to make bold stock calls. The head of research at Bank of America Securities remarked that a star analyst is "publicly out there taking risks."[12] Therefore, in cases in which the stock call is wrong, the all-star analyst has more reputational capital to expend. In contrast, non-all-star analysts without significant reputational capital should remain more cognizant of the potential damage to confidence and reputation from being wrong (Lee et al. 2023).

In summary, gaining all-star status can simultaneously increase the potential benefits and decrease the potential costs for an analyst to make highly visible calls on franchise stocks. This leads us to predict that the all-star award itself enables the recipient to make more positive, actionable stock calls, as proxied by optimistic forecasts, recommendations, and target prices, compared with analysts who do not win the award.

3. Empirical Design and Sample Construction

3.1. Implementing an RD Design to Measure Analyst Ranking Effects

In this subsection, we describe how we implement the regression discontinuity (RD) design to measure the effect of all-star awards on forecast optimism. We use a similar procedure to examine other outcome variables. We provide additional background and details about the RD design in Appendix B of our Internet Appendix.

Consider a case in which we wish to test whether Analyst A, ranked in ith place, has a significantly different forecast optimism from a lower-ranked Analyst B, ranked in $(i+1)$th place. Let $y_{A\,(B)}$ refer to the forecast optimism for the Analyst A (B). For every pair of analysts who are adjacent in rank (ith and $(i+1)$th places), let z_{AB} be the difference in their composite scores, which is their relative distance in the ranking (Howell 2017). From the ith analyst (or Analyst A)'s perspective, z_{AB} is a positive value, and from the $(i+1)$th analyst (or Analyst B)'s perspective, z_{AB} is a negative value. Then we select bandwidth θ for the maximum absolute value of z_{AB}. The bandwidth can be an arbitrarily small value, and different values can be used in the robustness checks. The RD design compares observations for which $0 < z_{AB} < \theta$ with those for which $-\theta < z_{AB} < 0$. Thus, we retain observations for which $|z_{AB}| < \theta$. Finally, we estimate the ranking effect by using a nonparametric regression that utilizes a subset of the analyst-pairs whose score differences are within a specified bandwidth.

We use the score difference z_{AB}, instead of rank i, as the forcing variable. When there are multiple runners-up, *II* does not publicly disclose the actual ranks (e.g., 4th, 5th, 6th, etc.) in its magazine or on its website, but rather, lists their names alphabetically. Our data, however, allow us to see the actual composite score of each analyst and thus to clearly identify who is the first runner-up (i.e., the 4th-ranked analyst). We can use small score differences to construct closer counterfactuals than if we use only the ranks of analysts. For example, using score differences enables us to ensure that a first runner-up analyst's score is within a small absolute or percentage difference from the third-place analyst's score. However, if we use rank as the forcing variable, a first runner-up's score can be as much as 35% less than that of the third-place analyst's score, which may suggest a large practical difference in skill between the analysts. Thus, in our setting, score difference is a continuous variable that has a meaningful support for the calculation of an optimal bandwidth.

We follow Lee and Lemieux (2010) to approximate the underlying relationship between analyst forecast optimism $y_{A(B)}$ (the dependent variable) and score difference z_{AB} with the inclusion of four polynomials of the first and second order that are different for each side. The ranking effect is represented by coefficient β in Equation (1) below.

$$y_{A(B)} = \alpha + \beta \cdot 1\left(pos_{A(B)} = i\right) + p(z_{AB},\ r) + p(z_{AB}, l) + f(A, B) + \varepsilon_i. \qquad (1)$$

In Equation (1), β is the ranking effect of interest. The term $1\left(pos_{A(B)} = i\right)$ is an indicator variable for whether the analyst has a higher rank (i.e., third place). $p(z_{AB}, r)$ includes two polynomials of the first and second order of the score differences for the observations on the right-hand side of the ranking (i.e., the positive score difference), and $p(z_{AB}, l)$ includes two polynomials of the first and second order of the score differences for observations on the left-hand side of the ranking (i.e., the negative score difference). The polynomials capture any continuous relationship between z_{AB} and y_j. In our setting, this nonparametric approach controls for the other determinants of forecast optimism that vary across analysts using a sufficiently flexible polynomial function of p (Imbens and Lemieux 2008, Lee and Lemieux 2010). The term $f(A, B)$ includes a set of fixed effects and controls. For our main analysis of forecast optimism, we include firm fixed effects and year-quarter fixed effects.

Because the RD design is identified only at the discontinuity, in the empirical estimation of Equation (1), the bandwidth θ should be chosen to balance the goal of staying as local to the zero cutoff as possible with that of ensuring that there are enough data to yield informative estimates. We follow the approach of Calonico et al. (2014) to calculate the optimal bandwidth that remarkably improves on alternative nonparametric estimators in consistency and robustness. In particular, we approximate the regression function on either side of the ranking with a weighted polynomial regression. We then estimate the coefficient β as the difference between these nonparametric regression functions on either side of the ranking. For robustness, we also employ a practical implementation of RD within various prespecified bandwidths. Our results are robust across these nonparametric estimation approaches using different bandwidths.

There are two important conditions for the validity of the RD design. First, the sole source of discontinuity should be the treatment (in our case, the all-star distinction). In other words, other observable and unobservable characteristics of the analysts to the left and to the right of the cutoff should be similar. We test the validity of this assumption and report the results in Section 4.1.

The second condition for the RD design's validity is a lack of self-selection near the cutoff. In our setting, if an analyst knew what the cutoff score was for becoming an all-star, understood that they were near it, and could exert extra effort to exceed it, then the RD design in the analyst ranking context would not be valid. Since our forcing variable is constructed based on score differences, it guarantees a similar number of observations on both sides of the cutoff. Thus, the conventional density test of McCrary (2008) does not apply (Kaniel and Parham 2017). However, a close examination of the institutional details of the *II* voting process, along with our discussions with the *II* representative who provided our data and multiple sell-side analysts familiar with the rankings, strongly suggests that manipulation and self-selection are highly unlikely in this setting. Before the rankings are released each year, analysts are unaware of their own or any other analyst's composite score, as well as the cutoff score required for ranking in the top three places within their industry. They also do not know the list of institutional investors who participate in the voting or for whom the institutional investors voted. Furthermore, even after the rankings are published and analysts can thus observe everyone's composite scores, the votes cast by individual buy-side analysts and portfolio managers remain undisclosed.[13] For these reasons, we believe our setting is particularly well-suited for the RD approach, especially compared with other settings using an RD design where the cutoff is publicly known in advance (e.g., Cuñat et al. 2012).

3.2. Sample of Third-Place and First Runner-Up Analysts

We obtain annual sell-side analyst ranking data directly from *II*, which includes the years from 2001 to 2014 for all industries. With an average of about 61 industries per year (the number varies from 55 to 65 over the years), there are a total of 849 industry-years of rankings data.[14] The data include composite scores for all analysts (their names and brokerage firms) ranked within the top three and runner-up positions of all industry-years. Table A.1 in Appendix A in our Internet Appendix shows that the median composite scores for the first-place, second-place, third-place, and first runner-up analysts are 19.09, 14.28, 11.47, and 9.71, respectively. After consolidating all the analysts who appear more than once, we identify 879 unique analysts.[15] Using the IBES Detail Recommendations file, we manually match each analyst's last name, first initial, and brokerage affiliation to obtain their unique IBES identifier.[16] This matching process yields a total of 1,472 analyst-years or 736 pairs of third-place and first runner-up analysts, which represents 87% (i.e., 736/849) of all industry-years in our sample period. The mean and median difference in composite scores between the third-place and first runner-up analysts are 1.57 and 1.26, respectively. Because analyst rankings are announced every October for each year in our sample, we define the postranking period as from November 1st to October 1st of the next year. In all regression tests, we use the indicator variable *Third-place analyst*, which is set to one for all third-place analysts and zero for all first runner-up analysts.

3.3. Variable Definitions and Summary Statistics

We use data from IBES for variables related to analysts' earnings-per-share (EPS) forecasts, price targets, and stock recommendations for all firms in their coverage. We also use data from Thomson Reuters for institutional ownership and conference call transcripts, CRSP for stock prices and returns, and Compustat for accounting variables. Finally, to examine potential promotions of analysts, we hand collect data from LinkedIn, specifically analysts' changes in job titles. We report in Table 1 descriptive statistics of the variables defined in this subsection, based on the samples of third- and first runner-up analysts whose composite scores fall within the optimal bandwidth of 1.555[17] generated by the approach proposed in Calonico et al. (2014).[18]

Our first proxy for positive-oriented and optimistic research is *Forecast optimism*, defined as each analyst's quarterly EPS forecast for a given firm, minus the consensus median (i.e., the median of all quarterly EPS forecasts issued by all analysts in the same quarter for the same firm), scaled by the firm's stock price at the last quarter-end. Accordingly, higher values indicate greater forecast optimism, and we multiply the value by 100 for ease of presentation. The mean (median) value for *Forecast optimism* is negative (zero), indicating that our sample of third-place and first runner-up analysts, on average, publish EPS forecasts that are below the median among all analysts.

In the subsample analyses of *Forecast optimism,* we test whether third-place analysts are more optimistic than first runner-up analysts in their forecasts for firms owned by institutional investors who are expected to trade most often and thus would likely generate the most commissions for the analysts' employing brokerages. We use the classifications of institutions from Bushee (1998, 2001) to identify transient institutions, which utilize short-horizon, long-short, and momentum trading strategies. We split the sample based on whether the ratio of transient investors' ownership to total institutional ownership is above the industry median in each year.

We also examine market reactions to analysts' quarterly EPS forecast revisions. Our variable of interest to measure market reactions is *CAR11*, the cumulative abnormal returns (CARs) using the four-factor model based on Fama and French (1996) and Carhart (1997), over a three-day window [−1, +1] surrounding the date of each analyst's earnings forecast revision for a given firm. To measure the magnitude of each analyst's revision, we define *Revision1* as the change in quarterly EPS forecast from the previous forecast, scaled by the stock price at the last quarter end, and *Revision2* as the change in quarterly EPS forecast from the previous forecast, scaled by the previous forecast.

We also proxy for optimism using analysts' stock recommendations. We focus on recommendation revisions (i.e., upgrades and downgrades) during the postranking period. IBES assigns numerical values to recommendation levels: 1 for "Strong Buy," 2 for "Buy," 3 for "Hold," 4 for "Sell," and 5 for "Strong Sell." We compute recommendation revision as the recommendation level minus the previous recommendation level for the same firm issued by the same analyst, multiplied by −1 so that positive (negative) values indicate upgrades (downgrades). We then compute *Recommendation optimism* as an analyst's recommendation revision minus the consensus recommendation revision, that is, the median of all recommendation revisions made by all analysts in the same quarter for the same firm. To capture the timeliness of recommendation revisions, we define *Time to revision* as the number of days between the analyst's revision and the previous recommendation, scaled by 365 days. We define *Downgrade* as a dummy variable that equals one if an analyst downgrades the stock compared with the previous recommendation, and zero otherwise. To capture the occurrence of a downgrade after a firm experiences bad news, we follow Firth et al. (2013) to identify a bad news day as the first day of a three-day period in which the cumulative stock return is negative and its absolute value exceeds three times the company's prior-year standard deviation of three-day stock returns.[19] We define *Bad news* as an indicator set to one (zero otherwise) for bad news days. The mean value for *Recommendation optimism* is positive, indicating that our sample of third-place and first runner-up analysts tend to revise their recommendations more positively than the median among all analysts, and approximately 19% of the recommendation revisions are downgrades.

Table 1. Summary Statistics

Variable	*N*	Mean	SD	5th	Median	95th
Forecast optimism	42,328	−0.0203	0.4994	−0.6536	0.0000	0.5542
CAR11	6,870	0.0009	0.0349	−0.0539	0.0000	0.0583
Revision1	6,870	−0.0002	0.0080	−0.0097	0.0000	0.0090
Revision2	6,870	−0.0234	0.2517	−0.7179	0.0000	0.3636
Recommendation optimism	6,853	0.0501	0.8546	−1.5000	0.0000	2.0000
Time to revision	6,853	1.0398	0.9357	0.0603	0.7342	3.3397
Downgrade	6,853	0.1897	0.3921	0.0000	0.0000	1.0000
Bad news	6,853	0.3417	0.4743	0.0000	0.0000	1.0000
Conference call priority	4,480	0.4744	0.2457	0.000	0.4939	0.8571
Promotion	326	0.0368	0.1886	0.0000	0.0000	0.0000
Forecast boldness	28,834	49.5250	31.2062	0.0000	50.0000	100.0000
Forecast frequency	28,752	1.4722	0.7596	1.0000	1.0000	3.0000
Forecast bias	42,173	0.3839	0.8446	0.0000	0.1293	1.5060
Positive bias	42,173	0.1793	0.6891	0.0000	0.0000	0.8253
Negative bias	42,173	0.2047	0.5585	0.0000	0.0395	0.8518
Size	42,328	8.9822	1.7346	6.2196	8.8638	12.0745
Book-to-market	42,328	0.4874	0.3605	0.0673	0.4098	1.2048
Sales growth	42,328	0.1119	0.2479	−0.2066	0.0755	0.5184
Leverage	42,328	0.6031	0.2157	0.2363	0.5956	0.9400
ROA	42,328	0.0499	0.0777	−0.0640	0.0507	0.1654
Horizon	42,328	35.8978	31.9238	−20.0000	49.0000	73.0000
Gender (F)	42,328	0.1347	0.3414	0.0000	0.0000	1.0000
Experience	42,328	20.2644	10.6986	6.2462	18.0758	40.8621
Past star	42,328	0.4218	0.4938	0.0000	0.0000	1.0000

Notes. This table reports the summary statistics for the variables used in the paper, based on the sample of third-place analysts and first runner-up analysts whose composite scores fall within an optimal bandwidth of 1.555, as used in Table 3. All variable definitions are discussed in Section 3.3.

We proxy for access to management based on conference call transcripts from Thomson Reuter's StreetEvents database. Following Jung et al. (2015), we identify the analysts in our base sample on the transcripts of the companies they cover to determine each analyst's order of participation in the call (e.g., first, second, third, etc.). For each conference call, we define *Conference call priority* as one minus the ratio of the analyst's order in the call to the total number of participants in the conference call. Thus, analysts who are chosen to ask questions earlier in the call are defined as receiving higher priority.

To examine job promotion, we manually look up as many analysts as we could on LinkedIn to see if they show changes in job titles at their same brokerage or a new brokerage within one year, two years, and three years of the rankings. We are able to do so for 326 analysts in our sample. We record the following job titles, in order from most junior to most senior: analyst, senior analyst, principal, vice president, senior vice president, director, executive director, managing director, and partner. We acknowledge that different brokerages use different titles, but we believe we are still able to capture promotions in general. *Promotion* is defined as a dummy variable that equals one if the analyst is promoted within a year, and zero otherwise.

Additionally, we examine other EPS forecast properties besides optimism, namely boldness and frequency. To define *Forecast boldness*, we follow Clarke and Subramanian (2006)—for each quarter in the postranking period, we rank all the analysts covering the same firm by their absolute deviation from the consensus mean of the quarterly EPS forecasts for that firm. Rankings are then scaled such that the boldness ranking is valued from 100 to 0, with higher values indicating greater boldness (absolute deviation from the consensus mean). We calculate *Forecast frequency* as the number of quarterly EPS forecasts for each analyst-firm-quarter in the postranking period.

Our final set of dependent variables tests the consequence associated with optimism, namely, forecast bias (also referred to as "accuracy"). We define *Forecast bias* as the absolute value of the difference between a quarterly EPS forecast and the actual EPS, scaled by the stock price at the last quarter end, and thus, smaller values of *Forecast bias* are indicative of more accurate forecasts. We further decompose *Forecast bias* into two measures: *Positive bias* and *Negative bias*. *Positive bias* is calculated as the EPS forecast minus the actual EPS when the forecast is greater than the actual, scaled by the stock price at the last quarter end, and zero otherwise; *Negative bias* is calculated as the actual EPS minus the EPS forecast when the forecast is less than or equal to the actual, scaled by the stock price at the last quarter end, and zero otherwise.

We include several control variables related to firm and analyst characteristics. *Size* is the natural logarithm of total assets; *Book-to-market* is the book value of equity divided by the market value of equity; *Sales growth* is the growth rate of annual sales; *Leverage* is long-term debt divided by total assets; *ROA* is net income divided by total assets; *Horizon* is the number of days between the date of the forecast issuance and the date of the fiscal quarter end; *Gender (F)* is an indicator variable that equals one for female analysts and zero otherwise;[20] *Experience* is the number of prior quarters an analyst has issued quarterly earnings forecasts for a firm covered (Mikhail et al. 1997); and *Past star* indicates whether the analyst was an all-star in the prior year.

4. Main Results

4.1. Validation

The literature that discusses RD best practices (e.g., Hahn et al. 2001, Imbens and Lemieux 2008, Lee and Lemieux 2010) suggests several tests to verify the validity of an RD design. In our setting, a valid RD design assumes quasi-random rankings around the cutoff. The key assumption is that there are no systematic pre-existing differences in characteristics between a third-place analyst and the first runner-up analyst. Discontinuity in any of analysts' observable characteristics before the rankings may violate the validity of the RD design. To validate this assumption, we follow Cuñat et al. (2012) and test whether the third-place ranking is associated with analyst forecast, recommendation, and other characteristics during the 12 months *before* the rankings are published, that is, November of year $t-1$ to October of year t.

We present the results in Table 2. Each row corresponds to a different characteristic variable (shown in column (1)) constructed at the analyst-year level. In column (2), we conduct *t*-test across various characteristics between the third-place and the runner-up analysts and report the difference. In column (3), each cell reports the coefficient from a separate regression in which the dependent variable is the characteristic listed in column (1) and the independent variable is an indicator which equals one if the analyst is ranked as the third-place all-star in the following year and zero otherwise. In these regressions, we control for year fixed effects and cluster the standard errors at the analyst level.

Panel A focuses on forecast and recommendation characteristics. We find that none of the forecast and recommendation characteristics are significantly different between the third-place and the runner-up analysts, consistent with the assumption of no systematic pre-existing differences before the rankings. In panel B, we examine additional analyst characteristics and outcomes, including *Conference call priority*, *Promotion*, analyst gender, average experience, and past star status, to determine whether the third-place and the runner-up analysts are significantly different in these dimensions prior to the rankings. Again, we do not find any significant differences.[21]

Table 2. Validation Tests: Pre-Existing Differences

(1)	(2)	(3)
Panel A: Forecast and recommendation characteristics		
Forecast optimism	−0.004	−0.004
	(0.007)	(0.006)
Recommendation optimism	0.051	0.051
	(0.034)	(0.036)
Time to revision	0.041	0.039
	(0.054)	(0.052)
Downgrade	−0.005	−0.005
	(0.015)	(0.014)
CAR11	−0.000	−0.000
	(0.001)	(0.001)
Forecast boldness	0.185	0.181
	(0.544)	(0.515)
Forecast frequency	−0.350	−0.381
	(0.281)	(0.260)
Forecast bias	0.012	0.008
	(0.032)	(0.029)
Panel B: Other analyst outcomes and characteristics		
Conference call priority	0.015	0.014
	(0.013)	(0.013)
Promotion	0.009	0.024
	(0.059)	(0.063)
Gender (F)	−0.014	−0.013
	(0.024)	(0.021)
Experience	0.733	0.744
	(0.825)	(0.739)
Past star	0.003	0.008
	(0.026)	(0.023)

Notes. This table investigates whether there is any pre-existing difference in analyst characteristics between the third-place analysts and first runner-up analysts within a score-difference bandwidth of 1.555, the optimal bandwidth used in Table 3. In column (1), each row corresponds to a different characteristic variable, with forecast and recommendation characteristics covered in panel A and additional analyst outcomes and characteristics in panel B. These variables are constructed at the analyst-year level based on the 12 months prior to the all-star ranking. In column (2), we conduct *t*-tests between the third-place and the first runner-up analysts across various characteristics and report the difference. In column (3), each cell reports the coefficient from a separate regression in which the dependent variable is the characteristic listed in column (1) and the independent variable is an indicator which equals one if the analyst is ranked as the third-place all-star in the following year and zero otherwise. In these regressions, we control for year fixed effects and cluster the standard errors at the analyst level.

***, **, and * statistical significance at the 1%, 5%, and 10% levels, respectively. All variable definitions are discussed in Section 3.3.

Additionally, quasi-randomness in rankings also requires that analysts' rankings are not sticky, and thus, are unpredictable. We find that for third-place analysts and first runner-up analysts within the optimal bandwidth of 1.555, 28.2% of third-place analysts (in year t) were also in third place in year $t-1$, and 22.3% of first runner-up analysts (in year t) were also first runner-up in year $t-1$. The fact that nearly 80% of the third-place and first runner-up analysts were in a different position in the prior year suggests that the *II*-rankings, at least among these positions, are not sticky. Furthermore, as discussed in Section 3.1, the institutional details on the all-star ranking voting procedure indicate that it is highly unlikely for analysts near an unobservable cutoff to manipulate the running variable or self-select into a third-place ranking. Overall, our tests support the validity of the RD design in this study's setting.

4.2. Analyst Ranking and Forecast Optimism

In this section, we test our prediction that third-place analysts, relative to first runner-up analysts, are more optimistic in their quarterly EPS forecasts in the post-ranking period. We estimate Equation (1) at the forecast level. The dependent variable is *Forecast optimism*, and the independent variable of interest is *Third-place analyst*, an indicator variable set to one for third-place analysts and zero for first runner-up analysts.

We present the results in Table 3. The models in columns (1) and (2) follow a nonparametric estimation using the optimal bandwidth generated by the approach proposed by Calonico et al. (2014), which employs a triangular kernel function to estimate optimal bandwidths. In our estimation, the optimal bandwidth is 1.555, and we have 42,328 forecast-level observations and 808 analyst-years. For robustness, the models in columns (3) and (4) use a bandwidth of 1.5, and the models in columns (5) and (6) use a bandwidth of 2. In columns (1), (3) and (5), we include firm fixed effects and year-quarter fixed effects; in columns (2), (4) and (6), we further control for firm and analyst characteristics. All standard errors are clustered at the firm level and reported in parentheses under coefficient estimates. We find that, across all specifications, the coefficient for *Third-place analyst* is positive and significant at the 5% level or better, indicating that third-place analysts make more optimistic forecasts relative to first runner-up analysts.[22]

We also provide a graphical presentation of the results in Figure 1. All observations with score differences within the optimal bandwidth are sorted, based on the score difference, into bins of size 0.25. Six bins on each side of zero are shown on the x-axis. We regress *Forecast optimism* using the specification in column (2) of Table 3, which includes firm and year-quarter fixed effects. For each observation, we then calculate adjusted forecast optimism by extracting the component of forecast optimism that is not explained by the fixed effects, polynomials, and other control variables. The graph plots adjusted forecast optimism on the y-axis, where each point represents the mean adjusted optimism for observations within their respective bin (with 90% confidence intervals). Points on the left (right) side of zero represent observations from first runner-up (third-place) analysts. The graph illustrates the jump in forecast optimism around the zero cutoff, consistent with the estimates from Table 3.

This first set of results show that third-place analysts are more optimistic in their quarterly EPS forecasts than first runner-up analysts in the year after the *II* rankings, which is consistent with our expectation that after winning the award, the winning analyst can publish positive-oriented research that induces more trading commissions. Before testing other proxies for positive and optimistic research, we note that in untabulated analyses, we find that our results are robust when we include polynomials of higher order, use narrower or wider bandwidths, or use the full sample of third-place and first runner-up analysts (i.e., not only the pairs within a bandwidth). We also examine whether our results are robust to specifications that include brokerage fixed effects, which control for any time-invariant confounding factors at the brokerage house level, as well as firm × year fixed effects, which control for any confounding factors related to covered firms. Additionally, we re-estimate our regressions excluding 2007 and 2008 from our sample to alleviate the concern that the 2008 financial crisis might confound our analyses. Our findings are also robust to a difference-in-differences estimation in which we find that the first runner-up analyst does not change his or her forecast behavior after the ranking, suggesting that our main result from the RD design is due to the third-place becoming more optimistic, rather than the first runner-up analysts becoming more conservative. Lastly, we repeat our analyses using two alternative measures: *Annual forecast optimism*, calculated as an analyst's annual EPS forecast minus the median annual EPS forecast by all analysts in the same quarter, scaled by the stock price at the previous year-end, and *Price target optimism,* defined as an analyst's price target for a firm's stock minus the median price target issued by all analysts in the same quarter for the same firm, scaled by the stock price at the previous year-end. Appendix D of the Internet Appendix presents the results, which show that the annual EPS and price target forecasts of third-place analysts are more optimistic than those of first runner-up analysts. Overall, our results remain highly significant in these additional robustness tests.

4.3. Analyst Ranking and Recommendation Revisions

In this section, we examine stock recommendation revisions (i.e., upgrades and downgrades) of third-place analysts relative to first runner-up analysts. First, we examine whether third-place analyses issue more optimistic recommendation revisions in the postranking period, compared with first runner-up analysts. Our main dependent variable in this analysis is *Recommendation optimism*, as previously defined. Panel A of Table 4 reports the results. We control for firm fixed effects and year-quarter fixed effects in column (1) and further add firm and analyst controls in column (2). In each column, the coefficient for *Third-place analyst* is positive and significant at the 5% level, suggesting that third-

Table 3. Analyst Ranking and Forecast Optimism

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. var.: Forecast optimism	Optimal bandwidth		Bandwidth of 1.5		Bandwidth of 2.0	
Third-place analyst	0.033**	0.037***	0.033**	0.037**	0.030**	0.032***
	(0.014)	(0.014)	(0.014)	(0.015)	(0.012)	(0.012)
Size		−0.003		−0.003		−0.014
		(0.010)		(0.011)		(0.009)
Book-to-market		−0.011		−0.007		−0.026
		(0.029)		(0.029)		(0.027)
Sales growth		−0.003		−0.006		0.011
		(0.017)		(0.018)		(0.015)
ROA		0.092		0.091		0.102
		(0.080)		(0.082)		(0.078)
Leverage		−0.046		−0.043		−0.054
		(0.047)		(0.049)		(0.042)
Horizon		0.001***		0.001***		0.001***
		(0.000)		(0.000)		(0.000)
Gender (F)		−0.000		−0.001		−0.002
		(0.009)		(0.009)		(0.008)
Experience		−0.001**		−0.001**		−0.001***
		(0.000)		(0.000)		(0.000)
Past star		−0.002		−0.002		−0.002
		(0.006)		(0.006)		(0.005)
Firm FE & Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
N	42,328	42,328	41,634	41,634	49,398	49,398
R^2	0.096	0.101	0.096	0.102	0.093	0.098

Notes. This table presents the regression analysis (Equation (1)) of the effect of analyst ranking on forecast optimism at the forecast level. For each analyst, the dependent variable *Forecast optimism* is calculated as the quarterly EPS forecast minus the quarterly consensus (i.e., the median of all quarterly forecasts in the same quarter), scaled by the stock price at the last quarter end. The key independent variable is *Third-place analyst*, a dummy variable that equals one if the analyst is a third-place analyst and zero if the analyst is a first runner-up analyst. The models in columns (1) and (2) use the optimal bandwidth (1.555) generated by the approach proposed in Calonico et al. (2014) with triangular kernel functions. Models in columns (3) and (4) use a bandwidth of 1.5, and models in columns (5) and (6) use a bandwidth of 2.0. We include polynomials of up to order 2 that are different for the third-place and first runner-up analysts and control for firm fixed effects and year-quarter fixed effects in all regressions. In columns (2), (4) and (6), we further control for firm characteristics including size, book-to-market ratio, sales growth, ROA, leverage, and forecast horizon and analyst characteristics including gender, experience and past all-star status. Standard errors are clustered at the firm level and included in the parentheses.

***, **, and * statistical significance at the 1%, 5%, and 10% levels, respectively. All variable definitions are discussed in Section 3.3.

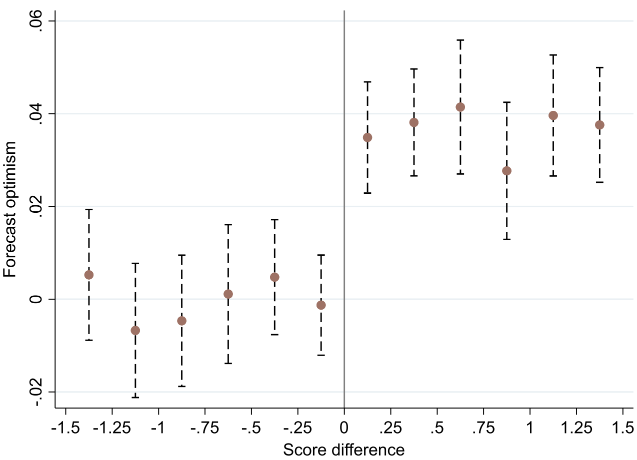
place analysts issue more optimistic recommendation revisions than first runner-up analysts.

Second, we examine whether third-place analysts are slower to downgrade a stock. Malmendier and Shanthikumar (2014) find that one manifestation of recommendation optimism is that it takes longer for analysts to issue downgrades than upgrades. Panel B of Table 4 reports the results. The dependent variable is *Time to revision*, as previously defined. The independent variables include *Downgrade*, a dummy variable that equals 1 if an analyst downgraded the stock (and 0 otherwise), and the interaction term *Third-place analyst* × *Downgrade*. We control for firm fixed effects and year-quarter fixed effects in column (1) and further add firm and analyst controls in column (2). We find that the coefficient on *Downgrade* is positive and significant, suggesting that it takes longer for analysts to downgrade. More importantly, we find that the coefficient for *Downgrade* × *Third-place analyst* is positive and statistically significant in each column, suggesting that third-place analysts are slower to downgrade stocks than first runner-up analysts.

Third, we examine whether third-place analysts are less likely to downgrade a stock following a firm's bad news. Prior studies have examined analysts' recommendation changes following news (Conrad et al. 2006) or shift in incentives, and in particular, bad news (O'Brien et al. 2005, Firth et al. 2013). Panel C of Table 4 reports the results. The dependent variable is *Downgrade*, and the independent variables include *Third-place analyst*, *Bad news*, and their interaction. We control for industry and year-quarter fixed effects in column (1) and add firm and analyst controls in column (2). In both specifications, we find that the coefficient on *Third-place analyst* × *Bad news* is negative and significant at the 1% level, suggesting that third-place analysts are less likely to downgrade than first runner-up analysts following bad news about a firm.

Overall, the results from Table 4 related to recommendation revisions are consistent with those from Table 3 that suggest third-place analysts are more optimistic in their research than first runner-up analysts. The results support a postaward effect that engenders award winners to publish optimistic research that generates more trading commissions.

Figure 1. (Color online) Comparing Optimism Between Third-Place and First Runner-Up Analysts



Notes. This figure illustrates the jump in forecast optimism around the zero cutoff. All observations with score differences within the optimal bandwidth are sorted, based on the score difference, into bins of size 0.25. Six bins on each side of zero are shown on the x-axis. We regress *Forecast optimism* using the specification in column (2) of Table 3, which includes firm and year-quarter fixed effects. For each observation, we then calculate adjusted forecast optimism by extracting the component of forecast optimism that is not explained by the fixed effects, polynomials, and other control variables. The graph plots adjusted forecast optimism on the y-axis, where each point represents the mean adjusted optimism for observations within their respective bin (with 90% confidence intervals). Points on the left (right) side of zero represent observations from first runner-up (third-place) analysts.

4.4. Subsample Analysis

We conduct a heterogeneity test to provide additional support for our finding that third-place analysts publish more optimistic research than first runner-up analysts following the rankings.[23] We conjecture that analysts generate more trading commissions for stocks owned by more frequent traders. We use the classifications of institutions from Bushee (1998, 2001) to identify transient institutions, which utilize short-horizon, long-short, and momentum trading strategies. We re-estimate Equation (1) using subsamples partitioned the level of transient institutional ownership, where high (low) ownership signifies that the percentage of shares owned by transient investors, divided by the percentage of shares owned by all institutions, is above (below) the median in the same year. Table 5 reports the results. We find that the coefficient on *Third-place analyst* (0.088) is positive, significant, and more than two times as large in the subsample of analysts covering firms with high transient ownership compared with the baseline reported in column (2) of Table 3; in comparison, it is insignificant and small in magnitude (−0.001) in the low transient ownership subsample. The difference between the two coefficients is statistically significant at the 1% level (with a p-value of 0.003 from a chi-squared test). Therefore, the effect of winning the award is more pronounced when firms are owned by institutional investors who trade more frequently. These results are consistent with analysts' incentives to publish research

Table 4. Analyst Ranking and Recommendation Revisions

	(1)	(2)
Panel A: Recommendation optimism		
Third-place analyst	0.140**	0.144**
	(0.064)	(0.064)
Firm FE & Year-Quarter FE	Yes	Yes
Firm Controls	No	Yes
Analyst Controls	No	Yes
N	6,853	6,853
R^2	0.192	0.192
Panel B: Time to revision		
Third-place analyst	0.109	0.100
	(0.069)	(0.069)
Downgrade	0.092***	0.098***
	(0.034)	(0.034)
Third-place analyst × Downgrade	0.089*	0.083*
	(0.047)	(0.047)
Firm FE & Year-Quarter FE	Yes	Yes
Firm Controls	No	Yes
Analyst Controls	No	Yes
N	6,853	6,853
R^2	0.368	0.371
Panel C: Downgrade		
Third-place analyst	0.011	0.009
	(0.017)	(0.017)
Bad news	0.568***	0.569***
	(0.015)	(0.015)
Third-place analyst × Bad news	−0.066***	−0.066***
	(0.020)	(0.020)
Industry FE & Year-Quarter FE	Yes	Yes
Firm Controls	No	Yes
Analyst Controls	No	Yes
N	6,853	6,853
R^2	0.500	0.501

Notes. This table presents the regression analysis of the effect of analyst ranking on recommendation revisions. The dependent variable *Recommendation optimism* in panel A is calculated as recommendation revision minus the median of all revisions for the same firm in the same quarter. The dependent variable *Time to revision* in panel B is calculated as the number of days between the focal recommendation and the previous recommendation issued by the same analyst for the same firm, scaled by 365 days. The dependent variable in panel C is *Downgrade*, a dummy variable that equals one if the analyst makes a downgrade recommendation revision, and zero otherwise. *Bad news* is a dummy variable that equals one for bad news days, as defined in Firth et al. (2013). The key independent variable is *Third-place analyst*, an indicator variable that equals one if the analyst is a third-place analyst and zero if the analyst is a first runner-up analyst. We use the bandwidth of 1.555 in Table 3 for consistency. We include polynomials of up to order 2 that are different for the third-place and first runner-up analysts in all columns. We control for year-quarter fixed effects and firm fixed effects in Panels A and B, and year-quarter fixed effects and industry fixed effects in panel C. In column (2) of all panels, we further control for firm characteristics including book size, book-to-market ratio, sales growth, ROA, and leverage, and analyst characteristics including gender, experience and past all-star status. Standard errors are clustered at the firm level and included in the parentheses.

***, **, and * statistical significance at the 1%, 5%, and 10% levels, respectively. All variable definitions are discussed in Section 3.3.

Table 5. Subsample Analysis

Dep. variable: Forecast optimism	(1) High transient ownership	(2) Low transient ownership
Third-place analyst	0.088***	−0.001
	(0.025)	(0.016)
Firm FE & Year-Quarter FE	Yes	Yes
Firm Controls	Yes	Yes
Analyst Controls	Yes	Yes
N	21,093	21,235
R^2	0.123	0.122

Notes. This table presents a subsample analysis of forecast optimism. For each analyst, the dependent variable *Forecast optimism* is calculated as the quarterly EPS forecast minus the quarterly consensus (i.e., the median of all quarterly forecasts in the same quarter), scaled by the stock price at the last quarter end. The key independent variable is *Third-place analyst*, a dummy variable that equals one if the analyst is a third-place analyst and zero if the analyst is a first runner-up analyst. We split the sample based on the ratio of transient investors' ownership to total institutional ownership (Bushee 1998, 2001). Specifically, for each firm, we examine whether its transient ownership ratio is above or below the median in the same year. We use the optimal bandwidth of 1.555 in Table 3 for consistency. We include polynomials of up to order 2 that are different for the third-place and first runner-up analysts and control for firm fixed effects and year-quarter fixed effects in all regressions. In column (2), we further control for firm characteristics including book size, book-to-market ratio, sales growth, ROA, leverage, and forecast horizon, and analyst characteristics including gender, experience and past all-star status. Standard errors are clustered at the firm level and included in the parentheses.

***, **, and * statistical significance at the 1%, 5%, and 10% levels, respectively. All variable definitions are discussed in Section 3.3.

that induces more trades for stocks owned by frequent traders.

4.5. Stock Market Reaction to Analyst Forecast Revisions

In this subsection, we study the underlying incentives for all-star analysts to be more optimistic in their forecasts to generate greater market reactions, actionable trading ideas, and trading commissions for their brokerage firm. We test whether the stock market reactions are greater for forecast revisions by third-place analysts than those by first runner-up analysts in the postranking period.

One challenge inherent in this analysis is that there can be confounding events surrounding the forecast revision day. For example, a third-place analyst and the paired first runner-up analyst may issue forecast revisions or recommendations on the same day. To isolate the market reaction specifically to each analyst, we exclude forecast revisions issued by both the third-place and first runner-up analysts in the same three-day window. Another challenge is that there are situations in which a third-place analyst issues forecast revisions in one quarter for one firm, and the paired first runner-up analyst issues forecast revisions for a different firm or in a different quarter. In these cases, it would be difficult to compare the market reactions, as stock prices are sensitive to time-varying and firm-specific information. For this reason, we impose the restriction that for each pair of third-place and first runner-up analysts, their forecast revisions must pertain to the same firm in the same quarter, but not in overlapping three-day windows.

Because a greater revision could lead to a greater market reaction, we estimate the sensitivity of the market reaction to each forecast revision by introducing the interaction term of *Third-place analyst* and *Revision1* (or *Revision2*), while controlling for the respective main effects. While the coefficient on *Third-place analyst* indicates the level effect of the all-star award on the market reaction, the coefficient on the interaction term indicates the difference in market reaction between the third-place analyst and the first runner-up analyst per unit of forecast revision.

Table 6 reports the results for market reactions to forecast revisions. The dependent variable is the three-day cumulative abnormal return (*CAR11*) around the day of each forecast revision, as previously defined,

Table 6. Stock Market Reaction to Forecast Revisions

Dependent variable: CAR11	(1)	(2)	(3)	(4)
Third-place analyst	0.004	0.004	0.004	0.004
	(0.002)	(0.002)	(0.002)	(0.002)
Third-place analyst × Revision1	0.403**	0.400**		
	(0.185)	(0.184)		
Third-place analyst × Revision2			0.008*	0.008*
			(0.004)	(0.004)
Revision1	0.044	0.043		
	(0.101)	(0.101)		
Revision2			−0.001	−0.001
			(0.003)	(0.003)
Firm FE & Year-Quarter FE	Yes	Yes	Yes	Yes
Firm Controls	No	Yes	No	Yes
Analyst Controls	No	Yes	No	Yes
N	6,870	6,870	6,870	6,870
R^2	0.166	0.167	0.163	0.164

Notes. This table presents the regression analysis of the stock market reaction to forecast revisions. The dependent variable *CAR11* is the 3-day cumulative abnormal returns (CARs) over a window of [−1, 1] around the day of each forecast revision. CARs are estimated using a four-factor model based on Fama and French (1996) and Carhart (1997). The key independent variable is *Third-place analyst*, a dummy variable that equals one if the analyst is a third-place analyst and zero if the analyst is a first runner-up analyst. *Revision1* is the change in quarterly EPS forecast from the previous forecast, scaled by the stock price at the last quarter end. *Revision2* is the change in quarterly EPS forecast from the previous forecast, scaled by the previous forecast. We use the optimal bandwidth of 1.555 in Table 3 for consistency. We introduce polynomials of up to order 2 that are different for the third-place and first runner-up and control for firm fixed effects and year-quarter fixed effects in all regressions. In columns (2) and (4), we further control for firm characteristics including book size, book-to-market ratio, sales growth, ROA, leverage, and forecast horizon, and analyst characteristics including gender, experience and past all-star status. Standard errors are clustered at the firm level and included in the parentheses.

***, **, and * statistical significance at the 1%, 5%, and 10% levels, respectively. All variable definitions are discussed in Section 3.3.

and the variable of interest is the interaction term. Columns (1) and (2) report results when we include *Revision1*, the change in quarterly EPS forecast from the previous forecast, scaled by the stock price at the last quarter end; columns (3) and (4) report results when we include *Revision2*, the change in quarterly EPS forecast from the previous forecast, scaled by the previous forecast. In columns (1) and (3), we include only firm and year-quarter fixed effects, while in columns (2) and (4), we further include firm and analyst controls. We find that across all specifications, the coefficient on the interaction term is positive and statistically significant. Column (2) shows that for a 10% increase in *Revision1*, the market reaction to the third-place analyst's revision is 4% greater than it is to the first runner-up analyst's revision. Our findings indicate that market reactions to third-place analysts' forecast revisions are greater than those to first runner-up analysts' revisions.

In untabulated tests, we also examine market reactions to forecast revisions in the second year after the rankings, again comparing third-place analysts and runner-up analysts. The purpose of these tests is to examine whether third-place analysts' superior market influence can persist in the longer term. We find that in the second year after the ranking, market reactions to third-place analysts' revisions are not significantly different from those to first runner-up analysts' revisions. This finding suggests that the market reaction effect might "reset" each year due to the annual nature of the rankings.

5. Additional Analyses

5.1. Career Benefits of Winning Analysts

In this subsection, we examine the effect of rankings on the career benefits of analysts, which could potentially motivate their behavior of issuing optimistic research outputs. To the extent that third-place analysts, relative to first runner-up analysts, experience an increase in reputational capital that they can leverage in various aspects of their job, we should be able to detect differences in their future career benefits. Specifically, we examine whether third-place analysts receive higher priority from management in earnings conference calls, expand their coverage of growth and large-cap stocks, and experience job promotions.

5.1.1. Conference Call Priority. We first consider whether all-star analysts get favorable treatment in subsequent conference calls. Cen et al. (2021) show that analysts chosen to ask a question earlier in a conference call is a proxy for better access to management. We test this notion in our setting using the variable *Conference call priority*, as previously defined, with higher values indicating higher priority. Panel A of Table 7 presents the results. We control for firm and year fixed effects in

Table 7. Analyst Ranking and Career Benefits

	(1)	(2)
Panel A: Conference call priority		
Third-place analyst	0.042*	0.040*
	(0.022)	(0.022)
Firm FE & Year FE	Yes	Yes
Firm Controls	No	Yes
Analyst Controls	No	Yes
N	4,480	4,480
R^2	0.380	0.387

	(1)	(2)	(3)	(4)
Panel B: Characteristics of newly covered firms				
	Market-to-book		Market cap	
Third-place analyst	0.276*	0.268*	0.307*	0.212***
	(0.147)	(0.142)	(0.169)	(0.081)
Industry FE & Year FE	Yes	Yes	Yes	Yes
Firm Controls	No	Yes	No	Yes
Analyst Controls	No	Yes	No	Yes
N	1,997	1,997	1,997	1,997
R^2	0.390	0.458	0.321	0.838

	(1)	(2)
Panel C: Promotion		
Third-place analyst	0.104*	0.110*
	(0.060)	(0.064)
Year FE	Yes	Yes
Industry FE	No	Yes
Analyst Controls	No	Yes
N	326	326
R^2	0.085	0.293

Notes. This table presents the regression analysis of the effect of analyst ranking on analysts' career benefits. Panel A examines the order to ask questions in conference calls. For each conference call, we define each analyst's priority as one minus the ratio of the analyst's order in the call over the total number of participants in each conference call. The dependent variable, *Conference call priority*, is then calculated as each analyst's average priority across all calls for a covered firm in the year after the ranking. Panel B examines the characteristics of firms newly covered by analysts after the ranking. The dependent variable in columns (1) and (2), *Market-to-book*, is the market equity to book equity ratio, and the dependent variable in columns (3) and (4), *Market cap*, is the natural logarithm of the value of market equity. Panel C examines analysts' job promotion. The dependent variable is *Promotion*, an indicator variable that equals one if the analyst is promoted within a year after the ranking and zero otherwise. In all panels, the key independent variable is *Third-place analyst*, a dummy variable that equals one if the analyst is a third-place analyst and zero if the analyst is a first runner-up analyst. We use the optimal bandwidth of 1.555 in Table 3 for consistency. We include polynomials of up to order 2 that are different for the third-place and first runner-up analysts in all regressions. We control for firm fixed effects and year fixed effects in panel A, industry fixed effects and year fixed effects in panel B, year fixed effects in column (1) of panel C as well as industry (as defined by *Institutional Investor*) fixed effects in column (2) of panel C. In even columns, we further control for firm characteristics including book size, book-to-market ratio, sales growth, ROA, and leverage, and analyst characteristics including gender, experience and past all-star status. Standard errors are clustered at the firm level in Panels A and B and at the analyst level in panel C and included in the parentheses.

***, **, and * statistical significance at the 1%, 5%, and 10% levels, respectively. All variable definitions are discussed in Section 3.3.

column (1) and firm and analyst characteristics in column (2). In both specifications, we find that the coefficient on *Third-place analyst* is positive and significant at the 10% level; the magnitude of the coefficients suggests a 4.2% higher priority in a conference call. These results suggest that after the ranking, third-place analysts have better access to management.

5.1.2. New Stock Coverage. We next consider whether all-star analysts are more likely to initiate new coverage of larger-cap and higher-growth stocks in the postranking period, which would be consistent with the potential to generate higher trading commissions. Panel B of Table 7 presents the results of this analysis. In columns (1) and (2), the dependent variable is *Market-to-book*; in columns (3) and (4), the dependent variable is *Market cap*, the natural logarithm of the value of market equity. We control for industry and year fixed effects in columns (1) and (3) and additionally include firm and analyst controls in columns (2) and (4). We find that the coefficient on *Third-place analyst* is consistently positive and significant across all columns, providing evidence that third-place analysts cover higher growth firms and larger market cap firms than first runner-up analysts after the rankings. In untabulated analysis, we find that the vast majority of the newly covered stocks were previously covered by a different analyst at the same brokerage firm, suggesting that the new all-star analyst assumed lead coverage of the stock. Overall, we believe the most common scenario is that newly ranked analysts expand their coverage into adjacent industries, either becoming the lead analyst for more than one industry coverage team or starting a new team as the lead. Anecdotal evidence supports our belief, as each year *Institutional Investor* highlights many ranked analysts who are recognized in the top three for multiple industries.

5.1.3. Job Promotion. Finally, we examine whether third-place analysts are more likely to have job promotions after the ranking. To conduct this analysis, we manually collect data from LinkedIn for 326 analysts, specifically their job titles during different years. Our dependent variable is *Promotion*, an indicator variable that equals one if the analyst is promoted to a higher position within one year after the ranking, as discussed in Section 3.3. Panel C of Table 7 presents the results. We control year fixed effects in column (1) and add industry (as defined by *II*) fixed effects and analyst controls in column (2). We find that the coefficient on *Third-place analyst* is positive and significant in both columns. The results remain robust (untabulated) when examining analysts' promotions within the second and third years following the award. These results suggest that all-star analysts are more likely to have better career opportunities than first runner-up analysts after the ranking.

5.2. Alternative Measures and Consequences of Analyst Outputs

Our main tests focus on measures of analysts' positive-oriented research involving optimistic earnings forecasts, target prices, and stock recommendations. In this section, we examine other forecast properties and consequences of optimistic research, including forecast boldness, frequency, and bias, again contrasting third-place analysts against first runner-up analysts.

5.2.1. Forecast Boldness. A commonly examined analyst forecast property is boldness, which is a measure of how far an analyst's forecast for a given firm deviates from the consensus (Clement and Tse 2005, Clarke and Subramanian 2006, Jegadeesh and Kim 2009). Analysts whose forecasts are near the consensus are viewed as herding with the crowd, a practice that tends to occur when an analyst is concerned about reputation loss from being incorrect. We conjecture that analysts who experience an increase in reputation after an all-star award are likely to be emboldened to stand apart from the herd. Doing so enables them to become more visible to buy-side clients (i.e., institutional investors). In fact, there is empirical evidence that some analysts systematically antiherd by underweighting consensus forecasts (Bernhardt et al. 2006). Therefore, we expect third-place analysts to be bolder in their forecasts after the ranking, compared with first runner-up analysts.

We estimate Equation (1) at the analyst-firm-quarter level, using *Forecast boldness* as the dependent variable, and present the results in panel A of Table 8. We control for firm fixed effects and year-quarter fixed effects in column (1) and add firm and analyst controls in column (2). We find that in both columns, the coefficient on *Third-place analyst* is positive and significant at the 5% level, indicating that third-place analysts are bolder in their forecasts than first runner-up analysts.

5.2.2. Forecast Frequency. Analysts who have become all-stars are likely to gain greater industry influence in the stocks they cover, and their forecast revisions are associated with greater market reactions. As a result, we conjecture that all-star analysts might revise their estimates more frequently than non-all-star analysts, which should also induce more trades. We estimate Equation (1) at the analyst-firm-quarter level, using *Forecast frequency* as the dependent variable, and present the results in panel B of Table 8. In both columns, the coefficient for *Third-place analyst* is positive and significant at the 1% level, suggesting that third-place analysts, compared with first runner-up analysts, tend to make more frequent forecast revisions after becoming

Table 8. Analyst Ranking and Other Forecast Properties

	(1)	(2)
Panel A: Forecast boldness		
Third-place analyst	2.339**	2.634**
	(1.150)	(1.148)
Firm FE & Year-Quarter FE	Yes	Yes
Firm Controls	No	Yes
Analyst Controls	No	Yes
N	28,834	28,834
R^2	0.091	0.092
Panel B: Forecast frequency		
Third-place analyst	0.141***	0.124***
	(0.030)	(0.029)
Firm FE & Year-Quarter FE	Yes	Yes
Firm Controls	No	Yes
Analyst Controls	No	Yes
N	28,752	28,752
R^2	0.232	0.273

Notes. This table presents the regression analysis of the effect of analyst ranking on forecast boldness and frequency. In panel A, the dependent variable is *Forecast boldness*. Following Clarke and Subramanian (2006), for each quarter, we rank all the analysts covering the same company by the absolute deviation from the consensus mean of the forecasts from all analysts for the same firm. Rankings are then scaled such that the boldness ranking is valued from 100 to 0, with higher values indicating greater boldness. In panel B, the dependent variable is *Forecast frequency*. For each firm, we count the number of forecasts made by each analyst in each quarter. In both panels, the key independent variable is *Third-place analyst*, a dummy variable that equals one if the analyst is a third-place analyst and zero if the analyst is a first runner-up analyst. We use the optimal bandwidth of 1.555 in Table 3 for consistency. We include polynomials of up to order 2 that are different for the third-place and first runner-up analysts and control for firm fixed effects and year-quarter fixed effects in all regressions. In column (2), we further control for firm characteristics including book size, book-to-market ratio, sales growth, ROA, and leverage, and analyst characteristics including gender, experience and past all-star status. Standard errors are clustered at the firm level and included in the parentheses.

***, **, and * statistical significance at the 1%, 5%, and 10% levels, respectively. All variable definitions are discussed in Section 3.3.

an all-star analyst. In untabulated analyses, we find that this result also holds for annual forecast frequency.

5.2.3. Forecast Accuracy.

In this subsection, we examine possible negative consequences associated with forecast optimism. While forecast optimism captures the extent to which an analyst's earnings forecast are above consensus, it is unclear how that correlates with forecast accuracy. For example, consider the following two scenarios. The first runner-up analyst's EPS forecast is \$0.50, while the third-place analyst's forecast is more optimistic at \$0.55. If the firm reports EPS of \$0.49 or less, then the third-place analyst is more optimistic and more inaccurate than the first runner-up. In contrast, if the firm reports EPS of \$0.56 or more, then the third-place analyst is the more optimistic and more accurate of the two. Therefore, we first compare the average absolute bias (*Forecast bias*) between third-place analysts and first runner-up analysts, and then, to capture these two scenarios separately, we decompose the bias measure into two truncated measures: *Positive bias* and *Negative bias*, as previously defined.

In columns (1) and (2) of Table 9, we find that there is a positive but insignificant difference in forecast bias between the third-place and first runner-up analysts. We then examine *Positive bias* and *Negative bias* separately, in columns (3) and (4) and in columns (5) and (6), respectively. The coefficients on *Third-place analyst* are significantly positive in columns (3) and (4), indicating that third-place analysts are more inaccurate than first runner-up analysts when actual EPS falls short of forecasts. We also find that the coefficients on *Third-place analyst* are significantly negative in column (5) and negative but not significant in column (6), indicating that third-place analysts are more accurate than first runner-up analysts when actual EPS exceeds forecasts. These results are consistent with the intuition of the two scenarios described above and explain why examining average bias without distinguishing the direction of the forecast error may not detect any significant differences. In addition, the economic magnitude and statistical significance of increased inaccuracy (columns (3) and (4)) are both greater than those of increased accuracy (columns (5) and (6)), suggesting that the consequence of information distortion is mainly reflected in the upper distribution of forecasts. Our findings further indicate that third-place analysts are more optimistic in both directions. In untabulated analyses, we find that these results also hold when we examine annual forecast bias.

It is worth noting that, as investors are typically more constrained in the number of shares they can sell when analysts are negative about a particular stock, relative to the number of shares they can buy when analysts are positive, information distortion due to positive bias may have a greater market impact. Therefore, the opposing effects of forecast optimism on positive and negative biases may not be fully offset for the average investor or at the aggregate market level.

5.3. Placebo Tests

In this subsection, we conduct two placebo tests. First, we compare third-place analysts with second-place analysts. As both are considered all-stars, there should not be any significant difference in their reputation, influence, or effort to generate trading commissions. Accordingly, we do not expect to find a significant difference in their forecast optimism. Second, we compare first runner-up analysts with other lower-ranked runner-up analysts (e.g., 5th, 6th, etc.), with the expectation that we should not observe any differences in forecast optimism because none are considered all-stars. In untabulated analyses of the first placebo test on forecast

Table 9. Analyst Ranking and Biased Research

	(1)	(2)	(3)	(4)	(5)	(6)
Dep variable:	Forecast bias		Positive bias		Negative bias	
Third-place analyst	0.011	0.021	0.039**	0.044**	−0.028*	−0.022
	(0.022)	(0.020)	(0.018)	(0.018)	(0.015)	(0.014)
Firm FE & Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm Controls	No	Yes	No	Yes	No	Yes
Analyst Controls	No	Yes	No	Yes	No	Yes
N	42,173	42,173	42,173	42,173	42,173	42,173
R^2	0.463	0.490	0.354	0.366	0.292	0.307

Notes. This table presents the regression analysis of the effect of analyst ranking on forecast accuracy. The dependent variable *Forecast bias* in columns (1) and (2) is calculated as the absolute value of the difference between quarterly forecast and the actual EPS, scaled by the stock price at the last quarter end. The dependent variable *Positive bias* in columns (3) and (4) is calculated as the forecast minus the actual EPS when the forecast is greater than the actual, scaled by the stock price at the last quarter end, and zero otherwise. The dependent variable *Negative bias* in columns (5) and (6) is calculated as the actual EPS minus the forecast when the forecast is smaller than or equal to the actual, scaled by the stock price at the last quarter end, and zero otherwise. The key independent variable is *Third-place analyst*, a dummy variable that equals one if the analyst is a third-place analyst and zero if the analyst is a first runner-up analyst. We use the optimal bandwidth of 1.555 in Table 3 for consistency. We include polynomials of up to order 2 that are different for the third-place and first runner-up analysts and control for firm fixed effects and year-quarter fixed effects in all regressions. We further control for firm characteristics including book size, book-to-market ratio, sales growth, ROA, leverage, and horizon, and analyst characteristics including gender, experience and past all-star status. Standard errors are clustered at the firm level and included in the parentheses.

***, **, and * statistical significance at the 1%, 5%, and 10% levels, respectively. All variable definitions are discussed in Section 3.3.

optimism, we find that the coefficient on *Second-place analyst*, an indicator variable that equals one if the analyst is a second-place analyst and zero if the analyst is a third-place analyst, is not significantly different from zero across all specifications. We also find that the market does not react to the second-place analysts' forecast revisions differently from those made by third-place analysts. Similarly, there are no significant differences in forecast optimism between first runner-up analysts and other runner-up analysts after the ranking, further highlighting that the all-star award is the key factor driving changes in analyst behavior. Overall, these placebo tests underscore our main finding that differences in optimistic forecasts are found between third-place analysts and first runner-up analysts, providing further support for our identification strategy.

6. Conclusion

In this paper, we use the setting of sell-side equity analysts and all-star rankings to examine the broad research question of whether winning an award affects the behavior of capital market professionals. We find that newly ranked all-star analysts are more optimistic in their forecasts and recommendations relative to first runner-up analysts that are ex-ante similar, which is consistent with the former publishing research that induces more trading commissions and career benefits. Third-place analysts are also more optimistic in their recommendation revisions and more reluctant to issue downgrades, even when covered firms experience bad news. Market reactions are greater for forecast revisions by third-place analysts than those by first runner-up analysts, suggesting that after the rankings, a third-place analyst can move the market more than a first runner-up analyst. Tests of career benefits reveal that third-place analysts, relative to first runner-up analysts who are ex-ante similar, get better access to the management in conference calls, expand their professional territories in covering higher-growth firms and firms with greater market valuation, and have more job promotions. Our evidence based on a novel data set and rigorous RD design suggests a causal relation between the all-star distinction and analysts' postaward behavior and is consistent with the conclusion that finance professionals who win a significant award are likely to become more, rather than less, strategic. Our research also implies an unintended consequence of industry awards that are presumably designed to reward superior performance.

Acknowledgments

The authors thank two anonymous referees, Ying Cao, Jacky Chau, Gus De Franco, Yiwei Dou, Kay Giesecke (the editor), Kose John, Jay Jung, Hangsoo Jyung, Stephannie Larocque, Lian Fen Lee, Runjing Lu, Jeffrey Ng, Tao Shen, Han Stice, Angie Wang, Wongsunwai Wan, Donghui Wu, George Yang, Danqing Young, Yinglei Zhang, and workshop participants at China Europe International Business School, Chinese University of Hong Kong, Concordia University, Fudan University, New York University, Tsinghua University, the University of Hong Kong, the Cass Business School and CeFARR Accounting Conference, the Financial Intermediation Research Society Annual Conference, and the MIT Asia Conference in Accounting for helpful suggestions and comments. The authors acknowledge the excellent research assistance from Yun Dai and Runming Huang.

Endnotes

[1] There is neither unifying evidence suggesting that incentives to maintain reputation dominate those to exploit reputation, nor

consistent evidence showing that professional awards affect overperformers more than underperformers. For example, Malmendier and Tate (2009) find that award-winning CEOs underperform relative to their industry peers, while Shi et al. (2017) show that superstar CEOs' competitors who do not win CEO awards undertake more intensive acquisition activities. Kaniel and Parham (2017) and Kirchler et al. (2018) show that rank incentives affect risk-taking in investment decisions, particularly among underperformers. Jiang et al. (2016) find more positive evidence among board directors that reputation concerns motivate independent directors to dissent with managers.

[2] *Institutional Investor* (*II*) designates all analysts whose votes are within 35% of the third-place analyst's as "runners-up." To be consistent with *II*'s terminology, we refer to the highest ranked runner-up as the "first runner-up," who is the fourth-place analyst.

[3] A research design that compares the winners of an award to those who scored just below the cutoff and did not receive the award can be used to estimate the treatment effect of the award itself across various outcomes. This is because the assignment of the award, under a set of reasonable assumptions, can be considered almost random among those who scored similarly well around the cutoff. We discuss in detail the implementation of the RD design and its identifying assumptions in the setting of analyst rankings in Section 3.1 and Appendix B in the Internet Appendix.

[4] We would not expect all analysts to focus solely on publishing optimistic research at all stages in their careers. We discuss analysts' changing incentives in Section 2.2.2.

[5] We also examine other proxies related to optimism in the paper, including price target forecast, recommendation, the speed of recommendation revisions, and recommendation downgrades, and we find consistent results.

[6] In addition, as pointed out by Lehmer et al. (2022), earnings forecasts occur more frequently, provide more precise information, and allow investors to define their own valuation models. For example, Brown et al. (2016) report that buy-side analysts view sell-side analysts' earnings forecasts to be more useful than recommendations.

[7] See Fang et al. (2020) for a review of how MiFID II affects commission revenue.

[8] *Institutional Investor* announced in March 2018 that it was discontinuing the print edition of its magazine, opting to become fully digital starting April 1, 2018.

[9] There have been various ranking treatments used by prior researchers. For example, Hong and Kubik (2003) stated in their introduction that "The top three vote getters in each industry are called All-Americans and are highly rewarded for this honor." Meanwhile, other papers have generally treated all top-three and runner-up analysts as all-stars (e.g., Drake et al. 2020). Based on the previously discussed institutional fanfare received by top three analysts relative to runners-up, we follow Hong and Kubik (2003) and Liu and Ritter (2011) in defining all-stars.

[10] More details can be found at https://www.institutionalinvestor.com/article/b1v582h07lxx97/The-50th-All-America-Research-Team (retrieved on September 1, 2024).

[11] In December 2019, Greenwich Associates was acquired by CRISIL (Credit Rating Information Services of India Limited), which itself is a subsidiary of S&P Global.

[12] See https://www.institutionalinvestor.com/article/b1v582h07lxx97/The-50th-All-America-Research-Team (retrieved on September 1, 2024).

[13] This inability to observe individual votes satisfies the conditions for RD design validity specified in Hartmann et al. (2011), with analysts being uncertain about their own composite score and the score differences between rival analysts.

[14] We exclude the entire "Macro" sector because the analysts do not cover specific firms, instead providing advice on macroeconomic strategies. The industries included in this sector are Accounting & Tax Policy, Convertibles, Economics, Equity Derivatives, Equity-Linked Strategies, Portfolio Strategy, Quantitative Research, Small Companies, Technical Analysis, and Washington Research.

[15] Our consolidation of analysts down to unique analyst names accounts for instances when an analyst changed their last name upon marriage, as well as analysts who changed their preferred first name.

[16] Not all brokerage firms are covered by IBES, but we are able to match 861 (about 98%) of the analysts from the *II* rankings to the IBES data sets. The primary reason for the high successful match rate is that the vast majority of ranked analysts work for major bulge bracket investment banks and brokerages, and these banks and analysts are well covered in the IBES data sets.

[17] For consistency, we use the same bandwidth of 1.555 for other dependent variables. Our results are robust to using their respective optimal bandwidths. However, sample sizes still differ based on frequency and availability of different dependent variables and control variables. We summarize sample sizes differences in Appendix C of the Internet Appendix.

[18] When computing the optimal bandwidth based on Calonico et al. (2014), we control for analyst-level covariates including analyst gender, past all-star status and experience. Our results are robust to the optimal bandwidth when covariates are not considered.

[19] We include only bad news days that occur more than 90 days before the end of the post-ranking period to ensure that any potential downgrades do not occur in the middle of next year's new rankings.

[20] Gender is inferred from analyst names using an online package of Genderize. We manually search analysts' gender online if inference based on the algorithm has a certainty ratio less than one.

[21] We also report the results from two determinants tests in Appendix E of the Internet Appendix. In the first test, all analysts ranked in the top three places and all runner-up analysts are included. Consistent with findings in the existing literature (e.g., Leone and Wu 2007, Bradshaw 2011), the results suggest that prior all-star status and access to management (as proxied by conference call priority) are associated with a better ranking. In the second test, when considering only third-place analysts and first runner-up analysts, none of the explanatory variables have significant predictive power for the all-star ranking. This suggests that the assignment to third versus fourth place is random, further validating our research design.

[22] For robustness, we also use an optimal bandwidth of 0.99 based on Imbens and Kalyanaraman (2012) and find similarly significant results.

[23] Subsample analyses based on differences in firm characteristics do not confound with the causal inference that relies on variations in analysts' rankings in our RD specifications, as our RD design controls for firm and year fixed effects.

References

Bernhardt D, Campello M, Kutsoati E (2006) Who herds? *J. Financial Econom.* 80(3):657–675.

Beyer A, Guttman I (2011) The effect of trading volume on analysts' forecast bias. *Accounting Rev.* 86(2):451–481.

Borjas GJ, Doran K (2015) Prizes and productivity: How winning the fields medal affects scientific output. *J. Human Resources* 50(3):728–758.

Bozanic Z, Chen J, Jung MJ (2019) Analyst contrarianism. *J. Financial Reporting* 4(2):61–88.

Bradley D, Gokkaya S, Liu X (2017) Before an analyst becomes an analyst: Does industry experience matter? *J. Finance* 72(2):751–792.

Bradley D, Jame R, Williams J (2022) Non-deal roadshows, informed trading, and analyst conflicts of interest. *J. Finance* 77(1): 265–315.

Bradshaw MT (2011) Analysts' forecasts: What do we know after decades of work? Unpublished working paper, Boston College, Chestnut Hill, MA.

Brown LD, Call AC, Clement MB, Sharp NY (2015) Inside the "black box" of sell-side financial analysts. *J. Accounting Res.* 53(1):1–47.

Brown LD, Call AC, Clement MB, Sharp NY (2016) The activities of buy-side analysts and the determinants of their stock recommendations. *J. Accounting Econom.* 62(1):139–156.

Bushee BJ (1998) The influence of institutional investors on myopic R&D investment behavior. *Accounting Rev.* 73(3):305–333.

Bushee BJ (2001) Do institutional investors prefer near-term earnings over long-run value? *Contemporary Accounting Res.* 18(2):207–246.

Calonico S, Cattaneo MD, Titiunik R (2014) Robust nonparametric confidence intervals for regression-discontinuity designs. *Econometrica* 82(6):2295–2326.

Carhart MM (1997) On persistence in mutual fund performance. *J. Finance* 52(1):57–82.

Cen L, Chen J, Dasgupta S, Ragunathan V (2021) Do analysts and their employers value access to management? Evidence from earnings conference call participation. *J. Financial Quant. Anal. (Oxford)* 56(3):745–787.

Chen T, Harford J, Lin C (2015) Do analysts matter for governance? Evidence from natural experiments. *J. Financial Econom.* 115(2): 383–410.

Clarke J, Subramanian A (2006) Dynamic forecasting behavior by analysts: Theory and evidence. *J. Financial Econom.* 80(1):81–113.

Clarke J, Khorana A, Patel A, Rau PR (2007) The impact of all-star analyst job changes on their coverage choices and investment banking deal flow. *J. Financial Econom.* 84(3):713–737.

Clement M, Tse SY (2005) Financial analyst characteristics and herding behavior in forecasting. *J. Finance* 60(1):307–341.

Conrad J, Cornell B, Landsman WR, Rountree BR (2006) How do analyst recommendations respond to major news? *J. Financial Quant. Anal. (Oxford)* 41(1):25–49.

Cowen A, Groysberg B, Healy P (2006) Which types of analyst firms are more optimistic? *J. Accounting Econom.* 41(1–2):119–146.

Cuñat V, Gine M, Guadalupe M (2012) The vote is cast: The effect of corporate governance on shareholder value. *J. Finance* 67(5):1943–1977.

Diamond DW (1989) Reputation acquisition in debt markets. *J. Political Econom.* 97(4):828–862.

Drake M, Joos P, Pacelli J, Twedt B (2020) Analyst forecast bundling. *Management Sci.* 66(9):4024–4046.

Dunbar CG (2000) Factors affecting investment bank initial public offering market share. *J. Financial Econom.* 55(1):3–41.

Emery DR, Li X (2009) Are the Wall Street analyst rankings popularity contests? *J. Financial Quant. Anal. (Oxford)* 44(2): 411–437.

Fama EF, French KR (1996) Multifactor explanations of asset pricing anomalies. *J. Finance* 51(1):55–84.

Fang B, Hope O (2021) Analyst teams. *Rev. Accounting Stud.* 26(2):425–467.

Fang B, Hope O, Huang Z, Moldovan R (2020) The effects of MiFID II on sell-side analysts, buy-side analysts, and firms. *Rev. Accounting Stud.* 25(3):855–902.

Firth M, Lin C, Liu P, Xuan Y (2013) The client is king: Do mutual fund relationships bias analyst recommendations? *J. Accounting Res.* 51(1):165–200.

Gallus J, Frey BS (2016) Awards: A strategic management perspective. *Strategic Management J.* 37(8):1699–1714.

Green TC, Jame R, Markov S, Subasi M (2014) Access to management and the informativeness of analyst research. *J. Financial Econom.* 114(2):239–255.

Groysberg B, Healy PM (2013) *Wall Street Research: Past, Present, and Future* (Stanford University Press, Redwood City, CA).

Groysberg B, Healy PM, Maber DA (2011) What drives sell-side analyst compensation at high-status investment banks? *J. Accounting Res.* 49(4):969–1000.

Gu Z, Li Z, Yang YG (2013) Monitors or Predators: The influence of institutional investors on sell-side analysts. *Accounting Rev.* 88(1):137–169.

Hahn J, Todd P, Van der Klaauw W (2001) Identification and estimation of treatment effects with a regression-discontinuity design. *Econometrica* 69(1):201–209.

Harford J, Jiang F, Wang R, Xie F (2019) Analyst career concerns, effort allocation, and firms' information environment. *Rev. Financial Stud.* 32(6):2179–2224.

Hartmann W, Nair HS, Narayanan S (2011) Identifying causal marketing mix effects using a regression discontinuity design. *Marketing Sci.* 30(6):1079–1097.

Hayes RM (1998) The impact of trading commission incentives on analysts' stock coverage decisions and earnings forecasts. *J. Accounting Res.* 36(2):299–320.

Holmström BR (1982) Managerial incentive problems: A dynamic perspective. Pasternack D, Liljeblom E, Ekholm A, eds. *Essays in Economics and Management in Honor of Lars Wahlbeck* (Swedish School of Economics, Helsinki, Finland), 209–230.

Hong H, Kubik JD (2003) Analyzing the analysts: Career concerns and biased earnings forecasts. *J. Finance* 58(1):313–351.

Howell ST (2017) Financing innovation: Evidence from R&D grants. *Amer. Econom. Rev.* 107(4):1136–1164.

Imbens GW, Kalyanaraman K (2012) Optimal bandwidth choice for the regression discontinuity estimator. *Rev. Econom. Stud.* 79(3): 933–959.

Imbens GW, Lemieux T (2008) Regression discontinuity designs: A guide to practice. *J. Econometrics* 142(2):615–635.

Irvine PJ (2004) Do analysts generate trade for their firms? Evidence from the Toronto stock exchange. *J. Accounting Econom.* 30(2): 209–226.

Jackson AR (2005) Trade generation, reputation, and sell-side analysts. *J. Finance* 60(2):673–717.

Jiang W, Wan H, Zhao S (2016) Reputation concerns of independent director: Evidence from individual director voting. *Rev. Financial Stud.* 29(3):655–696.

Jegadeesh N, Kim W (2009) Do analysts herd? An analysis of recommendations and market reactions. *Rev. Financial Stud.* 23(2):901–937.

Jensen M, Twardawski T, Younes N (2022) The Paradox of awards: How status ripples affect who benefits from CEO awards. *Organ. Sci.* 33(3):946–968.

Juergens JL, Lindsey L (2009) Getting out early: An analysis of market making activity at the recommending analyst's firm. *J. Finance* 64(5):2327–2359.

Jung MJ, Wong MHF, Zhang FX (2015) Analyst interest as an early indicator of firm fundamental changes and stock returns. *Accounting Rev.* 90(3):1049–1078.

Kaniel R, Parham R (2017) WSJ Category Kings—The impact of media attention on consumer and mutual fund investment decisions. *J. Financial Econom.* 123(2):337–356.

Kirchler M, Lindner F, Weitzel U (2018) Rankings and risk-taking in the finance industry. *J. Finance* 73(5):2271–2302.

Krigman L, Shaw WH, Womack KL (2001) Why do firms switch underwriters? *J. Financial Econom.* 60(2–3):245–284.

Lee DS, Lemieux T (2010) Regression discontinuity designs in economics. *J. Econom. Literature* 48(2):281–355.

Lee LF, Lo AK (2016) Do opinions on financial misstatement firms affect analysts' reputation with investors? Evidence from reputational spillovers. *J. Accounting Res.* 54(4):1111–1148.

Lee K, Manochin M (2021) Sell-side equity analysts and equity sales: A study of interaction. *Br. Accounting Rev.* 53(5):100977.

Lee K, Aleksanyan M, Harris E, Manochin M (2023) Throwing in the towel: What happens when analysts' recommendations go wrong? *Contemporary Accounting Res.* 40(3):1576–1604.

Lehmer T, Lourie B, Shanthikumar D (2022) Brokerage trading volume and analysts' earnings forecasts: A conflict of interest? *Rev. Accounting Stud.* 27(2):441–476.

Leone AJ, Wu JS (2007) What does it take to become a superstar? Evidence from institutional investor rankings of financial analysts. Unpublished working paper.

Li KK, You H (2015) What is the value of sell-side analysts? Evidence from coverage initiations and terminations. *J. Accounting Econom.* 60(2):141–160.

Liu X, Ritter JR (2011) Local underwriter oligopolies and IPO underpricing. *J. Financial Econom.* 102(3):579–601.

Maber DA, Groysberg B, Healy PM (2014) *The Use of Broker Votes to Reward Brokerage Firms' and Their Analysts' Research Activities* (Harvard Business School Working Knowledge, Boston).

Malmendier U, Shanthikumar D (2007) Are small investors naive about incentives? *J. Financial Econom.* 85(2):457–489.

Malmendier U, Shanthikumar D (2014) Do security analysts speak in two tongues? *Rev. Financial Stud.* 27(5):1287–1322.

Malmendier U, Tate G (2009) Superstar CEOs. *Quart. J. Econom.* 124(4):1593–1638.

Mayew WJ (2008) Evidence of management discrimination among analysts during earnings conference calls. *J. Accounting Res.* 46(3):627–659.

McCrary J (2008) Manipulation of the running variable in the regression discontinuity design: A density test. *J. Econometrics* 142(2): 698–714.

Michaely R, Womack KL (1999) Conflict of interest and the credibility of underwriter analyst recommendations. *Rev. Financial Stud.* 12(4):653–686.

Mikhail MB, Walther BR, Willis RH (1997) Do security analysts improve their performance with experience? *J. Accounting Res.* 35:131–157.

Mikhail MB, Walther BR, Willis RH (1999) Does forecast accuracy matter to security analysts? *Accounting Rev.* 74(2):185–200.

O'Brien PC, McNichols MF, Lin HW (2005) Analyst impartiality and investment banking relationships. *J. Accounting Res.* 43(4): 623–650.

Peltz M (2011) All-America Research Team—four decades of excellence. *Institutional Investor*. Accessed September 1, 2024, https://www.institutionalinvestor.com/article/2bszb8o25u6rjfteyz8jk/culture/all-america-research-team-four-decades-of-excellence.

Shi W, Zhang Y, Hoskisson RE (2017) Ripple effects of CEO awards: Investigating the acquisition activities of superstar CEOs' competitors. *Strategic Management J.* 38(10):2080–2102.

Soltes E (2014) Private interaction between firm management and sell-side analysts. *J. Accounting Res.* 52(1):245–272.

Stickel SE (1992) Reputation and performance among security analysts. *J. Finance* 47(5):1811–1836.