Anatomy of the Financial Analyst Rankings

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Abstract

We investigate the analyst rankings of *Institutional Investor* (I/I) and *The Wall Street Journal* (WSJ) in 1994-2001. We find that investment recommendation performance is a significant determinant of the rankings. The positive effect of earnings forecast accuracy on the rankings documented in prior research is significant even after adjusting for a variety of other factors. However, other determinants that have a primary component of recognition are generally much more important. Compared to other analysts in the year after becoming stars: (1) the forecasts of I/I stars are significantly more accurate—but only by a modest amount, and those of WSJ stars are not different; (2) the recommendations of I/I stars perform no better and those of WSJ stars perform significantly worse. Further, the behavior of both I/I and WSJ stars is generally consistent with that predicted by herding theories on the basis of career concerns over continuing to be a star (e.g., taking less risk in investment recommendations).

1. Introduction

The media regularly expends substantial resources investigating and reporting on various aspects of investing, such as the performance of financial analysts. For example, each year, *Institutional Investor* (I/I) publishes what it calls an All-American Research Team and *The Wall Street Journal* (WSJ) publishes what it calls "Best on the Street" analyst rankings. These analysts have been shown to be very important to the investment process [e.g., Stickel (1992), Krigman, Shaw, Womack (2001), and Cliff and Denis (2004)]. At the same time, there are innumerable efforts to identify analysts with more accurate earnings forecasts and more informative investment recommendations [see, e.g., Kothari (2001) and Lee (2001) for excellent reviews, and Barber, Lehavy, McNicholes, and Trueman (2001), Cooper, Day, Lewis (2001), Hong and Kubic (2003), and Jegadeesh, Kim, Krische, and Lee (2004) for some recent examples].

Our paper investigates I/I's and WSJ's financial analyst rankings.[1] We identify the determinants of being a star (being included in one of these lists) and the factors most important to repeating as a star, which sheds light on the extent to which the rankings can motivate analysts. We also analyze the performance (i.e., risk-adjusted performance of investment recommendations and accuracy of earnings forecasts) and behavior (i.e., risk-taking and bias) of analysts after they become stars to assess the value of the rankings to investors. Our paper offers insights into the relation between reputation and performance, and to the extent that ranked analysts are paid better, the relation between compensation and performance. Our paper also helps understand the relation between the rankings and the list of better performing analysts selected by the academic literature based on performance.

Being a star can help an analyst earn millions of dollars in additional compensation. Being an I/I star is reported to be among the three most important determinants of analyst compensation [Dorfman (1988, 1997), Hong and Kubik (2003), Kessler (2001), Laderman (1998), Michaely and Womack (1999),

[1] We refer to analysts in either group as "stars." Before 2000, WSJ called its rankings the "All-Star Analysts" rankings. WSJ had two sets of rankings. One was based on investment recommendations and the other was based on earnings forecasts. WSJ stopped the ranking based on earnings forecasts in 2002. For brevity, we only present the results based on WSJ's investment recommendation-based rankings. The results for the WSJ's rankings based on earning forecasts are similar and are available upon request.

and Stickel (1992)].[2] Financial analyst rankings may induce more informative and less biased research reports, and hence benefit the investment community. For example, if being a star reduces analyst bias, the rankings could become part of the solution in the efforts to reduce bias in analyst research, in the wake of the $1.4 billion settlement between regulators and investment banks concerning biased research in exchange for investment banking business [Smith, Craig, and Solomon (2003)]. Potential investor benefits cannot be overestimated; investors pay hundreds of millions of dollars for recommendation and forecast data, and the academic literature includes considerable efforts to identify better performing analysts with more informative recommendations and forecasts.

Despite their potential value, I/I's rankings have been widely criticized by institutional investors and analysts as being "popularity contents" [e.g., Dorfman (1988), Ip (1998), and Kessler (2001)]. Apparently, I/I does not choose to address this impression because it does not provide much information about its rankings. In fact, I/I actually guards the details of its process, and has rebuffed requests for explanations from research directors at major brokerage houses [Dorfman (1988)]. The secrecy in I/I's process may foster distrust among investment managers and research ananlysts who have concerns about the possibility of subjective manipulation to benefit favored analysts. To assess institutional investors' opinion on our own, we conducted an informal survey of participants at an institutional investor organization's conference. Institutional investors were asked to respond to the question: "Do you think I/I's ranking is a popularity contest." More than 90% agreed. The survey results are presented in Table 1.

In 1993, WSJ created its own rankings. WSJ also disparages I/I's rankings as popularity contests. WSJ publicizes its process and claims its rankings are determined solely by performance. And yet, WSJ explicitly imposes restrictions on analyst eligibility and measures recommendation performance using raw returns, which can bias the rankings and compromise their efficacy. Our paper documents the nature and extent of such biases and also, by identifying the similarities and differences between the two rankings, offers insights into I/I's opaque ranking process.

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[2] In this respect, I/I's rankings are said to be more important than WSJ's because they are based on the opinions of a large number of investment managers and have been in existence much longer.

Indeed, we find some differences between the rankings: Performance is a relatively much more important determinant of being a WSJ star than it is of being an I/I star. Also, for existing WSJ stars, performance is the driving determinant of repeating, as well as moving up or down in rank. These results are consistent with the idea that compared to WSJ's rankings, I/I's seem more like "popularity contests."

Surprisingly, however, the overall patterns in I/I's and WSJ's rankings share more similarities than differences. For both, better investment recommendation performance significantly improves an analyst's chance of being a star, as well as that of a non-star becoming a star and a star repeating. The positive impact of earnings forecast accuracy documented in prior research is also robust after adjusting for a variety of other factors. Further, the importance of performance relative to recognition is greater for repeating as a star than it is to becoming a star. However, in spite of the significance of performance, the effects of other determinants that have a primary component of recognition, such as brokerage house size and past star status, are substantially greater, even when controlling for performance. We find that recognition is a critical aspect of meeting WSJ's eligibility requirements. Although we cannot absolutely exclude the possibility that determinants associated with recognition also contain some trace of performance, our results are robust to a vast array of alternative performance measures that have been widely used in the literature. Thus, we cannot reject the idea that the rankings are "popularity contests."

The similarities between the rankings suggest that both rankings create implicit and/or explicit restrictions and, consequently, significant barriers to entry. The differences, however, suggest somewhat different restrictions. Although already being a star in one ranking significantly enhances the likelihood of becoming a star in the other ranking, it is not nearly as important as already being a star in the same ranking. Thus, the restrictions of the two rankings seem to be related, but different. For I/I, its implicit restrictions seem to create more severe barriers to entry than the explicit ones of WSJ. Becoming an I/I star might be likened to admission to an exclusive club. Continued membership—repeating as a star—is very likely. For WSJ, meeting the eligibility requirements might be likened to being invited to participate in a major tennis or golf tournament. Inclusion does not make the analyst a star; it only offers the opportunity to compete to be a star based on performance. Continuing the analogy, participants in one year are very likely to be invited to compete again the next year, although competition makes winning very uncertain.

The evidence on the investment value of the rankings is mixed. When compared to other analysts in the year after becoming stars, I/I stars perform no better with respect to investment recommendations, and WSJ stars perform significantly worse. With respect to earnings forecast accuracy, I/I stars are significantly more accurate, but only by a small margin, and WSJ stars are not significantly different. Both types of stars subsequently take less risk with investment recommendations, but I/I stars are bolder in earnings forecasts. Also, I/I stars are less optimistic in earnings forecasts, but they issue a greater proportion of buy recommendations. Although our results suggest limited investment value for the rankings, they are consistent with theories of herding that are based on career concern incentives and self-assessed ability [e.g., Diamond (1989), Graham (1999), Predergast and Stole (1996), Scharfstein and Stein (1990), Trueman (1994), Welch (2000), and Zwiebel (1995)].

The rest of the article is organized as follows: Section 2 describes the rankings and reviews related literature. Section 3 describes the data. Section 4 provides the primary results concerning the determinants of the rankings. Subsequent performance and the behavior of analysts after they become stars are considered in section 5. Section 6 ends our article with a summary and conclusion.

2. Financial Analyst Rankings and Related Literature

2.1. The Financial Analyst Rankings

In March, April, or May each year, I/I sends surveys to people such as directors of research and fund managers in U.S., European, and Asian investment funds, including the largest funds ranked by I/I. In 2001, I/I sent ballots to more than 780 institutions and received the opinions of more than 3,200 individuals from about 400 institutions [Dini (2001)]. On the survey forms we obtained, these individuals are asked to rank the four best analysts in each industry and fill in their full names. An analyst's I/I ranking is the weighted average of the returned scores, where the weights are the size of each respondent's institution. In its October issue each year, I/I publishes its lists of first, second, third, and runners-up teams, which are based on its rankings. Typically, an industry has only one analyst listed in each of the first and second teams, but multiple analysts from one industry often appear in the third and runners-up teams.

I/I does not reveal any restrictions it has for an analyst to be considered in their rankings, and its questionnaire does not provide a list of analysts for whom to vote. It is clear, however, that their procedure favors analysts at larger brokerage houses. Voters must recall or investigate analyst names (and correct spellings) to be able to vote. Because voters are more likely to vote for analysts with whom they are familiar, and analysts at small brokerage houses are less likely to be known, I/I's procedure puts analysts working at small brokerage houses at a distinct disadvantage.

Also, analysts at small brokerage houses do not have a large sales force to promote and publicize their work to institutional investors [Dorfman (1997)]. In addition, "analysts at regional firms often…devote their energy to finding winners among local stocks, typically smaller companies" [Dorfman (1994)], which limits an analyst's potential involvement with larger institutions that have substantially more investment in large-cap stocks. Dorfman (1994) reports that small brokerage houses "complain it's hard for them to achieve enough recognition to score well in the balloting." Finally, large brokerage houses have analysts in one division and, investment fund managers who can vote for analysts in another division. These investment funds are mostly among the top-300 U.S. money management operations. It seems plausible that investment fund managers are likely to vote for analysts in another division of their own house. And such a bias in favor of larger brokerage houses is clearly intensified by the fact that votes are weighted by the size of the respondent's institution.

Each year, *The Wall Street Journal* (WSJ) provides rankings of the top-five best performers in each industry. Recommendation performance is based on the raw return generated by the analyst's investment recommendations. The objective of WSJ's rankings is to focus on performance and to allow analysts from smaller firms to compete.[3] To be eligible for WSJ's rankings, an analyst must cover five or

[3] In an article announcing the first WSJ' ranking, Dorfman (1993) states: "Interesting though such polls [I/I's rankings] are, they are at best indirect measures of stock-picking skill and earnings-forecast accuracy. Analysts from large firms have an advantage in polls, as their fleet of salespeople help to keep an analyst's name in front of

more *qualified* stocks, and normally at least two of these must be among the ten largest stocks in its industry. To be qualified, a stock typically must have traded above a minimum stock price (normally $2), or have a market capitalization of more than $50 million. See Wiegold (1999) for examples of these restrictions.

WSJ restrictions eliminate a substantial proportion of analysts from their competition. In 2001, only 1,370, out of more than 4,000 potential analysts were eligible. Of those eligible, 433 stars were selected [Wiegold (2001)]. The proportions are similar in other years. Like I/I's process, WSJ restrictions also put analysts working for smaller houses at a substantial disadvantage because small- and medium-sized houses typically focus on the coverage of small- and mid-cap stocks, which are less likely to be WSJ *qualified* stocks. Dorfman (1994) notes that WSJ's "rule that analysts must cover at least two big companies to be eligible brought howls of protest from several regional brokerage firms."

WSJ rankings are based on performance during the prior *calendar* year. In contrast, the time period for the basis of I/I's rankings varies from year to year depending on when I/I sends the surveys, and when they are returned in a given year. For this reason, we examine the sensitivity of I/I's rankings to performance, when performance is measured over alternative 12-month periods, starting in each of the months January through July (e.g., one such period would be May though April). Because the results are essentially equivalent, we use analyst performance during the prior calendar year (January though December) with I/I's rankings to parallel WSJ's rankings.

2.2 Related Literature

2.2.1 Determinants of the Rankings

In the first part of our paper, we consider the idea of whether the rankings are "popularity contests." Our paper is closest in spirit to Stickel (1992) and a contemporaneous study by Leone and Wu (2002) that both show that greater earnings forecast accuracy increases the likelihood of being an I/I star, which we also find. Our paper is also related to research on the relation between earnings forecast

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the institutional money managers who cast the ballots. People who work for small firms may get few votes even though they make great stock picks or pinpoint-sharp earnings estimates."

accuracy and analysts' career concerns such as job turnover and termination [Hong and Kubik (2003)]. However, our paper differs from these papers in significant ways.

First, we study WSJ's rankings, in addition to I/I's rankings. As already noted, I/I's rankings have been criticized as a "popularity contest," perhaps in part because I/I does not reveal its ranking process. WSJ publicizes its process and touts its rankings as being based solely on performance. Contrasting WSJ's rankings with I/I's rankings provides insights into I/I's opaque ranking process.

Second, we consider recommendation performance in addition to forecast accuracy. Earnings forecasts and investment recommendations contain independent information, and many consider recommendations to be more important to investors than forecasts [Francis and Soffer (1997), and Womack (1996)]. Also, bias in recommendations is more severe than it is in forecasts [Lin and McNichols (1998)], and is the focus of the $1.4 billion regulatory settlement noted earlier. Finally, determining the rankings' relative emphasis on forecast accuracy versus recommendation performance is a prerequisite to understanding any performance incentives the rankings might create.

Third, we examine a range of other potential determinants by looking at their marginal impact on the probability of being a star. The fact that greater forecast accuracy and better recommendation performance significantly increases the likelihood of being an I/I star seems to imply that I/I's rankings offer incentives for analysts to perform better. However, our finding that recognition has a *much* greater impact on I/I's rankings than performance brings that implication into question. Analysts must decide how to allocate their limited time, effort, and resources to achieving various goals. I/I's rankings may encourage the pursuit of recognition—even at the expense of more accurate earnings forecasts and more informative investment recommendations.[4] Further, our results provide evidence on the relation between the rankings of I/I and WSJ and the academic literature that identifies analysts with more informative forecasts and recommendations.

[4] For example, Dorfman (1991) provides evidence that "Brokerage-house analysts are spending fewer hours analyzing stocks and more time selling them." In particular, he quotes one research director as saying: "Most of the guys know that they'll be visiting for *II* in the spring. I'm a lonely guy in March and April shortly before the balloting." In fact, analysts are known for their creative and persistent lobbying of money managers for votes [Dorfman (1988), Ip (1998), and Kessler (2001)].

2.2.2. Performance Subsequent to the Rankings

I/I stars make significantly more accurate earnings forecasts compared to non-stars [Stickel (1992) and Fang and Yasuda (2004)]. Stickel (1995) and Fang and Yasuda (2005) find mixed evidence about the value of the investment recommendations of I/I stars compared to those of non-stars. Gleason and Lee (2003) show that abnormal returns associated with earnings forecast revisions by I/I and WSJ stars are not different from non-stars. As part of WSJ's ranking process, the top three WSJ stars in an industry can each recommend a stock for the subsequent year. Desai, Liang, and Singh (2000) show that these "featured recommendations" perform significantly better than risk-adjusted benchmarks. We directly compare both the earnings forecast accuracy and the risk-adjusted performance of the investment recommendations of I/I and WSJ stars with those of non-stars.

2.2.3. The Impact of the Rankings on Analyst Behavior

To our knowledge, our paper is the first to directly consider the impact of star status on analyst behavior. Our first objective is to examine whether the rankings have beneficial effects on analyst behavior. For example, if being a star reduces analyst bias, the rankings could become part of the solution in the efforts to reduce bias in analyst research, and their benefits to investors could be substantial. To this extent, our paper is somewhat related to Fang and Yasuda (2004), who find that the greater accuracy in earnings forecasts by I/I stars disappears for stars that work for top IPO underwriters. Because forecast bias is associated with involvement in the investment banking business, they hypothesize that analysts trade off the compensation from higher external reputation with that from involvement in investment banking. We directly measure and examine biases in recommendations and forecasts for both I/I and WSJ stars to further test their hypothesis. It is important to examine biases in both investment recommendations and earnings forecasts because recommendation bias has been found to be more important and more dramatic than bias in forecasts [Lin and McNichols (1998)]. It is also important to directly measure biases because the difference in performance may be due to factors other than biases. Further, we also examine WSJ star status, in addition to I/I star status.

Our second objective is to investigate whether the effects of star status on analyst behavior are consistent with both career concerns created by the rankings and the comparative advantage of stars in making earnings forecasts and investment recommendations as predicted by the prior theoretical work on herding [e.g., Diamond (1989), Predergast and Stole (1996), Scharfstein and Stein (1990), Trueman (1994), Welch (2000), and Zwiebel (1995)]. In this respect, our paper is also related to Hong, Kubik, and Solomon (2000) and Clement and Tse (2005) who show that experience and self-assessed ability affect analyst risk-taking. Our paper differs from these two studies in a few important ways. We measure reputation using star designation and control for experience. We examine both risk-taking and bias behavior. We also examine the behavior reflected in both investment recommendations and earnings forecasts. Interestingly, we find analysts sometimes behave very differently for investment recommendations versus earnings forecasts. However, these differences are still consistent with the theoretical work on herding.

3. Data

3.1. Analyst Sample

Our data are primarily from the Institutional Brokers Estimate System (I/B/E/S). It has advantages over other databases, such as First Call and Zacks. For example, I/B/E/S provides each analyst's name, brokerage affiliation, earnings forecasts, investment recommendations, and a unique code that allows us to track analysts even if they change affiliations, and to merge earnings forecasts and investment recommendation databases.[5]

The earnings forecast database starts in 1983. The investment recommendation database starts in October 1993, and includes both brokerage house-specific recommendations and standardized I/B/E/S

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[5] First Call does not identify individual analysts, which precludes tracking the analysts and merging the earnings forecast and investment recommendation databases. Zacks does not include large houses such as Merrill Lynch, Goldman Sachs, and Donaldson, Lufkin & Jenrette, which make up about 10% of all I/B/E/S recommendations. I/B/E/S includes all of the major houses plus a larger number of smaller houses.

recommendations. The standardized I/B/E/S recommendations are integer ratings from 1 through 5, corresponding to "strong buy," "buy," "hold," "underperform," and "sell."

Following Clement (1999), Jacob, Lys, and Neale (1999), and Hong and Kubik (2003), we exclude analysts who have earnings forecasts in the I/B/E/S database prior to 1984 to avoid left-censored bias for experience.[6] We also delete analysts with only "hold" recommendations. We focus on the years 1994-2000 because we want to obtain a parallel sample of forecasts and recommendations and because the WSJ rankings start in 1993. This procedure leaves 4,051 analysts and 15,178 analyst-year observations. Because the I/B/E/S database sometimes assigns two codes to the same analyst, our sample is further reduced to 4,019 analysts after we merge the data for these analysts. Our sample is reduced to 3,510 analysts and 12,398 analyst-year observations by requiring CRSP stock returns to create a three-month *recommendation portfolio* within each year. See Appendix A for details about portfolio creation.

3.2 Summary Statistics

Table 2 presents characteristics of average analysts. Variable definitions are given in Appendices A and B. We use t-tests to compare the mean characteristics of stars and non-stars before and after rankings.[7] With few exceptions, stars and non-stars are significantly different before and after rankings, which points to the importance of including various analyst characteristics when examining the rankings.

Table 3 reports summary statistics for the rankings. Panel A reports the unconditional probabilities, which are each category's proportion of the sample. For example, the unconditional probability of being an I/I star is 12.72% because that is the proportion of analysts in our sample who are I/I stars. The unconditional probability of being a WSJ star is 8.24%. The proportion of analysts who repeat from one year to the next is 79.07% for I/I stars, but only 23.78% for WSJ stars. The proportion of non-stars in one year who become stars in the next year is 3.49% for I/I and 8.00% for WSJ. Among the

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[6] Chevalier and Ellison (1999) argue there may be survivorship bias in screened data such as ours because analysts in our initial sample who do not survive from 1984 until at least 1993 are excluded. To investigate this potential bias, we analyzed separately the sub-sample of analysts who started in 1993 and after. We do not find any difference in the results.

[7] Using rank-score tests to compare medians yields similar results, and is therefore not reported.

I/I stars who repeat, only 38.05% fall in rank, so that 61.95% maintain or improve their rank in the subsequent year. Among the WSJ stars who repeat, 86.89% fall in rank, so that only 13.31% maintain or improve their rank in the subsequent year.

Panel B of Table 3 shows in greater detail the movement in ranks from one year to the next. A rank of 5 for I/I, and 6 for WSJ, denotes a non-star. The Panel points to differences in the two rankings. In I/I's rankings, a large proportion of stars either repeat at the same rank or are within one rank of their previous year's rank. For example, 76.1% of analysts on the third team in one year are on the second, third, or runners-up teams in the next year (18.7 + 29.7 + 27.7 = 76.1%). The same percentage for WSJ rankings is 11.1%. If WSJ's rankings are based solely on recommendation performance, and we use it as a benchmark, the stability in I/I star status implies that I/I's rankings are not being driven by recommendation performance.

4. Determinants of the Analyst Rankings

We examine the determinants of the rankings using the following probit model, which analyzes the relation between star status and analyst characteristics:

$$\Pr(\text{STAR}_t = 1) = \Phi\left\{\begin{array}{l} a_0 + a_1\text{INFORATIO}_{t-1} + a_2\text{ACCURACY}_{t-1} + a_3\text{NREC}_{t-1} + a_4\text{NSTOCK}_{t-1} \\ +a_5\text{RISKLEVEL}_{t-1} + a_6\text{BOLDNESS}_{t-1} + a_7\text{IISTAR}_{t-1} + a_8\text{WSJSTAR}_{t-1} \\ +a_9\text{BROKERSIZE}_{t-1} + a_{10}\text{FIRMSIZE}_{t-1} + a_{11}\text{IPOREP}_{t-1} + a_{12}\text{TOP300}_{t-1} \\ +a_{13}\text{PCTBUY}_{t-1} + a_{14}\text{OPTIMISM}_{t-1} + a_{15}\text{EXPERIENCE}_{t-1} \\ +\text{Yearly Dummy Variables} \end{array}\right\} \quad (1)$$

where STAR_t equals 1 if the analyst is a star in year *t* and 0 otherwise. INFORATIO stands for information ratio. It is the t-statistic for the intercept of a market model regression of daily analyst recommendation portfolio returns on the CRSP value-weighted NYSE/AMEX/NASDAQ market index within a given calendar year.[8] The construction of analyst recommendation portfolios is described in Appendix A. ACCURACY and BOLDNESS are relative accuracy and relative boldness measures from

[8] INFORATIO has been used extensively as a performance measure, because it controls for both systematic and idiosyncratic risks of an investment. As discussed later, our results are robust to various performance measures and are available upon request.

Hong et al. (2000), and OPTIMISM is a relative optimism measure from Hong and Kubik (2003), calculated on a one-year basis. These measures control for the forecasts, and number, of other analysts covering the same stock. Additional detail about their construction is given in Appendix B.

We include a set of variables to examine other factors that might also affect star status, in addition to the performance measures, INFORATIO and ACCURACY. The number of research reports issued (NREC), which Jacob et al. (1999) use to measure the timeliness of reports, should also proxy for analyst effort. Jacob et al. (1999) argue that the number of stocks covered (NSTOCK), or broader coverage, should increase industry knowledge. These two variables are interesting because the aspects they represent are said to be important to buy-side investors. RISKLEVEL is the market beta of an analyst's recommendation portfolio from a market model regression and PCTBUY is the percentage of buy and strong buys among an analyst's recommendations. We include RISKLEVEL and BOLDNESS to examine the impact of risk-taking behavior on star status and we include PCTBUY and OPTIMISM to examine the impact of analyst bias. To assess the validity of the widespread belief among practitioners that I/I's rankings are popularity contests, we include two variables measuring past analyst reputation: IISTAR and WSJSTAR are dummy variables that equal one if the analyst is an is an I/I or WSJ star in the prior year, and zero otherwise. We include BROKERSIZE, FIRMSIZE, and IPOREP as measures of recognition for an analyst's house. Stickel (1995) uses BROKERSIZE to proxy for a brokerage house's marketing ability and FIRMSIZE to proxy for the information environment of a covered firm. Hong and Kubik (2003) use BROKERSIZE to a proxy for a brokerage house's prestige and FIRMSIZE as a measure of the attention buy-side investors give to a firm. Because analysts are typically used in IPO road shows, IPOREP is also likely to increase analyst recognition.[9] We include TOP300 to examine the impact of allowing investment managers in one division of a house to vote for analysts in another division of the same house in I/I's rankings. Finally, we include EXPERIENCE, the number of years that an analyst has been submitting reports to I/B/E/S, to examine the impact of experience.

[9] It has been argued that these recognition measures may include a component of performance. Our inclusion of performance measures in the model should control for this possibility, and render these measures to be primarily measures of recognition. However, in addition, as described later, we use numerous performance measures to examine the robustness of our results with respect to performance and recognition.

In the rest of this section, we examine the I/I and WSJ rankings separately using this model. For each type of rankings, we consider the determinants of being a star for the entire sample, as well as those for existing stars repeating and for non-stars becoming stars. We also examine movement in rank across years for existing stars.

4.1. I/I's Rankings

The results for I/I's rankings are shown in Table 4. For each variable in each column, the coefficient estimate and its significance level are given, along with the variable's effect on the marginal probability that the dependent variable is one (given first in the brackets below the coefficient estimate), and the normalized effect (given second in the brackets).[10]

As shown in Panel A of Table 4, recommendation performance (INFORATIO) is significant in every column, except for repeating stars moving up in rank. Forecast accuracy (ACCURACY) is a significant determinant of being an I/I star in column (1), which is the main finding of Stickel (1992) and Leone and Wu (2002). In addition, we find that ACCURACY is significant for stars repeating as shown in column (3) and helps to reduce the chances a repeating star's rank will fall as shown in column (5). However, it is not a significant determinant for non-stars becoming I/I stars. Therefore, although both recommendation performance and forecast accuracy are significant determinants for stars to repeat as stars, only recommendation performance is a significant determinant for non-stars becoming stars. Our results are consistent with prior findings that earnings forecasts and investment recommendations contain independent information [e.g., Francis and Soffer (1997)]. Our results also suggest that investment recommendation is at least as important as forecast accuracy. As described in the next section, our findings are similar when we use various alternative performance measures.

[10] Following convention, we define the effect of a continuous (dummy) variable on the marginal probability as the change in the probability of becoming a star for a one-standard deviation (0 to 1) change in the variable. These effects are calculated with all other variables at their means. Normalizing the marginal effect (i.e., dividing the marginal effect by the unconditional probability) helps with interpreting the effect of the variable, especially when making comparisons across different regressions [Hong and Kubik (2003)].

We now consider the *relative* contribution of analyst characteristics in being a star, as shown in column (1) of Panel A. Thirteen of the fifteen variables are significant at the 10% level of significance. Ten are significant at the 5% level and eight are significant at the 1% level. The normalized effects of IISTAR and BROKERSIZE are the largest of all the variables by a wide margin: 225.57% and 61.95%, respectively. The dominating effect of IISTAR is consistent with the very large proportion of I/I stars who repeat as stars (79.07%). The other statistically significant variables have an absolute value of normalized effect ranging from 4.12% to 19.09%.

Becoming an I/I star clearly increases recognition and substantially enhances an analyst's reputation. "People close to investment banking deals note cynically that the rosters of co-managers for major offerings bear striking resemblance to Institutional Investor Rankings" [Pratt (1992)]. The same holds for an analyst moving to a larger brokerage house. The pronounced effects of both BROKERSIZE and IISTAR, even when *controlling for performance*, make it hard to reject the idea that recognition is a dominating aspect of being an I/I star.

In decreasing size of absolute value of normalized effect, the other variables significant at the 5% level are FIRMSIZE (19.09%), WSJSTAR (17.89%), IPOREP (13.65%), TOP300 (13.35%), NSTOCK (9.94%), EXPERIENCE (-7.10%)[11] , ACCURACY (6.81%), and INFORATIO (5.96%). The value for NREC (significant on the 10% level) is 4.98%, so analyst effort and timeliness do not have a pronounced effect on I/I's rankings. The significance and values for NSTOCK and EXPERIENCE show much greater effects for industry knowledge and experience. The value for TOP300 may indicate that allowing managers to vote for analysts at the same house increases the likelihood that these analysts will become I/I stars. The rest of the variables significant at the 5% level other than the two performance measures are known within the investment community to increase an analyst's recognition. For example, covering larger companies or being a WSJ star both offer an analyst considerable recognition. Similarly, analysts used in road shows marketing IPOs also gain recognition. Although some of the recognition variables

[11] At first blush, it may seem counter intuitive that experience is a negative attribute. However, it is negative only on a conditional basis, controlling for the other variables. With respect to experience alone, stars have more experience than non-stars, as can be seen in Table 2.

may also contain a performance component, we adjust for performance when examining their effects. We find similar results using various alternative performance measures, which are described in the next section. Further, although ACCURACY and INFORATIO are both significant, the other variables that have a large component of recognition have a much greater effect. Even the *combined* economic significance of these two performance variables, measured as the sum of their normalized effects, would rank seventh among all the statistically significant variables. Because of the dominant importance of recognition variables, and the comparatively modest effect of the two performance measures, we cannot reject the idea that I/I's rankings are indeed to a large extent a "popularity contest."

4.1.1. Sensitivity Analysis

There are, of course, alternative ways to measure analyst performance, and there are certain factors that might impact the measures we use. Therefore, we also measure performance in virtually every other way possible that it has been measured in prior research. Because none of our additional sensitivity analysis results are materially different from those shown, they are not tabulated but are available upon request. Our results showing the positive effects of performance on the chances of being a star are robust, but do not reject the notion that I/I's rankings are largely "popularity contests." All the sensitivity tests are also performed on all the other analyses in the rest of the paper. In all cases, the results are not materially different, but are available upon request.

Because I/I's rankings may depend on performance over a longer horizon than one year, we include performance measures over the second and third years before the rankings (they are insignificant). We also measure recommendation performance from 1994 to the year prior to the I/I ranking in a particular year, earnings forecast accuracy from 1983 to the year prior to the I/I ranking in a particular year, and control for analyst characteristics in the same years in Equation (1). In essence, we use all the available data to measure analyst performance up to a particular year. We use a wide variety of alternative methods of forming recommendation portfolios.[12] We measure recommendation performance with numerous alternative methodologies.[13] To control for industry momentum, we replace the market index of the market model with an analyst-specific index by matching the stocks in individual analyst portfolios with industry indexes based on two-digit SIC codes. To address the potential effect of bias on performance, we exclude IPO research coverage where the brokerage house of an analyst is a lead underwriter [Dugar and Nathan (1995), Hong and Kubic (2003), Lin and McNichols (1998), and Michaely and Womack (1999)]. Finally, we exclude forecasts within three days of any prior forecasts for the same stock, and recommendations within the time spans of already outstanding recommendations of other analysts to address cross-sectional correlation among research reports due to herding [Stickel (1990) and Welch (2000)].

Past performance may be one of the factors influencing characteristics that strongly reflect recognition. One paper by Hong and Kubik (2003) shows that greater accuracy in the prior three years of earnings forecasts is one of the factors that improve an analyst's chances of moving to a larger brokerage house. We use numerous measures and methodologies to purge any performance influence from the characteristics that strongly reflect recognition. As already noted, several measures of performance, including both forecast accuracy and recommendation performance from two through eighteen years prior, are insignificant when they are included in Equation (1). To further control for any potential performance influence in those characteristics as much as allowed by our sample, we use the following two-step regressions.

In the first step regression, for the ranking in each sample year, we regress each of the other continuous independent variables in Equation (1) separately on ACCURACY and INFORATIO from the

[12] For example, we form portfolios by giving a weight of 1 and 0.5 respectively to stocks with ratings of 1 and 2 and a weight of -0.5 and -1 respectively to stocks with ratings of 4 and 5. We form portfolios using only recommendations with ratings of 1 and 5. We also use alternative portfolio length requirements such as one month and six months. Finally, we use value-weighted analyst portfolios.

[13] For example, we use the Fama and French (1993) model and the Carhart (1997) model. We use matching portfolios based on size, book-to-market, and momentum, or based on size and industry, as alternative adjustments for risk. We combine factor models with matching methodologies as recommended by Daniel, Grinblatt, Titman, and Wermers (1997), and Eckbo, Masulis, and Norli (2000). Finally, we use raw-return performance measured as average returns as well as buy-and-hold returns.

current and every prior sample year possible (plus a constant). For example, for use in the 1996 ranking, we regress each of these other variables for 1995 on five variables: ACCURACY and INFORATIO for 1995 and 1994 plus a constant. For use in the 2001 ranking, each of these other variables is regressed on fifteen variables: seven measures each of ACCURACY and INFORATIO (1994-2000) plus a constant.[14]

In the second step regression, we estimate Equation (1) using the residuals from the first step regressions in place of the original continuous independent variables. This orthogonalization removes the influence of performance in the current and prior years on the other variables. We estimate Equation (1) using the entire sample and using the sample of each individual year. We find qualitatively the same results as those reported in Section 4.1.

Finally, we exclude performance measures in column (1). If the significance of variables reflecting recognition is because the variables are related to performance, the marginal effects of those variables should improve considerably when the performance measures are excluded. In fact, the marginal effects of these variables are essentially unchanged when performance measures are excluded, which is the expected outcome if these variables do not have a significant component of performance.

4.1.2. Becoming, and Continuing to be, an I/I Star

We now consider the other four columns in Panel A of Table 4. The results from estimating Equation (1) for non-stars in the prior year is shown in column (2). The overall pattern for non-stars is similar to the pattern for the entire sample. This is not surprising because non-stars make up 87.28% of the entire sample. Among the thirteen variables showing any significance for the entire sample, only four are insignificant for non-stars. The variables most related to recognition again dominate in both statistical and economic significance. Among the other three variables that are not significant for the entire sample, only RISKLEVEL is significant for non-stars. As with the entire sample, this evidence cannot reject recognition as the driving force by which non-stars become I/I stars.

[14]We also include ACCURACY for each year from 1984 (the earnings forecast database starts in 1983) up to the year prior to the ranking year to further control for any potential influence of performance on other characteristics.

Column (3) shows the results for stars in the prior year. The overall pattern for existing I/I stars is quite different from the pattern in columns (1) and (2). Only four of the thirteen variables showing any significance for the entire sample are significant for existing I/I stars: BROKERSIZE, ACCURACY, INFORATIO, and EXPERIENCE. Also, both the absolute and relative importance of the performance measures is much greater to stars than to non-stars. The normalized effect of the only significant performance measure in column (2), INFORATIO, is 5.78%. In column (3), both performance measures are significant, with a combined normalized effect of 17.27%. In addition, the combined absolute value of the normalized effects of all the variables that are significant at the 5% level in column (2) is 192.35%, whereas the same value in column (3) is 37.42%. Despite this, there are notable similarities between I/I stars and non-stars. Although the normalized effect of BROKERSIZE is about one third of what it is in columns (1) and (2), it is still dominant. Its effect is larger than the combined effects of the two performance measures, and it is still the only variable significant at the 1% level in column (3).

Columns (4) and (5) report the results from estimating Equation (1) for the subset of analysts that are stars in the prior year, where the dependent variable is a zero-one variable that indicates the direction of movement (DOM) in the analyst's rank from the prior year.[15] The lowest rank is stars who do not repeat. For column (4), the dependent variable equals 1 for stars whose rank increased by at least one level or who repeat at rank 1. For column (5), the dependent variable equals 1 for stars whose rank decreases by at least one level.

The effects of ACCURACY and INFORATIO are particularly interesting. As shown in column (3), better performance in both earnings forecasts and investment recommendations helps an I/I star repeat. However, better performance does not help an I/I star move up in rank in column (4). Instead, as shown in column (5), better performance reduces the likelihood an existing I/I star's rank will fall.

In summary, there are two striking patterns connected with becoming, and continuing to be, an I/I star. First, recognition cannot be rejected as being the driving determinant for a non-star to become an I/I

[15] We also analyze the direction of movements for stars with an ordered probit model, where the dependent variable is 0 if a star moves down by one or more ranks, 1 if a star who is not on the first team repeats at that rank, 2 if a first team star repeats at that rank, and 3 if a star moves up by one or more ranks. We find similar results.

star. For non-stars seeking stardom, the value of greater recognition is an order of magnitude larger than the value of better performance. The second pattern is that except for brokerage size, the determinants that help non-stars become I/I stars are different from those that help I/I stars repeat and/or improve their rank. Performance becomes much more important to existing I/I stars than to non-stars, although the impact of performance is still well short of that of recognition. The overall results cannot reject the hypothesis that I/I's rankings include a substantial component of "popularity contest."

In Section 5, we test the herding theories mentioned earlier. Anticipating that, we now look at predictions that these theories imply about the behavior of analysts after they become I/I stars, based on the results in Panel A of Table 4 and career concern incentives created by the I/I rankings. For risk-taking behavior, although RISKLEVEL is not significant for the entire sample, it is significant for both non-stars and I/I stars—but with *opposite* signs.[16] Taking more risk increases a non-star's chance of becoming an I/I star. However, after becoming an I/I star, taking more risk decreases the chance of repeating. Thus, incentives induced by I/I's rankings should have a negative effect on RISKLEVEL when analysts become I/I stars. Although BOLDNESS is significant for the overall sample, it is not significant in any other column of Panel A. So these results do not offer a prediction about the effect of I/I star status on BOLDNESS. In terms of analyst bias, PCTBUY helps existing stars move up in rank, which would create an incentive for I/I stars to have a greater PCTBUY than non-stars. As shown in columns (3) and (5), OPTIMISM has a significantly negative effect for stars trying to repeat and increases the chance of suffering a lower rank if they do repeat. This predicts that I/I stars will have less OPTIMISM than non-stars.

4.1.3. Time Period and Industry Effects

[16] We also follow Chevalier and Ellison (1999) for our sensitivity analysis and use three additional measures to examine the risk-taking behavior of analysts: 1) residual return standard deviations in the market model regression where the recommendation portfolio returns are the dependent variables; 2) absolute deviations of market betas of individual analysts from the means of market betas across all analysts within a year; and 3) residual return standard deviations of individual analysts from the means of residual return standard deviation across all analysts within a year. We find similar results.

Panel B of Table 4 examines the sensitivity of the results across time and industries. We present the results for (1) all analysts broken into two time periods (1995-1998 and 1999-2001)[17], and (2) analysts from four industries (technology, internet, utilities, and financial).[18] The results in Panel B are very similar to the results for the entire sample in column (1) of Panel A. Therefore, the results do not appear to depend to any material degree on a sub-time period or particular industry.

4.2. WSJ's Rankings

Table 5 presents the results for WSJ's rankings in a parallel format to those presented in Table 4 for I/I's rankings. The results for the entire sample are again presented in column (1) of Panel A. The most important difference between the two rankings is that, based on the normalized effect, performance measured by INFORATIO is considerably more important for being a WSJ star than it is for being an I/I star.[19] The normalized effect of this variable is 25.94%, more than twice the combined effect of ACCURACY and INFORATIO for I/I's rankings, which is 12.77%. This combined effect is the third largest for WSJ's rankings, compared to the combined effects of ACCURACY and INFORATIO being the seventh largest for I/I's rankings. This finding is to some extent consistent with WSJ's professed use of raw return performance as the basis for its rankings. In addition, the marginal impacts of BROKERSIZE and FIRMSIZE are much smaller for WSJ's rankings than for I/I's rankings, and neither TOP300 nor IPOREP (largely measures of recognition) are significant for WSJ's rankings. These facts are also consistent with WSJ's ranking being more dependent on performance, and I/I's rankings being more like "popularity contests." In particular, the fact that TOP300 is insignificant for WSJ's rankings suggests that by allowing money managers to vote for analysts in the same brokerage houses, I/I's process gives a significant advantage to analysts in brokerage houses that have a large money management operation.

[17] Analyzing the sample by each year yields similar results.
[18] We obtain industry classification codes from the University of Chicago's Center for Research in Securities Prices (CRSP). Industry classifications for Internet and technology industries are obtained from Jay Ritter's website. Utility and financial firms are companies with SIC codes from 4000 to 4999 and from 6000 to 6999, respectively.
[19] Because we examine WSJ's recommendation-based rankings, ACCURACY being insignificant is not surprising.

It is therefore surprising that the overall pattern of the determinants of being a WSJ star is so similar to that of being an I/I star. As with I/I's rankings, variables that have a primary component of recognition are driving determinants of WSJ's rankings. For example, WSJSTAR, IISTAR, and BROKERSIZE, have normalized effects of 60.09%, 29.97%, and 20.30%, respectively. Thus, past star status is extremely important to WSJ's as well as I/I's rankings. Although WSJ's explicit restrictions favor analysts who cover larger companies, they result in implicit restrictions that favor existing stars working at large brokerage houses.

The key role of recognition is especially surprising because WSJ promotes their rankings as depending *solely* on performance. As we show in the next section, our finding is most likely due to WSJ's eligibility requirements, which are directly related to recognition. For example, as we discussed earlier, these requirements put analysts working for smaller houses at a substantial disadvantage and are therefore related to brokerage house size. As a consequence, WSJ's restrictions apparently parallel I/I's ranking process, and make recognition a significant component of being a WSJ star. Our finding that both rankings are affected most by having been a star in that same ranking also supports the idea that the rankings' each have unique restrictions that exclude a significant proportion of analysts.

4.2.1. Becoming, and Continuing to be, a WSJ Star

As with I/I's rankings, the overall pattern in column (2) for non-stars (91.76% of the entire sample) is predictably quite similar to that of the entire sample. Even though the importance of performance relative to recognition is much greater for WSJ rankings than I/I rankings, the results in column (2) are nevertheless strikingly similar to those for I/I. The marginal effects of recognition measures are still much larger than that of performance. The results for existing WSJ stars (8.24% of the entire sample) in column (3) are in marked contrast with those for both non-stars and existing I/I stars: INFORATIO and RISKLEVEL, the only significant variables, have a significance level of 1% and 10%, respectively, and based on the normalized effect, INFORATIO is by far the primary determinant. As shown in columns (4) and (5), INFORATIO is also the primary determinant of existing WSJ stars moving up or down in rank. The impact of INFORATIO on the status of existing stars is significant evidence supporting WSJ's claim that its rankings are based on recommendation performance among eligible analysts.

Of course, existing WSJ stars have previously met the eligibility requirements, and are likely to meet them again. Thus, in terms of repeating, recommendation performance becomes the primary determinant. However, non-stars must first meet the eligibility requirements before being allowed to compete on the basis of performance. As a result, although performance is a significant factor for non-stars, variables with a primary component of recognition are important to meeting WSJ's eligibility requirements, and critical determinants of becoming a WSJ star.

As with the I/I results, anticipating tests of herding theories in Section 5, we now look at the predictions these theories imply about the behavior of analysts after they become WSJ stars, based on the results in Panel A of Table 5 and career concern incentives created by the WSJ rankings. The incentives predict that WSJ stars will choose a lower RISKLEVEL because of the negative effect a higher RISKLEVEL has on repeating stars. Because the positive effect of higher PCTBUY in the overall sample seems to be mainly due to its positive effect on non-stars, WSJ star status may have a weakly negative effect on PCTBUY. This is because becoming a WSJ star *reduces* the incentive for a higher PCTBUY, but does not create an incentive for reducing PCTBUY. These theories do not offer predictions concerning analyst behavior in terms of BOLDNESS and OPTIMISM, because neither variable is significant in any of the columns.

4.2.2. Time Period and Industry Effects

Panel B of Table 5 examines the sensitivity of the results across time and industries, paralleling those in Table 4. It presents the results for (1) all analysts broken into two time periods, and (2) analysts from four industries. The results in Panel B are very similar to those for the entire sample. Therefore, the results do not appear to depend to any material degree on a sub-time period or particular industry.

4.3. Comparing the Rankings

There are some comparative differences between the rankings. Performance is a relatively more important determinant of being a WSJ star than it is of being an I/I star. This greater importance can be seen in two ways: the increased marginal effect of performance and the reduced marginal effect of recognition. In the case of existing WSJ stars, performance is the driving determinant of repeating, as well as moving up or down in rank. In fact, RISKLEVEL is the only other variable with any significance (10% level), and it has less than one fourth the impact. Performance being critical for existing WSJ stars is consistent with WSJ's claim that their rankings are based solely on performance. That recognition is less important to being a WSJ star than to being an I/I star is consistent with Dorfman (1994): "Small firms do considerably better in the All-Star Analysts Survey than they do in cracking the Institutional Investor magazine All-America Research Team… small firms complain it's hard for them to achieve enough recognition to score well in the balloting." Our results suggest that performance is less important to I/I's rankings than it is to WSJ's rankings.

Yet that is not the whole story. The overall patterns in I/I's and WSJ's rankings share more similarities than differences. Several variables that have a primary component of recognition are the driving attributes of being both an I/I star and a WSJ star. In both rankings, such variables are of critical importance for a non-star to become a star. Further, in both cases, the importance of performance relative to recognition is greater to repeating as a star than it is to becoming a star. Our results indicate that eligibility restrictions imposed by WSJ effectively create recognition prerequisites for a non-star to become a WSJ star. Although some restrictions on analyst eligibility certainly may be reasonable, the extent of WSJ' restrictions seems to have defeated its own objectives to provide rankings based solely on performance and to allow analysts from smaller firms to compete. This is consistent with the fact that a substantial proportion of the analyst population is regularly excluded from WSJ's rankings. Therefore, the results cannot reject the idea that WSJ's rankings also have a "popularity contest" component, although its impact is certainly less pronounced than it is in I/I's rankings.

The similarities between the rankings indicate that both rankings create significant barriers to entry. The difference in results for the rankings, however, suggests differences in those barriers. Our finding that status in one ranking is significantly affected by past status in the other ranking but is even more driven by past status in the same ranking, also indicates that the barriers of the two rankings are correlated, but different. As noted earlier, WSJ has explicit eligibility restrictions that preclude a large portion of analysts from being considered for its rankings, whereas I/I does not reveal any explicit restrictions. But once meeting WSJ's reqeuirements, analysts are ranked only based on raw return performance. The results indicate that the combined effect of I/I's restrictions are likely to limit eligibility more than that of WSJ's restrictions.

The two sets of barriers affect analysts in somewhat different ways. Becoming an I/I star might be likened to being admitted to a club, where repeating as a star (continuing membership) is very likely. Being allowed to compete in WSJ's rankings might be likened to being invited to participate in a major tournament. It offers the opportunity to compete, but the analyst must win the tournament to be designated a star. Further, participants in one year are very likely to be invited back the next year to compete again, but the fact that WSJ's rankings are based on raw return performance and the uncertain nature of competition make it difficult to repeat as a star.

The club-like nature of I/I's rankings is consistent with the amount of campaigning by analysts among people who fill out I/I's survey. Those who are not in the club seek admission, and those who are in the club want to assure their continued membership. In contrast, campaigning for WSJ star status is almost unheard of.

The "club" versus "tournament" aspect of the two rankings may also stem from a particular difference in ranking processes. WSJ always identifies five stars each year. I/I usually designates one analyst per industry for each of its first and second teams. However, the third and runners-up teams can each have multiple analysts within the same industry. Thus, I/I has the flexibility to include additional analysts if, for whatever reason, it does not want to drop a particular star out of its ranking.

5. Subsequent Performance and Behavior

In this section, we investigate the performance of analysts after they become stars to gauge the investment value of the rankings. We also gauge the effect of reputation incentives on analyst behavior and test the herding theories by investigating the behavior of analysts after they become stars. We use I/I and WSJ star status as the proxy for superior reputation. Prior research has frequently used experience as a proxy for reputation level. The rankings are likely to be more direct measures of reputation. The Fama-MacBeth (1973) regression model shown in Equation (2) is used with each of six dependent variables (INFORATIO, ACCURACY, OPTIMISM, PCTBUY, RISKLEVEL, and BOLDNESS) in the year after an analyst becomes a star.

$$\begin{aligned}\text{Dependent Variable}_{t+1} = a_0 + a_1\text{IISTAR}_t + a_2\text{WSJSTAR}_t + a_3\text{NREC}_t + a_4\text{NSTOCK}_t \\ + a_5\text{BROKERSIZE}_t + a_6\text{FIRMSIZE}_t + a_7\text{EXPERIENCE}_t + \varepsilon_t\end{aligned} \quad (2)$$

where the last five independent variables, including experience, are included as control variables.

Table 6 reports mean coefficients and their significance levels based on time-series distributions of coefficients from calendar-year regressions. We first consider the performance of existing stars. The results in column (1) show that existing I/I stars do not perform better and existing WSJ stars actually perform significantly worse than other analysts in terms of risk-adjusted recommendation performance. The results in column (2) of Table 6 are consistent with Stickle (1992), who finds that I/I stars make more accurate forecasts in the year after they become stars, and Hong et al. (2000), who show that more experienced analysts have more accurate forecasts. WSJ stars do not outperform other analysts in forecast accuracy, but this is not surprising because we are using WSJ’s recommendation-based rankings.

To understand the economic significance of the two statistically significant differences in performance between stars and non-stars, we can compare the results in Table 6 with those in Table 2. The average ACCURACY for I/I non-stars in the year after rankings is 49.78 in Table 2. Based on the coefficient estimate of IISTAR (1.110) in column (2) of Table 6, I/I stars are about 2% (= 1.110 / 49.78) more accurate than non-stars, suggesting modest economic significance. The INFORATIO of WSJ non-stars is 0.29 in Table 2, whereas the coefficient estimate of WSJSTAR is -0.131 in column (1) of Table 6.

Thus, the recommendations of WSJ stars are about 45% (= 0.131 / 0.29) less informative than WSJ non-stars, which is a sizable deterioration in performance.

Now consider the behavior of existing stars. Recall that, on the basis of career concerns, theories of herding predict that although I/I's rankings do not create a career concern incentive for BOLDNESS, they do create incentives for I/I stars to have a lower RISKLEVEL, less OPTIMISM, and a greater PCTBUY, compared to non-stars. Although WSJ's rankings do not create any career concern incentives for BOLDNESS and OPTIMISM, they do create an incentive for WSJ stars to choose a lower RISKLEVEL and eliminate an incentive to choose a higher PCTBUY.

Given our findings in columns (1) and (2) of Table 6, herding theories also offer predictions about risk-taking behavior on the basis of self-assessed abilities. These theories predict that I/I stars are more likely to take risks in forecasts (a higher level of BOLDNESS), and not likely to take risks in recommendations (a lower RISKLEVEL) because they perform significantly better on forecasts but not significantly different on recommendations, compared to other analysts. WSJ stars are not likely to take risks in forecasts and are likely to avoid risks in recommendations because they do not perform differently on forecasts and perform significantly worse on recommendations, than other analysts. Predictions based on self-assessed abilities are therefore quite similar, and not contradictory, to those based on career concerns.

Taken together, career concerns and self-assessed abilities predict that I/I stars will have a lower RISKLEVEL and less OPTIMISM, but larger PCTBUY and greater BOLDNESS. As shown in Columns (3), (4), (5), and (6) of Table 6, except for the insignificant estimate of PCTBUY, the results are consistent with these predictions.

For WSJ stars, the predictions are a lower RISKLEVEL, and possibly a lower PCTBUY. Table 6 shows that there is a significantly negative coefficient for WSJSTAR with RISKLEVEL, and insignificant coefficients for PCTBUY, OPTIMISM, and BOLDNESS. Thus, as with I/I stars, the results for WSJ stars are largely consistent with herding theories.

The collective evidence here and elsewhere [Stickle (1992), Leone and Wu (2002), and Fang and Yasuda (2004)] shows that stars perform and act differently than other analysts in certain ways. It has also been shown that analyst bias is affected by investment banking deals [e.g., Dugar and Nathan (1995), Hong and Kubic (2003), Lin and McNichols (1998), and Michaely and Womack (1999)]. It is possible that stars face a trade-off between higher compensation from a better personal reputation (continuing as a star) and higher compensation from promoting investment banking deals. In fact, Fang and Yasuda (2004, 2005) find evidence consistent with such a trade-off, showing that greater forecast accuracy and more informative investment recommendations occur on average only for I/I stars working at brokerage houses with lower underwriting reputations.

We test the above idea further for both I/I and WSJ stars using recommendation performance, and directly using bias measures of OPTIMISM and PCTBUY. We add IPOREP, and also its interactions with IISTAR and WSJSTAR, respectively, to the first four regressions in Table 6. First consider the results related to I/I stars. The results for forecast accuracy in column (2') are consistent with Fang and Yasuda (2004). The interaction term of IPOREP and IISTAR is negative and significant at the 1% level. However, the results for recommendation performance in column (1') are different from those for ACCURACY and also different from Fang and Yasuda (2005). The interaction term between IPOREP and IISTAR is insignificant. When we directly examine bias, column (4') shows that I/I stars at higher IPOREP firms are no different from non-stars in OPTIMISM, whereas column (3') shows that I/I stars at higher IPOREP firms actually have a lower PCTBUY. Finally, we find none of the coefficient estimates for the interaction term between IPOREP and WSJSTAR to be significant in the four regressions in columns (1'), (2'), (3'), and (4'). Overall, our results do not offer additional support for the hypothesis that stars trade-off higher compensation from a better personal reputation against higher compensation from promoting investment banking deals.

6. Summary and Conclusion

This paper studies the financial analyst rankings of *Institutional Investor* (I/I) and *The Wall Street Journal* (WSJ). Our results first confirm past findings of a positive relation between earnings forecast accuracy and subsequent I/I rankings, and then show that this relation is robust even when controlling for various analyst characteristics. Our results also show that recommendation performance is at least as important as forecast accuracy for I/I's rankings, and that recommendation performance is even more important to WSJ's rankings than it is to I/I's rankings.

Despite their significant relation to the two noted performance measures, the results cannot reject the idea that both rankings include a substantial component of "popularity contest," although less so for WSJ's rankings. The rankings share important similarities. For both rankings, recognition is a primary determinant of being a star, and a driving attribute by which a non-star can become a star. Also, performance is more important to repeating as a star than it is to becoming a star. WSJ's explicit restrictions create implicit barriers that significantly damage, if not defeat, WSJ's proclaimed objective of providing rankings based solely on performance that also allow analysts from smaller firms to compete.

There are also some differences between the rankings. Performance is much more important to being a WSJ star than it is to being an I/I star. For existing WSJ stars, performance is the primary determinant of repeating, as well as moving up or down in rank. WSJ's emphasis on performance for repeating stars makes it more difficult for WSJ stars to repeat, and this can be seen in the proportion that do repeat (23.78%). The contrasting large majority of I/I stars who repeat (79.078%) therefore implies that I/I's rankings are likely to be more of a "popularity contest" than WSJ's rankings.

The critical importance of recognition is intertwined with explicit and/or implicit eligibility requirements to be considered for the rankings. WSJ specifies eligibility restrictions that eliminate a substantial majority of analysts from consideration. I/I does not reveal any explicit restrictions. However, its questionnaires require the identification of specific analysts by name and the votes are weighted by the size of the respondent's institution, which at a minimum creates implicit eligibility requirements in addition to any explicit restrictions I/I might have. Our results suggest that the total effect of I/I's restrictions is more severe than that of WSJ.

The similarities between the rankings indicate similarities in the overall effects of the restrictions. The differences in results, however, suggest differences in the particular restrictions themselves. Our finding that status in one ranking is significantly affected by past status in the other ranking, but is even more driven by past status in the same ranking, also indicates that the restrictions of the two rankings are related, but different. Meeting WSJ's requirements might be likened to being invited to participate in a major tournament. The analyst is offered the opportunity to compete, but must win the tournament to be designated a star. Tournament participants in one year are very likely to be invited back the next year to compete again. However, even for stars in the previous year, the random nature of competition makes it difficult to repeat as a star. In contrast, becoming an I/I star might be likened to admission to a club. Once admitted, analysts tend to continue from year to year as I/I stars. Being dropped from membership, i.e., failure to repeat as an I/I star, is uncommon.

When we compare the ex post performance of stars and non-stars to understand the investment value of the rankings, I/I stars do no better, and WSJ stars significantly underperform by about 45%, with respect to investment recommendations. In terms of earnings forecasts, WSJ stars are no different, and I/I stars are significantly more accurate, but only by about 2%. The limited investment value of the rankings is surprising, given the resources devoted to them, the attention paid to them in the press, their impact on analyst compensation, and the prestige they bring to the analyst's brokerage house.

To test extant herding theories, we also examine the risk-taking and bias behavior after analysts becomes stars. For risk-taking behavior, after becoming I/I or WSJ stars, analysts reduce the risk level of their recommended portfolios; but I/I stars tend to be somewhat bolder in their earnings forecasts. For bias behavior, I/I stars issue a greater proportion of buy recommendations among all the recommendations they make, but are less optimistic in their earnings forecasts. WSJ stars are not significantly different from non-stars. These results do not suggest any clearly beneficial effects of the rankings on analyst behavior. Although the results of the rankings may seem somewhat contradictory at first glance, they are largely consistent with the predictions of herding theories that are based on both career concern incentives (created by the desire to be a star) and the self-assessed ability of stars.

Despite the positive connection between the rankings and analyst performance, our results certainly do nothing to dispel the widely held belief that the rankings include a substantial component of "popularity contest." In fact, our findings raise significant questions about the value of the financial analyst rankings. The links between the rankings and analyst recognition, which are an order of magnitude larger than those between the rankings and performance, cast serious doubt on the value to investors of the current practice of tying analyst compensation to star status.

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Appendix A: Variable Definitions

All the variables are calculated within a calendar year. For the analysis, we create an analyst's *recommendation portfolio* similar to the methodology used by the *Wall Street Journal*. The recommendation portfolio is made up of long positions in stocks the analyst rated 1 or 2 and short positions in stocks rated 4 or 5. Portfolio returns are calculated using CRSP daily returns. Stocks are added to the portfolio as of the recommendation date. Stocks are removed from the portfolio as of the date of any *revision* to the ratings of 3. A stock's classification changes when a superseding recommendation alters the stock's classification. Not all superseding recommendations alter a stock's classification. For example, an upgrade from 2 to 1 is not a revision because the stock would already be included as a long position. In contrast, a downgrade from a rating of 3 to 4 is a revision because the stock would have changed from being excluded to being a short position. Reiteration of a previous recommendation does not change a stock's classification. Returns within each year accumulate from the recommendation date until either (1) the date of revision, or (2) the end of the year, if there is no revision during the remainder of the year. The return from each recommendation position is equally weighted to make up the portfolio's return. A minimum time period of three-months is required for the overall recommendation portfolio with each year for estimation purposes.

INFORATIO	t-statistic for the intercept of a market model regression of daily analyst recommendation portfolio returns on the CRSP value-weighted NYSE/AMEX/NASDAQ market index within a given calendar year.
ACCURACY	Hong and Kubik's (2003) measure of relative earnings forecast accuracy on a one-year basis.
NREC	Logarithm of the number of recommendations the analyst issues.
NSTOCK	Logarithm of the number of stocks an analyst covers.
RISKLEVEL	Market beta of the analyst's recommendation portfolio from the market model regression.
BOLDNESS	Hong et al.'s (2000) measure of boldness in earnings forecasts on a one-year basis.
IISTAR and WSJSTAR	Dummy variables that is equal to 1 if the analyst is an I/I or WSJ star, respectively, and zero otherwise.
BROKERSIZE	Logarithm of the number of analysts employed by the analyst's house. For analysts who switch houses within a given year, we use the time-weighted average of the two houses.
FIRMSIZE	Logarithm of the mean market capitalization of the companies the analyst covered at the end of the prior calendar year.
IPOREP	Underwriter reputation for the period 1992-2000 from Loughran and Ritter (2004).
TOP300	Dummy variable that is equal to 1 if the analyst's brokerage house was ranked by I/I as a top-300 U.S. money management operation and zero otherwise.
OPTIMISM	Hong and Kubik's (2003) measure of relative optimism in earnings forecasts on a one-year basis.
PCTBUY	Percentage of buy and strong buys among the analyst's recommendations. We do not use a parallel measure of Hong and Kubik's earnings forecast optimism measure for recommendations because of the disproportion among the five recommendation categories (in particular, the dearth of 4s and 5s).
EXPERIENCE	Number of years analysts have been submitting reports to I/B/E/S.

Appendix B. Construction of ACCURACY, BOLDNESS, and OPTIMISM

Let $F_{i,j,t}$ be the last earnings per share (EPS) forecast of year-end earnings issued by analyst i on company j between January 1st and July 1st of year t. Let the actual EPS of the company be $A_{j,t}$, the company's stock price be P_j, and $F_{-i,j,t}$ be the average of $F_{i,j,t}$ made by all other analysts except analyst i. So $F_{-i,j,t}$ is a measure of the consensus forecast.

To construct ACCURACY and Boldness, we follow three steps. For ACCURACY, as the first step, we calculate forecast error$_{i,j,t}$ as $| F_{i,j,t} - A_{j,t} | / P_j$. Second, all analysts covering a particular company j in year t are assigned a ranking based on their forecast errors for that company. For example, the best analyst (the one with the smallest forecast error) receives a rank of 1 and the second best receives a rank of 2. If more than one analyst has the same forecast error, they are assigned the midpoint value of the ranks they take up. Third, we calculate a score measure

$$Score_{i,j,t} = 100 - [\frac{Rank_{i,j,t} - 1}{N_{j,t} - 1}] \times 100$$

where $N_{j,t}$ is the number of analysts who cover company j in year t. The relative accuracy measure, ACCURACY, is the average accuracy scores over all the companies covered by analyst i in year t.

For BOLDNESS, as the first step, we calculate deviation from consensus as $| F_{i,j,t} - F_{-i,j,t} |$. Second, all analysts covering a particular company j in year t are assigned a ranking based on their deviations from consensus for that company. Third, we calculate the boldness score measure in the exactly the same way as the third step for ACCURACY. The relative boldness measure, BOLDNESS, is the average boldness scores over all the companies covered by analyst i in year t.

We also create an indicator variable $I_{i,j,t}$ that equals one if $F_{i,j,t} - F_{-i,j,t} > 0$. The relative optimism measure, OPTIMISM, is the average of these indicator variables over all the companies covered by analyst i.

Table 1: Survey Results

We conducted an informal survey of institutional investors at a conference of a institutional investor organization. We asked them to respond to the question “Do you think I/I’s ranking is a popularity contest?” This table contains the results of our survey.

Do you think I/I’s ranking is a popularity contest?		
Yes	20	90.91%
No	2	9.09%
Total	22	100%

Table 2: Summary Statistics of the Variables

Table 2 reports the characteristics of the average analyst. Please see Appendix A for variable definitions. There are 12,398 analyst-year observations for 3,510 unique analysts. We also conduct the t-test for the difference in means of variables between stars and non-stars. We report the significance level of the t-tests under the columns for stars. FIRMSIZE is in billions of dollars. ***, **, and * indicate that t-statistics are significant at the 1%, 5%, and 10% levels, respectively. The data are from January 1994 through December 2001.

		The Year Before Ranking				The Year After Ranking			
	Entire	I/I		WSJ		I/I		WSJ	
	Sample	Non-Stars	Stars	Non-Stars	Stars	Non-Stars	Stars	Non-Stars	Stars
INFORATIO	0.28	0.26	0.42***	0.23	0.78 ***	0.27	0.36 **	0.29	0.26
ACCURACY	50.13	49.62	53.56***	49.97	51.68 ***	49.78	52.81 ***	50.04	51.37 ***
NREC	12.96	12.70	14.68***	12.78	14.69 ***	12.64	15.33 ***	12.82	14.89 ***
NSTOCK	14.54	14.03	17.91***	14.29	16.97 ***	13.87	19.62 ***	14.18	19.70 ***
RISKLEVEL	0.90	0.90	0.93**	0.90	0.87 *	0.90	0.89	0.91	0.84 ***
BOLDNESS	50.18	49.77	52.89***	50.02	51.74 ***	49.89	52.34 ***	50.08	51.51 ***
BROKERSIZE	40.67	35.78	73.15***	39.64	50.73 ***	36.60	71.29 ***	39.73	53.97 ***
FIRMSIZE	6.32	5.85	9.41***	6.25	7.01 *	5.81	10.17 ***	6.11	9.22 ***
IPOREP	6.58	6.31	8.41***	6.52	7.22 ***	6.34	8.38 ***	6.53	7.36 ***
TOP300 (%)	47.38	42.42	80.25***	46.50	55.94 ***	42.86	81.32 ***	46.51	59.71 ***
PCTBUY (%)	39.74	40.60	34.05***	39.89	38.27 *	40.69	32.64 ***	40.02	35.87 ***
OPTIMISM	48.08	48.11	47.90	48.06	48.34	48.16	47.53	48.01	49.08
EXPERIENCE	6.27	6.00	8.04***	6.15	7.41 ***	5.86	9.32 ***	6.07	9.14 ***

Table 3: Summary Statistics of Rankings

Table 3 presents summary statistics for the *Institutional Investor* (I/I) and *The Wall Street Journal* (WSJ) rankings in the period 1994-2000. Panel A reports the percentage of I/I and WSJ stars of the entire analyst population, the percentage of analysts who are stars in the current year given their star status in the prior year, and the percentage of existing stars who experience ranking changes in the current year. Each column of Panel B presents the status changes for analysts with a specific status in the prior year. The percentages in each column sum to 100. Ranks 1-4 for I/I rankings stand for the first, second, third, and runners-up teams of I/I stars. Ranks 1-5 for WSJ rankings are the star analysts ranked as the best through the fifth-best performing analysts by the WSJ. Rank 5 for I/I rankings and rank 6 for WSJ rankings denote non-stars. For example, the first column for I/I rankings shows the percentage of prior year first team stars who obtain various statuses in the current year. The last row of Panel B reports the number of analysts in each of the five or six categories in the prior year.

Panel A. Unconditional Probabilities of Star Status

		I/I	WSJ
Percentage of Sample Analysts Classified as Stars:		12.72	8.24
Percentage of Stars by Past Status:	Stars	79.07	23.78
	Non-stars	3.49	8.00
Percentage of Stars Who Change Ranks:	Up	19.15	8.81
	Down (including becoming non-stars)	38.05	86.69
	Stay at rank 1	15.92	0.59
	Stay at other Ranks	26.89	3.91

Panel B. Status Changes given Analysts' Status in the Prior Year

Institutional Investor Ranking

Current Year Rank	Prior Year Rank 1	2	3	4	5
1	67.8%	21.3%	6.9%	4.9%	0.2%
2	15.7	40.4	18.7	8.4	0.3
3	5.7	17.2	29.7	13.4	0.7
4	2.4	10.2	27.7	35.5	2.3
5	8.4	10.8	17.0	37.7	96.5
Number of analysts	370	314	347	546	10821

The Wall Street Journal Ranking

Current Year Rank	Prior Year Rank 1	2	3	4	5	6
1	2.9%	4.0%	6.3%	6.4%	2.9%	1.6%
2	5.4	5.4	1.0	3.4	2.5	1.7
3	3.4	5.9	6.3	5.9	5.4	1.6
4	5.4	5.4	3.8	3.4	6.4	1.6
5	6.8	5.0	6.3	4.9	4.4	1.5
6	76.1	74.3	76.4	75.9	78.4	92.0
Number of analysts	205	202	208	203	204	11376

Table 4: The Determinants of *Institutional Investor* Star Rankings

Table 4 reports the determinants of the *Institutional Investor* (I/I) rankings from the probit model of Equation (1). In Panel A, for columns (1)-(3), the dependent variable is 1 if the analyst is a star in year *t,* and zero otherwise. For columns (4)-(5), the dependent variable is the star's direction of movement (DOM) in rank from the previous year. For column (4), the dependent variable equals 1 for stars whose rank increase by at least one level or who repeat at rank 1. For column (5), the dependent variable equals 1 for stars whose rank decreases by at least one level (The lowest rank is existing stars who do not repeat as stars.). The dependent variable in Panel B is the same zero-one indicator variable for being an I/I star as in Column (1) of Panel A. In Panel B, industry classifications for Internet and technology industries are obtained from Jay Ritter's website. Utility and financial firms are companies with SIC Code between 4000 and 4999 and between 6000 and 6999, respectively. The unconditional probability is the percentage with a dependent variable of 1. The left number in the brackets is the marginal effect of the variable on the probability of being a star. The effect of continuous variables on marginal probability equals the change in the probability of becoming a star for a one-standard deviation change in this variable, while the effect of dummy variables equals the change in probability with a change in the dummy variable from 0 to 1. Both are calculated with other variables held constant at their means. The right number in the brackets is the left number divided by the unconditional probability (group proportion), which is the "normalized" effect of that variable on the dependent variable. INFORATIO is the t-statistic for the intercept of a market model regression of daily analyst recommendation portfolio returns within a given calendar year on the CRSP value-weighted NYSE/AMEX/NASDAQ market index. ACCURACY is Hong and Kubik's (2003) measure of relative earnings forecast accuracy on a one-year basis. NREC is the logarithm of the number of recommendations the analyst issue. NSTOCK is the logarithm of the number of stocks an analyst covers. RISKLEVEL is the market beta of the analyst's recommendation portfolio from the market model regression. BOLDNESS is Hong et al.'s (2000) measure of boldness in earnings forecasts on a one-year basis. IISTAR and WSJSTAR are dummy variables that are equal to 1 if the analyst is an I/I or WSJ star, respectively, and zero otherwise. BROKERSIZE is the logarithm of the number of analysts employed by the analyst's house. For analysts who switch houses within a given year, we use the time-weighted average of the two houses. FIRMSIZE is the logarithm of the mean market capitalization of the companies the analyst covered at the end of the prior calendar year. IPOREP is the underwriter reputation for the period 1992-2000 from Loughran and Ritter's (2004). TOP300 is a dummy variable that is equal to 1 if the analyst's brokerage house was ranked by I/I as a top-300 U.S. money management operation and zero otherwise. OPTIMISM is Hong and Kubik's (2003) measure of relative optimism in earnings forecasts on a one-year basis. PCTBUY is the percentage of buy and strong buys among the analyst's recommendations. EXPERIENCE is the number of years analysts have been submitting reports to I/B/E/S. ***, **, and * indicate that t-statistics are significant at the 1%, 5%, and 10% levels, respectively. The data are daily from January 1994 through December 2001.

Panel A. Baseline Results

	Entire Sample	By Star Status		Stars' DOM	
		Non-Stars	Stars	Up	Down
	(1)	(2)	(3)	(4)	(5)
UNCONDITIONAL PROBABILITY	12.72%	3.49%	79.07%	35.07%	38.05%
INFORATIO $_{t-1}$	0.05***	0.05 **	0.06 **	0.03	-0.06 **
	[0.76, 5.96]	[0.20 , 5.78]	[6.08 , 7.69]	[1.11 , 3.15]	[-2.93 , -7.70]
ACCURACY $_{t-1}$	0.01**	0.01	0.01 **	0.01	-0.01 *
	[0.87, 6.81]	[0.16 , 4.64]	[7.57 , 9.58]	[1.08 , 3.07]	[-2.76 , -7.26]
NREC $_{t-1}$	0.07*	0.13 **	0.04	0.04	-0.06
	[0.63, 4.98]	[0.32 , 9.17]	[2.39 , 3.02]	[1.02 , 2.92]	[-1.52 , -3.99]
NSTOCK $_{t-1}$	0.14***	0.16 **	-0.03	0.04	0.07
	[1.26, 9.94]	[0.39 , 11.23]	[-1.22 , -1.54]	[0.61 , 1.73]	[1.19 , 3.12]
RISKLEVEL $_{t-1}$	0.05	0.12 ***	-0.11 *	0.06	0.12 *
	[0.35, 2.75]	[0.25 , 7.15]	[-4.42 , -5.59]	[0.96 , 2.75]	[2.30 , 6.06]
BOLDNESS $_{t-1}$	0.01*	0.01	0.01	0.01	0.01
	[0.63, 4.96]	[0.23 , 6.47]	[0.81 , 1.02]	[0.55 , 1.57]	[0.61 , 1.61]
IISTAR $_{t-1}$	2.21***				
	[28.69, 225.57]				
WSJSTAR $_{t-1}$	0.18***	0.23 ***	0.10	0.27 ***	-0.15 *
	[2.28, 17.89]	[0.79 , 22.57]	[7.73 , 9.78]	[9.61 , 27.40]	[-5.52 , -14.51]
BROKERSIZE $_{t-1}$	0.60***	0.64 ***	0.44 ***	0.20 *	-0.36 ***
	[7.88, 61.95]	[2.26 , 64.66]	[15.93 , 20.15]	[3.13 , 8.93]	[-6.33 , -16.63]
FIRMSIZE $_{t-1}$	0.12***	0.17 ***	0.01	0.01	-0.04 *
	[2.43, 19.09]	[0.87 , 24.85]	[0.88 , 1.11]	[-0.06 , -0.18]	[-1.91 , -5.02]
IPOREP $_{t-1}$	0.13**	0.31 ***	-0.14	0.17 *	0.08
	[1.74, 13.65]	[1.08 , 30.83]	[-10.93 , -13.83]	[6.08 , 17.33]	[2.93 , 7.71]
TOP300 $_{t-1}$	0.13***	0.16 **	0.03	-0.05	0.05
	[1.70, 13.35]	[0.56 , 16.11]	[2.64 , 3.34]	[-1.65 , -4.70]	[1.74 , 4.57]
PCTBUY $_{t-1}$	0.14*	0.15	0.14	0.30 **	-0.12
	[0.52, 4.12]	[0.15 , 4.30]	[2.68 , 3.39]	[2.53 , 7.21]	[-1.09 , -2.88]
OPTIMISM $_{t-1}$	-0.05	0.07	-0.34 *	-0.19	0.37 **
	[-0.14, -1.06]	[0.05 , 1.51]	[-4.88 , -6.17]	[-1.20 , -3.43]	[2.54 , 6.69]
EXPERIENCE $_{t-1}$	-0.02***	-0.01	-0.02 *	-0.01	0.03 ***
	[-0.90, -7.10]	[-0.17 , -4.83]	[-5.42 , -6.86]	[-0.88 , -2.51]	[4.72 , 12.41]
Pseudo-RSQ	0.56	0.22	0.04	0.02	0.03
# Observations	12,398	10,821	1,577	1,577	1,577

Panel B. Sensitivity Tests by Different Sample Periods and Industries

	Sample Period		Industry			
	1995-1998	1999-2001	Technology	Internet	Utility	Financial
UNCONDITIONAL PROBABILITY	13.00%	13.21%	8.94%	10.45%	16.67%	14.26%
INFORATIO $_{t-1}$	0.06**	0.06 ***	-0.07	-0.06	0.10	0.11 **
	[0.80, 6.19]	[1.06 , 8.06]	[-0.86 , -9.58]	[-0.94, -9.03]	[2.22, 13.31]	[2.28 , 16.00]
ACCURACY $_{t-1}$	0.01**	0.01	0.01	-0.02	0.01	0.01
	[1.06, 8.14]	[0.76 , 5.73]	[0.98 , 10.93]	[-2.30, -21.99]	[2.60, 15.58]	[0.02 , 0.17]
NREC $_{t-1}$	0.07	0.02	-0.17	0.49	0.56	0.03
	[0.62, 4.74]	[0.21 , 1.60]	[-0.97 , -10.87]	[2.36, 22.61]	[6.41, 38.45]	[0.25 , 1.72]
NSTOCK $_{t-1}$	0.14**	0.18 **	0.37	-0.22	-0.40	0.13
	[1.38, 10.59]	[1.54 , 11.68]	[2.07 , 23.21]	[-1.15, -10.97]	[-4.30, -25.79]	[1.10 , 7.71]
RISKLEVEL $_{t-1}$	0.22***	-0.10 *	-0.03	-0.98**	1.22**	0.26
	[1.62, 12.43]	[-0.78 , -5.93]	[-0.22 , -2.42]	[-6.62, -63.36]	[6.14, 36.82]	[1.39 , 9.74]
BOLDNESS $_{t-1}$	0.01	0.01 **	0.01	0.02	0.01	0.01
	[-0.02, -0.17]	[1.09 , 8.21]	[0.88 , 9.82]	[2.64, 25.23]	[-0.31, -1.87]	[0.20 , 1.38]
IISTAR $_{t-1}$	2.20***	2.17 ***	2.03 ***	2.45***	3.19***	2.27 ***
	[28.47, 219.05]	[28.41 , 215.04]	[22.76 , 254.72]	[25.64, 245.27]	[54.04, 324.25]	[31.94 , 223.88]
WSJSTAR $_{t-1}$	0.16*	0.18 **	0.50 **	-0.21	-0.38	0.42 *
	[2.04, 15.68]	[2.36 , 17.86]	[5.63 , 62.95]	[-2.23, -21.34]	[-6.37, -38.21]	[5.94 , 41.63]
BROKERSIZE $_{t-1}$	0.66***	0.64 ***	0.56 ***	1.99**	0.37*	0.62 ***
	[8.27, 63.63]	[8.83 , 66.87]	[5.68 , 63.50]	[17.00, 162.65]	[5.51, 33.05]	[8.73 , 61.20]
FIRMSIZE $_{t-1}$	0.15***	0.13 ***	0.06	-0.07	0.28	0.08
	[2.74, 21.04]	[2.65 , 20.04]	[1.00 , 11.19]	[-0.80, -7.68]	[3.76, 22.56]	[1.51 , 10.55]
IPOREP $_{t-1}$	0.06	0.13	0.16	-0.69	-0.34	0.27
	[0.73, 5.61]	[1.63 , 12.37]	[1.77 , 19.76]	[-7.23, -69.12]	[-5.75-, 34.50]	[3.82 , 26.75]
TOP300 $_{t-1}$	0.08	0.16 *	0.17	-0.22	1.39***	0.21
	[1.03, 7.90]	[2.12 , 16.08]	[1.86 , 20.81]	[-2.25, -21.56]	[23.52, 141.09]	[2.99 , 20.98]
PCTBUY $_{t-1}$	0.04	0.34 ***	0.05	-0.80	0.50	0.36
	[0.15, 1.12]	[1.19 , 8.98]	[0.14 , 1.57]	[-2.12, -20.27]	[1.94, 11.62]	[1.24 , 8.71]
OPTIMISM $_{t-1}$	-0.28*	0.14	-0.31	0.47	0.57	0.02
	[-0.74, -5.69]	[0.40 , 3.05]	[-0.63 , -7.06]	[0.91, 8.68]	[1.74, 10.46]	[0.06 , 0.42]
EXPERIENCE $_{t-1}$	-0.01	-0.02 ***	0.01	-0.02	-0.02	-0.01
	[-0.60, -4.62]	[-1.23 , -9.34]	[0.14 , 1.52]	[-0.82, -7.82]	[-1.01, -6.03]	[-0.63 , -4.45]
Pseudo-RSQ	0.56	0.57	0.54	0.55	0.69	0.62
# Observations	6,101	6,297	1,023	220	270	1,353

Table 5: The Determinants of *The Wall Street Journal* Rankings

Table 5 reports the determinants of *The Wall Street Journal* (WSJI) rankings from the probit model of Equation (1). In Panel A, for columns (1)-(3), the dependent variable is 1 if the analyst is a star in year *t,* and zero otherwise. For columns (4)-(5), the dependent variable is the star's direction of movement (DOM) in rank from the previous year. For column (4), the dependent variable equals 1 for stars whose rank increase by at least one level or who repeat at rank 1. For column (5), the dependent variable equals 1 for stars whose rank decreases by at least one level (The lowest rank is existing stars who do not repeat as stars.). The dependent variable in Panel B is the same zero-one indicator variable for being an I/I star as in Column (1) of Panel A. In Panel B, industry classifications for Internet and technology industries are obtained from Jay Ritter's website. Utility and financial firms are companies with SIC Code between 4000 and 4999 and between 6000 and 6999, respectively. The unconditional probability is the percentage with a dependent variable of 1. The left number in the brackets is the marginal effect of the variable on the probability of being a star. The effect of continuous variables on marginal probability equals the change in the probability of becoming a star for a one-standard deviation change in this variable, while the effect of dummy variables equals the change in probability with a change in the dummy variable from 0 to 1. Both are calculated with other variables held constant at their means. The right number in the brackets is the left number divided by the unconditional probability (group proportion), which is the "normalized" effect of that variable on the dependent variable. INFORATIO is the t-statistic for the intercept of a market model regression of daily analyst recommendation portfolio returns within a given calendar year on the CRSP value-weighted NYSE/AMEX/NASDAQ market index. ACCURACY is Hong and Kubik's (2003) measure of relative earnings forecast accuracy on a one-year basis. NREC is the logarithm of the number of recommendations the analyst issue. NSTOCK is the logarithm of the number of stocks an analyst covers. RISKLEVEL is the market beta of the analyst's recommendation portfolio from the market model regression. BOLDNESS is Hong et al.'s (2000) measure of boldness in earnings forecasts on a one-year basis. IISTAR and WSJSTAR are dummy variables that are equal to 1 if the analyst is an I/I or WSJ star, respectively, and zero otherwise. BROKERSIZE is the logarithm of the number of analysts employed by the analyst's house. For analysts who switch house within a given year, we use the time-weighted average of the two house. FIRMSIZE is the logarithm of the mean market capitalization of the companies the analyst covered at the end of the prior calendar year. IPOREP is the underwriter reputation for the period 1992-2000 from Loughran and Ritter's (2004). TOP300 is a dummy variable that is equal to 1 if the analyst's brokerage house was ranked by I/I as a top-300 U.S. money management operation and zero otherwise. OPTIMISM is Hong and Kubik's (2003) measure of relative optimism in earnings forecasts on a one-year basis. PCTBUY is the percentage of buy and strong buys among the analyst's recommendations. EXPERIENCE is the number of years analysts have been submitting reports to I/B/E/S. ***, **, and * indicate that t-statistics are significant at the 1%, 5%, and 10% levels, respectively. The data are daily from January 1994 through December 2001.

Panel A. Baseline Results

	Entire Sample	By Star Status		Stars' DOM	
		Non-Stars	Stars	Up	Down
	(1)	(2)	(3)	(4)	(5)
UNCONDITIONAL PROBABILITY	8.24%	8.00%	23.78%	9.40%	86.69%
INFORATIO $_{t-1}$	0.19***	0.19***	0.24***	0.19 ***	-0.17 ***
	[2.14, 25.94]	[1.77, 22.08]	[7.00, 29.42]	[2.20 , 23.44]	[-18.82 , -21.71]
ACCURACY $_{t-1}$	0.01	0.01	0.01	0.01	0.01
	[0.09, 1.05]	[0.02, 0.23]	[1.39, 5.83]	[-0.10 , -1.08]	[-0.16 , -0.18]
NREC $_{t-1}$	0.01	0.03	-0.06	-0.03	0.08
	[0.09, 1.13]	[0.18, 2.29]	[-1.01, -4.23]	[-0.20 , -2.12]	[4.98 , 5.75]
NSTOCK $_{t-1}$	0.17***	0.16***	0.15	-0.02	-0.14
	[1.12, 13.54]	[0.89, 11.10]	[1.57, 6.61]	[-0.07 , -0.79]	[-5.57 , -6.43]
RISKLEVEL $_{t-1}$	-0.05*	-0.03	-0.13*	-0.12	0.12 *
	[-0.24, -2.91]	[-0.16, -1.99]	[-1.63, -6.87]	[-0.62 , -6.59]	[5.49 , 6.33]
BOLDNESS $_{t-1}$	0.01	0.01	0.01	0.01	0.01
	[0.30, 3.67]	[0.27, 3.40]	[0.37, 1.56]	[0.25 , 2.71]	[1.20 , 1.38]
IISTAR $_{t-1}$	0.27***	0.32***	0.12	0.23 *	-0.18
	[2.47, 29.97]	[2.55, 31.90]	[2.92, 12.29]	[2.17 , 23.04]	[-15.92 , -18.36]
WSJSTAR $_{t-1}$	0.53***				
	[4.95, 60.09]				
BROKERSIZE $_{t-1}$	0.18***	0.20***	-0.04	0.03	-0.03
	[1.67, 20.30]	[1.63, 20.40]	[-0.74, -3.11]	[0.26 , 2.75]	[-2.24 , -2.59]
FIRMSIZE $_{t-1}$	0.04***	0.04***	-0.02	0.02	0.02
	[0.50, 6.12]	[0.50, 6.29]	[-0.71, -2.98]	[0.21 , 2.19]	[2.08 , 2.40]
IPOREP $_{t-1}$	-0.07	-0.11**	0.16	-0.08	-0.12
	[-0.67, -8.17]	[-0.89, -11.11]	[3.88, 16.33]	[-0.78 , -8.33]	[-10.46 , -12.06]
TOP300 $_{t-1}$	-0.04	-0.04	-0.04	-0.15	0.12
	[-0.39, -4.75]	[-0.29, -3.66]	[-0.84, -3.53]	[-1.45 , -15.47]	[10.28 , 11.86]
PCTBUY $_{t-1}$	0.15**	0.14**	0.26	0.05	-0.23
	[0.40, 4.84]	[0.31, 3.93]	[1.54, 6.46]	[0.11 , 1.19]	[-4.89 , -5.64]
OPTIMISM $_{t-1}$	-0.03	-0.03	-0.06	-0.10	-0.06
	[-0.06, -0.67]	[-0.05, -0.61]	[-0.26, -1.11]	[-0.17 , -1.76]	[-0.93 , -1.07]
EXPERIENCE $_{t-1}$	0.01**	0.01*	0.02	0.02	-0.01
	[0.37, 4.53]	[0.31, 3.83]	[1.38, 5.79]	[0.59 , 6.30]	[-4.09 , -4.72]
Pseudo-RSQ	0.09	0.08	0.06	0.04	0.04
# Observations	12,398	11,376	1,022	1,022	1,022

Panel B. Sensitivity Tests by Different Sample Periods and Industries

	Sample Period		Industry			
	1995-1998	1999-2001	Technology	Internet	Utility	Financial
UNCONDITIONAL PROBABILITY	9.24%	9.35%	5.24%	5.45%	11.85%	7.02%
$INFORATIO_{t-1}$	0.18***	0.20***	0.39***	0.61***	0.21**	0.17 ***
	[1.79, 19.41]	[2.41, 25.78]	[3.02, 57.57]	[4.79, 87.90]	[3.38, 28.53]	[1.72 , 24.55]
$ACCURACY_{t-1}$	0.01	0.01	-0.01	0.03	0.01	0.01
	[0.05 , 0.53]	[0.10, 1.10]	[-0.70, -13.29]	[1.98, 36.29]	[1.94, 16.35]	[-0.13 , -1.78]
$NREC_{t-1}$	-0.02	0.04	-0.05	0.04	0.33	0.21 *
	[-0.14, -1.48]	[0.25, 2.68]	[-0.15, -2.94]	[0.10, 1.81]	[2.66, 22.47]	[0.90 , 12.77]
$NSTOCK_{t-1}$	0.17***	0.17***	0.12	-0.34	-0.31	-0.15
	[1.17, 12.61]	[1.05, 11.26]	[0.39, 7.42]	[-0.91, -16.77]	[-2.29, -19.36]	[-0.64 , -9.14]
$RISKLEVEL_{t-1}$	0.02	-0.09*	0.09	-0.69*	-0.12	0.10
	[0.10, 1.07]	[-0.46, -4.90]	[0.33, 6.30]	[-2.43, -44.57]	[-0.43, -3.63]	[0.28 , 3.93]
$BOLDNESS_{t-1}$	0.01	0.01*	0.01	0.01	0.01	0.01
	[0.15 , 1.65]	[0.45, 4.84]	[0.43, 8.29]	[0.87, 15.96]	[0.50, 4.18]	[-0.12 , -1.74]
$IISTAR_{t-1}$	0.19***	0.33***	-0.26	-0.59	0.18	0.19
	[1.79, 19.37]	[3.06, 32.72]	[-1.73, -32.93]	[-3.23, -59.23]	[2.09, 17.67]	[1.32 , 18.79]
$WSJSTAR_{t-1}$	0.52***	0.54***	0.82***	1.45**	0.43*	0.61 ***
	[4.77, 51.59]	[5.04, 53.93]	[5.45, 104.02]	[7.87, 144.35]	[5.12, 43.23]	[4.27 , 60.80]
$BROKERSIZE_{t-1}$	0.17***	0.20***	0.05	0.76	0.11	0.23 ***
	[1.56, 16.82]	[1.98, 21.19]	[0.31, 5.88]	[3.37, 61.71]	[1.18, 9.96]	[1.62 , 23.08]
$FIRMSIZE_{t-1}$	0.10***	-0.01	0.01	-0.22	0.10	0.04
	[1.28, 13.84]	[-0.04, -0.48]	[0.14, 2.69]	[-1.25, -22.84]	[0.89, 7.55]	[0.34 , 4.82]
$IPOREP_{t-1}$	-0.08	-0.09	0.29	-0.19	-0.40	-0.33 **
	[-0.70, -7.53]	[-0.82, -8.72]	[1.92, 36.58]	[-1.03, -18.95]	[-4.73, -39.93]	[-2.31 , -32.87]
$TOP300_{t-1}$	-0.01	-0.10	-0.08	-0.52	0.37	0.07
	[-0.09, -0.92]	[-0.92, -9.85]	[-0.53, -10.13]	[-2.84, -52.13]	[4.43, 37.40]	[0.50 , 7.10]
$PCTBUY_{t-1}$	0.06	0.29***	0.44	-0.09	0.18	0.36
	[0.16, 1.71]	[0.72, 7.66]	[0.77, 14.68]	[-0.12, -2.27]	[0.49, 4.15]	[0.63 , 8.97]
$OPTIMISM_{t-1}$	0.05	-0.11	0.40	-1.63	0.11	-0.24
	[0.10, 1.09]	[-0.22, -2.32]	[0.50, 9.45]	[-1.62, -29.67]	[0.23, 1.97]	[-0.36 , -5.19]
$EXPERIENCE_{t-1}$	0.01*	0.01	0.01	0.05	0.01	0.05 ***
	[0.45, 4.83]	[0.39, 4.12]	[0.14, 2.76]	[1.01, 18.49]	[0.38, 3.23]	[1.33 , 18.93]
Pseudo-RSQ	0.09	0.10	0.14	0.34	0.11	0.11
# Observations	6,101	6,297	1,023	220	270	1,353

Table 6: Subsequent Performance and Behavior

Table 6 reports the results of Fama-MacBeth (1973) regression given in Equation (2) that examines analyst performance and behavior in the year after becoming a star. INFORATIO is the t-statistic for the intercept of a market model regression of daily analyst recommendation portfolio returns on the CRSP value-weighted NYSE/AMEX/NASDAQ market index. ACCURACY is Hong and Kubik's (2003) measure of relative earnings forecast accuracy on a one-year basis. PCTBUY is the percentage of buy and strong buys among the analyst's recommendations. OPTIMISM is Hong and Kubik's (2003) measure of relative optimism in earnings forecasts on a one-year basis. RISKLEVEL is the market beta of the analyst's recommendation portfolio from the market model regression. BOLDNESS is Hong et al.'s (2000) measure of boldness in earnings forecasts on a one-year basis. IISTAR and WSJSTAR are dummy variables that are equal to 1 if the analyst is an I/I or WSJ star, respectively, and zero otherwise. IPOREP is the underwriter reputation for the period 1992-2000 from Loughran and Ritter's (2004). NREC is the logarithm of the number of recommendations the analyst issue. NSTOCK is the logarithm of the number of stocks an analyst covers. BROKERSIZE is the logarithm of the number of analysts employed by the analyst's house. For analysts who switch houses within a given year, we use the time-weighted average of the two houses. FIRMSIZE is the logarithm of the mean market capitalization of the companies the analyst covered at the end of the prior calendar year. EXPERIENCE is the number of years analysts have been submitting reports to I/B/E/S. ***, **, and * indicate that t-statistics are significant at the 1%, 5%, and 10% levels, respectively. The data are daily from January 1994 through December 2001.

	PERFORMANCE $_{t+1}$				BIAS $_{t+1}$				RISK TAKING $_{t+1}$	
Variables	INFORATIO		ACCURACY		PCTBUY		OPTIMISM		RISKLEVEL	BOLDNESS
	(1)	(1')	(2)	(2')	(3)	(3')	(4)	(4')	(5)	(6)
IISTAR $_t$	0.025	0.064	1.110 ***	4.726 ***	0.007	0.205 ***	-0.012 **	-0.031	-0.033 **	0.908 **
WSJSTAR $_t$	-0.131 ***	-0.096	-0.049	0.386	0.015	0.014	0.004	0.024	-0.054 **	0.531
IPOREP $_t$		0.004		0.147 *		-0.001		-0.003		
(IISTAR $_t$)(IPOREP $_t$)		-0.004		-0.444 **		-0.024 ***		0.002		
(WSJSTAR $_t$)(IPOREP $_t$)		-0.005		-0.059		0.000		-0.003		
NREC $_t$	0.008	0.008	0.831 *	0.886 *	0.059 ***	0.060 ***	-0.002	-0.003	-0.018	0.326
NSTOCK $_t$	0.145 *	0.146 *	-1.283 ***	-1.258 ***	-0.090 ***	-0.091 ***	0.004	0.003	0.039	-0.651 **
BROKERSIZE $_t$	-0.017	-0.023	2.015 ***	1.776 ***	-0.054 ***	-0.053 ***	0.000	0.004	0.048 ***	1.757 ***
FIRMSIZE $_t$	0.027	0.027	-0.028	-0.021	-0.006 ***	-0.006 ***	0.007 ***	0.006***	0.023	-0.171
EXPERIENCE $_t$	-0.001	-0.001	0.122 ***	0.120 ***	-0.001	-0.001	0.000	0.000	-0.016 ***	0.070