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Does Competition between Stars Increase Output? Evidence from Financial Analyst Forecasts[*]

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ABSTRACT

Top sportsmen often refer to competition against other top sportsmen as a motivation to exert more effort. We examine whether a similar pattern exists among another group of top professionals – star analysts. Our evidence suggests that star analysts concentrate their efforts and generate substantially more accurate earnings forecasts in multi-star stocks, in which they cross paths with other stars. We further show that the higher accuracy in multi-star stocks is not driven by other changes in the information environment of the firms. Our results suggest that competition among stars has substantial effects on the largest firms in financial markets.

JEL classification: G20; G23; G24

Keywords: Star analysts, tournament incentives, forecast error, earnings predictability, firms' information environment

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"I wouldn't be the player that I was, without Larry Bird" (Magic Johnson)

1 Introduction

In professional sports, star players have stated that the rivalry against other stars had caused them to become better players. Magic Johnson–whose quote opens this paper–states that absent the competition with his main rival at the time Larry Bird, he would not have attained the level of performance that he had. In a recent interview, John McEnroe said that the main reason for his quick demise in the late 80s was the early retirement of Bjorn Borg that caused him to lose motivation.[1] The notion that one's full potential is not fulfilled in the absence of their archrival is not necessarily rational. Burnham (2013) suggests that such behavior may have biological and evolutionary foundations. In particular, Wingfield's "challenge hypothesis" posits that male-male competition modulates the energy devoted to mating effort (Wingfield, Hegner, Dufty, and Ball (1990)). The economics literature offers a more rational view. In their seminal work, Lazear and Rosen (1981) suggest that pay according to relative ranking is an optimal contract in the labor market, as agents allocate their effort in response to the rules of a tournament. Rosen (1983) highlights the importance of 'superstars' in a tournament. Baik (1994) shows that effort levels are higher in contests with homogenous contestants–closely ranked in respect to their ability levels–than when the contestants are heterogenous. Empirical work on star competition has thus far been confined to sports economics. Berger and Nieken (2004) find that tournaments between homogeneous contestants are more intense. In asymmetric matchups, on the other hand, the ex ante favorite team plays significantly less intensely, while the ex ante underdog team does not reduce the intensity of its play. Brown (2011) shows that the presence of a single and undisputed superstar can lead to reduced effort from other participants, as the less talented may optimally give up. In the business domain, evidence is scarce and remains indirect at best. Ammann, Horsch and Oesch (2016) suggest that CEOs increase productivity and innovation activity when competing against a prestigious media award winner.

We study the incentive effect of competition among stars. If homogeneous contests lead economic agents to exert more effort, then competition among stars should lead to a

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[1] https://lastwordontennis.com/2019/03/02/five-famous-or-infamous-tennis-feuds/. Similarly, one of the most talented soccer players ever, Lional Messi, indicated after the move of his archrival Cristiano Ronaldo from Spain to Italy that he missed the Portuguese, who always inspired him (https://www.legit.ng/1241336-messi-admits-he-misses-ronaldo-competition-and-still-communicates-with-neymar.html).

substantial increase in productivity. We study this hypothesis using financial analysts' earnings forecasts. Recent survey evidence in the analyst domain suggests that stars see other stars as their main rival and pay special attention when competing with other stars.[2] Analyst forecasts present an especially rich–if not the best–setting to study the effect of star competition. First, analysts are ranked on a regular basis by several outlets of which the most prestigious one is the Institutional Investor (I/I) magazine. Second, an analyst's effort can be observed by comparing the earnings forecast to the eventual actual earnings. In particular, star analyst accuracy is less affected by conflict of interests, career concerns and other strategic considerations.[3] Most importantly, a star analyst typically covers many firms–with some covered by other stars and some are not. Using this rich environment, we study the effect of competition between stars by examining the accuracy of star analysts' earnings forecasts in firms that other star(s) also cover (multi-star stocks), as opposed to their accuracy in firms in which they are the only star (single-star stocks). Our findings suggest that star analysts are significantly more accurate in multi-star stocks than in single-star stocks. Furthermore, the *consensus* forecast in multi-star stocks is much more accurate than that in single-star stocks. The latter result is consistent with the special status of star analysts in the financial markets.[4] Our results are robust to the introduction of a novel instrumental variable, and we perform additional tests that rule out various alternative explanations to our competition hypothesis.

We determine star status according to Institutional Investor's annual All-American Research Team. Each year, Institutional Investor proclaims the top three analysts in various industries and sectors. Accordingly, we define stars as those in the top three places. We then

[2] Brown, Call, Clement, and Sharp (2015) report that existing star analysts are more likely than other analysts to state that being an I/I star is important for their career advancement. Anecdotally, one analyst described the benefits of being an I/I star as "your external stamp of approval" and that "Your access to management teams is greatly increased by your II ranking." Another said, "The II rankings … give you significant leverage within your own firm". Baum, Bowers, and Mohanram (2015) find that, when only competition among non-star analysts is considered, accuracy is negatively rather than positively correlated with the level of overlap across analyst portfolios (multipoint contact), consistent with a collusive view of mutual forbearance.

[3] While analysts in general may forego some forecast accuracy in order to differentiate themselves (Banerjee (2019)), star analysts have been shown to herd less, to be less optimistic during hot equity periods, and to not revise recommendations when they switch brokerage houses (Hong, Kubik, and Solomon (2000); Clarke, Khorana, Patel, and Rau (2007); and Fang and Yasuda (2009)).

[4] A recent paper by Do and Zhang (2019) documents that, when a star analyst initiates coverage in a stock, the accuracy of other analysts also improves. Previous literature supports the notion that the consensus analyst forecast is a good predictor of actual earnings, i.e. superior over time-series models (Conroy and Harris (1987); O'brien (1988)). Bradshaw, Drake, Myers and Myers (2012) find that analysts' forecasts are only less informative over longer horizons, for smaller or younger firms, and when analysts forecast negative or large changes in EPS.

divide the portfolio of each star analyst into two types of stocks–stocks covered by at least one other star (multi-star stocks) and stocks in which all other analysts are ordinary–as in non-star–analysts (single-star stocks). On average, the portfolio of stars includes roughly 60% multi-star stocks and 40% single-star stocks.[5] Consistent with Clarke, Khorana, Patel, and Rau (2007), we find that star stock selection is very sticky as they hardly change their portfolio after becoming a star. In contrast, the stocks that star analysts cover often change their status from multi-star to single-star and vice versa as some existing stars are demoted while new stars are elected from one year to the next. In our sample, only about one third of stocks followed by a star analyst remain single- or multi-star throughout our sample period, whereas about one quarter switch status at least three times.

In our baseline results, we compare the accuracy of star analysts in multi-star stocks to that in single-star stocks, and find that star analysts are significantly more accurate in multi-star stocks. This effect is economically important as we find that the decrease in forecast error is of roughly 25%. Furthermore, as star analysts cover mainly large stocks, most of the empirical findings in this paper are about the largest and most visible firms in the financial markets. We also use our baseline results to test several alternative explanations. Since the portfolio of stars is extremely sticky, our results are not likely to be driven by stars changing their coverage choice in response to changes in firms' information environment. Indeed, our results persist even when we exclude from the sample stars that change their stock coverage often. Our results also persist when we limit the sample only to stocks that change their status from multi-star to single-star at least once during our sample period, ruling out the possibility that any cross-sectional differences between single- and multi-star stocks are behind our results.[6] We further examine whether institutional investors may use analyst rankings in order to signal to analysts which stocks gain/lose interest, however the evidence is inconsistent with such notion.

One may argue that, rather than our competition argument, the higher accuracy in multi-star stocks simply reflects a higher quality of analyst coverage. The latter explanation suggests that analyst quality is positively correlated with star status. Thus, when a stock changes from multi-star to single-star, the overall quality of analyst coverage decreases and

[5] When we define stars as those in the first and second place only, the coefficients in our tests are typically larger, although we usually lose power in our tests. Conversely, when we add runner-ups, almost all large stocks become multi-star stocks and hence we lose our results.

[6] Our results remain significant even when we limit the sample to stocks that alternate from multi- to single-star status three times, i.e. complete two full round-trips.

with it the accuracy of all analysts that cover the stock. In order to distinguish between the quality explanation and our competition explanation, we utilize a special feature in star analyst competition–the timeline characteristics of the I/I rankings themselves. Each year, the rankings are published in October but are based on the performance of the analyst up until the previous year. It is this lag that allows us to distinguish between the two stories. Consider for example a stock covered by two star analysts but one of them is not re-selected in the following year. Early in the year of demotion, the soon-to-be-demoted star had already been recognized as low quality by the I/I survey respondents, and his contribution to firms' information environment at that time is already low. The remaining star, however, assumes that she is still competing against another star, as she is yet unaware of the upcoming demotion prior to the publication of the rankings in October. We compare the forecast error of the remaining (i.e. non-demoted) star at this period to her forecast error in the subsequent year, after the demotion of her rival becomes public. Our findings suggest that the forecast error of the remaining star increases substantially once she learns that her rival is no longer a star. Notably, the increase in forecast error is limited to cases in which the demotion of one star leads to the stock changing status from multi-star to a single-star, and not to stocks which remain multi-star despite the demotion (for example, when the number of stars decreases from three to two). We also note that, in contrast to brokerage house mergers and closures during which analysts lose their jobs or change their portfolio and choose to stop covering the firm in the process, our instrumental variable–a shift in a firm's status from multi-star to single-star type following the demotion of one or several star analysts covering it–does not require any of the analysts to drop coverage.[7] Indeed, the spike in star analyst forecast error after her rival is demoted persists when the demoted analyst continues to cover the stock. The latter result further supports the competition explanation over any change in the quality of analyst coverage.

Our previous results are consistent with the notion that competition among stars increases star output. In our last set of tests, we examine one implication that emerges from our competition hypothesis–the merit effect. If a star analyst indeed exerts more effort in competition with other stars, then the better star analyst is more likely to outperform the other star(s). This outperformance should not be limited to generating more accurate forecasts, but

[7] Do and Zhang (2019) document that a decrease in analyst coverage is associated with a deterioration in the firm information environment. While these results are consistent with positive relation between competition and effort, they may also be explained simply by the effect of less coverage that leads to information about the firm.

also more broadly reflected in subsequent rankings. We measure the outcome of star competition by examining the number of multi-star stocks in which a star analyst was the most accurate star. Then, we examine whether the merit of the better star analyst is reflected in the subsequent I/I rankings. Our assumption here is that analyst accuracy is correlated with other dimensions along which Institutional Investor evaluates analysts: industry knowledge, written reports, stock picks, timely communication with investors, and responsiveness to investor requests (Yin and Zhang (2014)).[8] Our results show a strong relation between the number of multi-star stocks in which the analyst is the most accurate star and promotion in the I/I rankings in the subsequent year. This relation subsumes the effect of the commonly used average accuracy as well as the success of the star against the entire analyst community.

This study is not the first paper to examine the effect of competition among analysts. In their seminal work, Hong and Kacperczyk (2010) show that an unexpected decrease in the number of analysts following a firm leads to an increase in optimism bias. The competition in Hong and Kacperczyk (2010) relates to the inability of firms to suppress negative news. In order to ensure that our results are not driven by similar economic forces, we divide our sample into negative and positive earnings surprises, and our results persist even when we exclude firms with negative news. Yin and Zhang (2014) show that, consistently with the incentives in a risk-taking tournament (e.g. Brown et al (1996)), analysts that are behind in their interim rankings in the I/I tournament (or intra-broker competition) are significantly bolder in their future forecasts. Their finding is largely on the second moment of the forecast error, however its effect on effort and output remains unclear. Our paper is also related to Hartford et al. (2014) suggesting that analysts do not exert the same effort in all the stocks that they cover. Specifically, Harford et al. (2014) demonstrate that analysts are more accurate in larger stocks with high trading volume and high institutional holdings, and argue that analysts exert more effort in stocks with high institutional interest. Our findings are largely separate from theirs, as we show that competition among star analysts plays a key

[8] Stickel (1992) and Leone and Wu (2007) document that all-star analysts produce more accurate earnings forecasts, suggesting that forecast accuracy is an important indicator of analysts' performance in the I/I tournament. Furthermore, the literature has shown that forecast accuracy is correlated with other channels through which analysts contribute to the information environment, such as recommendation profitability (Loh and Mian (2006)) and initial price reaction (Green, Jame, Markov, and Subasi (2014)). Kecskés, Michaely and Womack (2016) find that about one-third of recommendation changes are motivated by concurrent earnings estimate revisions, and that such earnings-based recommendations have a significantly greater stock price effect.

role, not in the cross-section between small and large firms, but rather *within* the largest most visible stocks in the financial markets.

Focusing on the competition among stars rather than the competition among the entire analyst community allows us to make several contributions to the literature. First, as previously discussed, it allows us to develop a novel instrumental variable. Aside from the ability to separate between competition and coverage quality, breaks in competition between stars merely due to the demotion of one of them happens frequently–unlike brokerage house mergers and closures that occur sporadically and cluster in time. Second, studying the competition among stars allows us to highlight the importance of star analysts in the financial markets. Recent academic literature doubts whether being a star analyst carries as much importance as previously assumed. Brown, Call, Clement, and Sharp (2016) report, for example, that star status is not an important attribute in buy-side research.[9] We are able to show the large influence of stars in the financial markets, as the loss of competition between stars is accompanied by a large increase in forecast errors. This is consistent with earlier work, and recently Do and Zhang (2019), who show that analysts are much more influential when elected as stars.[10] Most importantly, unlike most of the papers that find the effect of analyst coverage (in general) to be mostly related to small and medium stocks (e.g. Derrien and Kecskés (2013) and Kelly and Ljungqvist (2012)), our findings are related to the largest and most central stocks in the financial markets. Finally, we note that the ability to identify ex ante–at the beginning of the earnings cycle–large differences in earnings predictability among large firms can serve as a springboard to further research. Classical questions such as the effect of earnings predictability on earnings announcement returns or post earnings announcement drift can be reexamined using our new setting.

The rest of the paper is organized as follows. In Section 1, we discuss the data and methodology. In Section 2, we examine the effect of star competition on forecast accuracy.

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[9] More specifically, the I/I rankings are important to sell-side analysts, but are less so to buy-side analysts. Brown et al. (2016) report that star status is not an important attribute in buy-side research. At the same time, one buy-side analyst in the poll states that “the only people who care about it are the sell-side analysts, because for some reason their firms think if they have an II-ranked analyst, they should get paid more and get a bigger bonus.”

[10] Cliff and Denis (2004) and Krigman et al. (2001) show that managers seek star analyst coverage more than ordinary analyst coverage. Irvine, Lipson, and Puckett (2006) find that star analyst recommendations have a stronger effect on institutional trading. Loh and Stulz (2011) report that star analyst recommendations are much more influential than those of ordinary (non-star) analysts. Similarly, Kelly and Ljungqvist (2012) provide evidence that star analyst coverage reduces the firm’s cost of capital more than coverage by ordinary analysts.

In Section 3, we examine the implication of doing well in star competition on subsequent rankings, and in Section 4 we conclude.

1. Data, Methodology, and Summary Statistics

1.1 Data and methodology

Our data is drawn from three main sources. The data on analysts' earnings forecasts comes from the Institutional Brokers' Estimate System (I/B/E/S) files. We limit the sample period to 2002–2015, as many papers show that the nature of analyst estimates changed materially after the adoption of the Regulation Fair Disclosure (FD). Throughout the paper, we concentrate on the earnings per share (EPS) forecast for the next fiscal year. Institutional ownership data is sourced from Thomson Reuters Institutional 13f Holdings - s34. Institutional Ownership (IO) is defined as the sum of all institutional holdings divided by shares outstanding. Because 13f data only include long positions, the IO is winsorized to a maximum of 1. Analysts' rankings are drawn from the files of I/I.

We determine star status according to *Institutional Investor*'s annual All-American Research Team. Each year, *Institutional Investor* proclaims the top three analysts in various industries and sectors. We therefore define stars as those in the first, second, or third All-American teams. Although additional runner-up(s) may be nominated, they are excluded from the All-American Research Team and accordingly not considered stars in our analysis. The vast majority of analysts included in the team are selected as stars in a single industry. However, close to 10% of star analysts are selected in more than one industry. In such cases, in order to avoid double counting, we consider the higher ranking as the star analyst's ranking for that year. We manually match the remaining analyst-years from I/I rankings with the I/B/E/S files.

Throughout our sample period, we have 39,019 unique analyst-year observations, of which 5.2% relate to stars. We exclude from the sample non-U.S. stocks and stocks that are missing either actual earnings or market value. In this paper, we want to study the effects of competition against star analyst(s). As such, we also exclude all stocks that are covered by one analyst, in which case there is no competition of any kind. The resulting sample includes 42,099 firm-years of which 64.1% are not covered by any star analyst, 14.5% by a single star analyst (single-star stocks), and 18.5% by two or more star analysts (multi-star stocks). In order to compare analysts' performance across different stocks, we need a measure of accuracy. For this purpose, we introduce the metric of forecast error, which we define as the absolute difference between the forecast and realized earnings scaled by the realized earnings. We note that realized earnings (and accuracy) are only announced one year after the forecast was made (after the forecast's fiscal-year end). In order to reduce the potential influence of outliers (most of which are driven by obvious data errors), we exclude from our sample all forecasts with an error larger than 4. We follow Clement and Tse (2005) in defining the control variables and normalizing them relative to all analysts covering the firm (whether stars or non-stars) using the following formula, in which analyst *i* covers firm *j* at year *t*:

$$Characteristic_{ijt} = \frac{Raw\,Characteristic_{ijt} - Raw\,Characteristic\,min_{jt}}{Raw\,Characteristic\,max_{jt} - Raw\,Characteristic\,min_{jt}}.$$

As noted by Clement and Tse (2005), the normalization of all variables to a value between 0 and 1 allows us to examine their relative importance by directly comparing the coefficients.

Our focus is on the competition between existing stars and thus we require that the analyst is ranked as a star in the year that the forecast is made. For every firm that an analyst covers, we include in our study only the earliest announcement in each year.[11] We focus on the earliest announcement rather than on the last announcement for two reasons. First, the earliest forecast is arguably the most challenging because the forecast horizon is the longest.[12] Second, previous literature shows that analysts' forecasts are subject to herding and hence later announcements carry less information regarding analysts' quality. Therefore, for each firm an analyst covers, we maintain only the earliest EPS forecast for the next fiscal year as long as it is made before the end of the fiscal year.

1.2 Summary statistics

We start our empirical investigation by dividing the I/B/E/S universe into three types of stocks: (1) stocks that are not covered by any star analyst, (2) stocks that are covered by a single star analyst, and (3) stocks that are covered by more than one star analyst (henceforth called "multi-star" stocks). In Table 1 we present summary statistics of accounting variables, market performance, and analyst coverage for each category.

[11] Our results remain qualitatively the same when we use the latest announcement.
[12] Cooper, Day and Lewis (2001), among others, report an inverse relationship between analyst forecast timeliness and accuracy.

(Insert Table 1 about here.)

The first row presents our sample size (in firm-years) under each category. Almost two-thirds of the firms in the I/B/E/S universe are not covered by any star analyst, and the rest are divided almost equally between firms that are covered by a single star analyst and multi-star stocks. The second row presents the number of large firms. Throughout the paper, we refer to firms that are larger than the median size of the New York Stock Exchange (NYSE) as large firms. We find that more than 70% of all large firms are covered by at least one star analyst, and close to 50% of all large firms are multi-star stocks. Focusing on firm size, our results show that multi-star stocks are larger than those covered by a single star analyst, which are in turn larger than those not covered by any star analyst. Importantly, the proportion of firms smaller than the lowest NYSE-size quintile is less than 20% in single-star stocks and drops down to only 4% in multi-star stocks.

Institutional ownership is around 75% in stocks that are covered by at least one star analyst, compared with roughly 60% in stocks with no star coverage. Multi-star stocks are also more profitable than other stocks. The proportion of firms with a negative net income decreases with star analyst coverage. Among stocks with no star coverage, the proportion of negative earnings is four times higher than in multi-star stocks. Analyst coverage (i.e., counting both stars and ordinary analysts) increases with the number of star analysts that cover the stock. The average number of analysts that cover stocks with no star coverage is 7.2, but this number increases to more than 12 for stocks with single-star coverage and further increases to 20.4 for multi-star stocks. Analyst coverage increases throughout our sample period, as evidenced by the change in the number of analysts (compared with the previous year), but multi-star stocks experience the sharpest increase. The average increase in coverage for multi-star stocks is almost 50% more than the increase for stocks covered by a single star analyst (0.96 and 0.66, respectively). The average forecast error across all analysts also decreases with coverage by star analysts—from 0.55 for stocks with no star coverage to 0.41 for stocks with single-star coverage and 0.31 for multi-star stocks.

Panel B presents data regarding the coverage choice of star analysts. A star analyst covers an average of 12.3 stocks and close to 60% are multi-star stocks. The fact that star analysts typically cover many multi-star stocks is of utmost importance in studying the relation between star status and forecast error. In particular, it is likely that changes in information environment will offset each other at the portfolio level. Most importantly, it is extremely unlikely that changes in the information environment of one particular firm out of many in the star analyst's portfolio will affect star status.

A star analyst initiates coverage of 1.8 stocks per year on average and our unreported results show that roughly three-quarters of initiations represent large firms. Most initiations take place within two years after the analyst becomes a star. The last row reports the number of firms that are abandoned. Of the 12.3 firms that star analysts' cover, only 0.6 firms are dropped each year on average. This suggests that star analysts' coverage portfolios are very sticky, with over 95% of the firms carried over from year to year. Specifically, star analysts are unlikely to drop stocks after they initiate coverage. The fact that star analysts hardly ever modify their coverage portfolio suggests that star analysts do not self-select into stocks with a better information environment. More specifically, star analysts do not constantly change their stock coverage in response to changes in individual firms' information environment.

2 Competition among stars and output

2.1 Baseline results

We examine the effect of competition between star analysts on their effort and accuracy. We hypothesize that high-quality agents view other high-quality agents as their main rivals. If star analysts indeed view other stars as their main competitors, then the above suggests that they will exert more effort when covering a stock that is also covered by other star analysts (multi-star stock) compared with a stock that no other star covers (single-star stock). If higher effort leads to higher productivity, then the emerging hypothesis is that star analysts will be more accurate in multi-star stocks than in single-star stocks that they cover.

Our analysis, as showcased in Table 2, focuses on the effect of competition on star analyst accuracy. Accordingly, the sample used for our regression estimations only consists of forecasts made by star analysts. The dependent variable is the forecast error, defined as the absolute difference between the forecast and the realized earnings, scaled by the realized earnings. The main independent variable is the binary variable *multi-star*, to which we assign a value of 1 if more than one star analyst covers the stock, and 0 otherwise. In order to mitigate the problem of large differences between small and large stocks, we drop all firms below the NYSE size median. There are a total of 18,157 forecasts made by star analysts during our sample period. Control variables include the market value of equity (*firm size*); the total number of analysts (whether stars or non-stars) that cover the stock (*No. of analyst*); the number of days elapsed since the previous forecast on the same stock by any analyst (*days* *elapsed*); the number of days remaining until the end of the fiscal year (*forecast horizon*); the order in which analysts submitted their forecast (*order*); the number of analysts employed by the analyst's brokerage house (*brokerage size*); the general experience of the analyst (*general experience*) as measured by the number of years that the analyst has been in the I/B/E/S database; and the specific experience of the analyst covering the firm (*firm experience*) as measured by the number of years the analyst has covered the firm. The level of institutional holdings (*institutional ownership*) and the change in institutional ownership compared with the previous year (*delta_IO*). All control variables are normalized to take a value between 0 and 1 relative to all analysts covering the firm (whether stars or non-stars) as described in the methodology section.

(Insert Table 2 about here.)

Model 1 in Table 2 finds that multi-star status has a negative and significant correlation with analysts' forecast error. This result is consistent with the univariate analysis in Table 1 and persists after controlling for year, firm, and analyst-fixed effects. Firm fixed-effects account for cross-sectional heterogeneity in the complexity of forecasting the firm's earnings, whereas analyst fixed-effects account for heterogeneity in analyst quality. In Model 2, we add the control variables. The coefficient of the multi-star dummy hardly changes (from -0.046 to -0.051) and remains highly significant. The effect is economically significant: a decrease of 0.05 in absolute error accounts for over 20% of star analysts' average error. Looking at the control variables, star analysts are more accurate in larger firms, consistent with larger firms attracting more investor attention and analyst coverage, leading to a richer information environment. In line with previous findings (Clement and Tse (2005) among others), analysts become more accurate as time approaches the earnings announcement date. Hence, the coefficient of *forecast horizon* is positive and significant in all specifications. Surprisingly, the coefficient of *order* is also positive and significant in some specifications, suggesting that relatively earlier announcements are more accurate. A possible explanation is that some analysts who announce later than others deviate from the consensus to try to stand out (Bernhardt, Campello, and Kutsoati (2006)). We find no evidence that competition with analysts in general improves star analyst accuracy, as the number of analysts that cover the stock, whether stars or not, is positively correlated with forecast error.[13] This is consistent with our interpretation that star analyst accuracy is mostly affected by the competition with other stars. Both the level and the change in institutional ownership are negative but statistically insignificant.

We further decrease the heterogeneity in the information environment that may drive the multi-star effect. In Model 3, we only include firms in the highest-size quintile. These firms are very large, with a market value of over $1 billion, and enjoy widespread analyst coverage. The median analyst coverage among these firms is 25, and over 95% of these firms are covered by 10 analysts or more. Furthermore, hardly any firms in the highest-size quintile experience negative earnings. Overall, these stocks are likely to have minimal variation in their information environment over time. The results show that the coefficient of the binary variable multi-star is barely affected.

The results in Table 1 Panel B suggest that the portfolio of analysts is extremely sticky after they become stars. This seems to preclude explanations that suggest that our results are driven by analysts changing their portfolio in response to changes in the information environment or according to the interests of institutional investors. To further examine this possibility, we perform the following test. We exclude from the sample all stocks that the star initiated covering after becoming a star. The results presented in Model 4 show that the multi-star binary variable is barely affected even after excluding stocks whose coverage is initiated by the analyst after becoming a star. We can also report that further limiting the sample to stocks that are selected by a star analyst in the first four years of her career does not materially change our results. Similarly, eliminating all analysts that drop coverage after becoming a star does not change the coefficient of multi-star stocks. To sum, given the stickiness of star coverage and the previous tests, it is extremely unlikely that our results are driven by analysts that actively select easier-to-predict stocks.

Our results in Table 2 are consistent with our argument that competition between stars drives the higher accuracy in multi-star stocks. In these tests we control for the large variation in both stock characteristics and analysts' quality using control variables and fixed effect variables. To further ensure that our results are not driven by any cross-sectional differences we perform several tests whose results are presented in Table 3.

[13] The high correlation between the number of analysts and size makes this difficult to interpret. Still, one possible explanation is that competition among ordinary analysts might exacerbate catering to investor beliefs (Mullainathan and Shleifer (2005)).

(Insert Table 3 about here.)

In Model 1, we eliminate any cross-sectional variation between stocks by using the same set for multi-star and single-star stocks. We do so by focusing only on stocks that shift from multi-star to single-star or vice versa at least once during our sample period. Results in Model 1 show that, looking at the same stock, the forecast error of star analysts is significantly lower during times when another star covers the stock than during times when no other star covers the stock. In Model 2, we further limit the sample to include only stocks that experience at least two round trips from multi-star to single-star and vice versa. This more restricted subsample is meant to mitigate the concern that monotonic trends in the information environment drive both the change in star coverage and forecast errors. The results show that the coefficient of the binary variable multi-star remains significant and strong, even when we eliminate any heterogeneity in information environment. These results are inconsistent with the notion that cross-sectional variation in the information environment, whether observable or not, drives the difference in accuracy between multi-star and single-star stocks.

Another alternative explanation is that some analysts are endowed with higher ability, and I/I respondents, who are capable of detecting this higher ability, promote these analysts in the rankings. Multi-star stocks, in this case, simply represent the presence of two (or more) high-ability analysts, rather than any direct competition between stars. If so, the number of high-ability analysts would subsume our competition effect. To distinguish between the ability and competition explanations, we define a *career-star* analyst as an analyst who is selected as star at some point in his/her career. We then add the *number of career-stars* that cover a stock as a control variable and re-estimate the same regression as in Table 2. Our results in Model 3 show that the coefficient of multi-star variable hardly changes in magnitude and remains statistically significant. This result is at odds with the alternative argument which posits that accuracy is mainly driven by the number of high-ability analysts covering the stock. We conduct several additional robustness tests. First, we limit the sample to include only stocks covered by at least two career-star analysts. In the resulting subsample, the only difference between multi-star and single-star stocks is whether the career-star is currently reigning—i.e., whether the existing star is currently competing with another existing star or against a career-star.[14] Our unreported results show that the coefficient of multi-star remains negative and significant in this subsample.

In Model 4, we add an interaction variable between multi-star status and number of career stars in order to examine the significance of career-stars in multi-star and single-star stocks separately. Reigning stars are likely to increase their effort (and thus improve their forecast accuracy) when they identify up-and-coming stars who also cover the stock. That is, stars are likely to increase their effort in a single-star stock as soon as they expect the promotion of an ordinary analyst covering the same stock. Our results show that the number of career stars coefficient is negative and statistically significant, indicating that the existence of career-star analysts–mostly consisting of future stars–does indeed induce more effort among single-star stocks. The coefficient of the interaction variable, on the other hand, is positive and of the same magnitude, suggesting that career stars–or *potential* competition–have little effect on analyst accuracy in multi-star stocks, in which rivals' effort is already high.

2.2 Instrumental Variable Approach

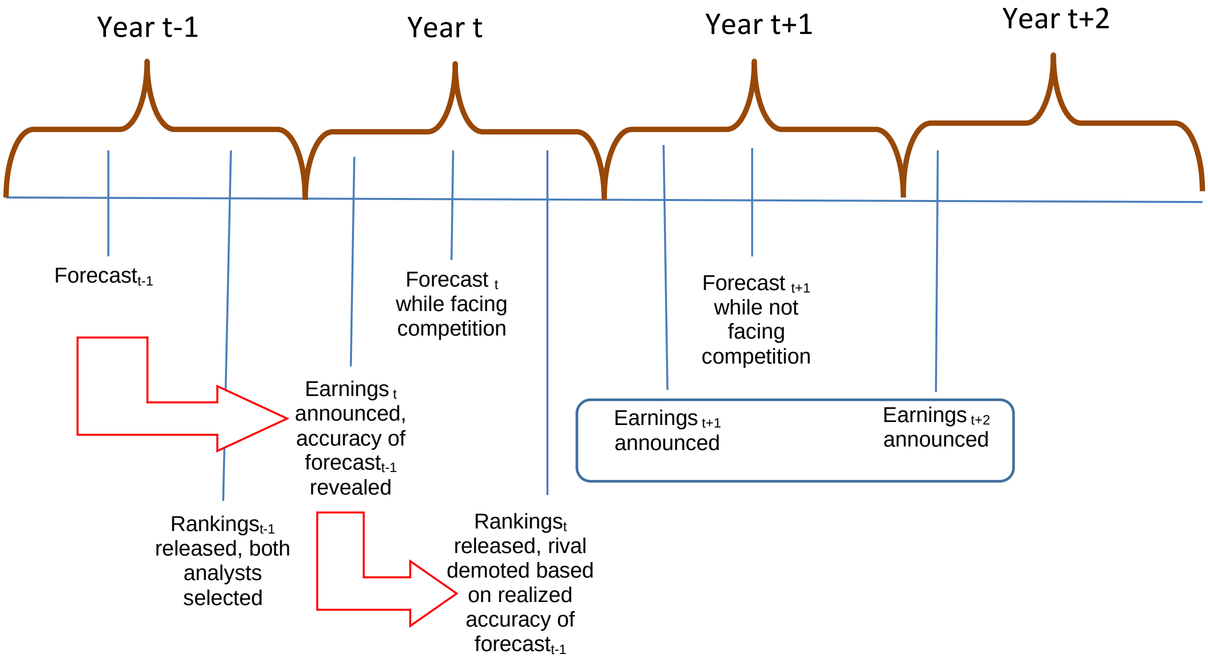
Our results so far suggest that star analysts generate less-accurate forecasts in stocks in which they are the sole star and more accurate in stocks in which they compete with other star analysts (multi-star stocks). Furthermore, our analysis indicates that the higher accuracy is not driven by time-invariant differences between multi-star and single-star stocks or by the ability of I/I respondents to identify analysts endowed with superior ability. One remaining concern is that the higher accuracy might be due to time-varying changes in the firm's information environment and/or time-varying changes in the quality of the analysts that cover the firm.

To facilitate a causal interpretation of the effect of analyst coverage on the firm's information environment, the existing literature has used instrumental variables. Two such variables are brokerage house mergers (Hong and Kacperczyk (2010)) and brokerage house closures (Kelly and Ljungqvist (2012)), both of which represent an exogenous negative shock to analyst coverage.[15] These papers document that a decrease in analyst coverage is largely

[14] Notably, in terms of forecasts, 50% of all forecasts of career-star analysts are made before they become stars, 40% while they are reigning, and less than 10% after they lose star status.
[15] Other instrumental variables used include the addition of the stock to the S&P 500 Index (Yu (2008)) and loss of coverage due to death of analysts in 9/11 (Kelly and Ljungqvist (2012)).

associated with a deterioration of the firm's information environment. Therefore, the use of brokerage house mergers and closures is not appropriate for our research question, as it would not meet the exclusion restriction.[16] To infer whether the change in forecast error is driven by information or by competition, we need a shock to competition between stars that is unrelated to either analyst coverage or the firm's information environment.

We therefore introduce a novel instrumental variable in order to separate the two alternative stories: a break in the multi-star status of a stock following the demotion of one or several star analysts covering it. Importantly, in the setting we consider, analysts do not walk away; they all continue to cover the firm, but some have lost their place in the rankings. We focus on stocks that switch from multi-star to single-star merely because some of the analysts covering them were demoted in the rankings. The following timeline demonstrates the sequence of events surrounding the demotion of rival stars (for a firm with a December fiscal year end).



[16] In brokerage house mergers and closures, a star who is let go will no longer continue to cover the firm (Wu and Zang (2009)). This can potentially reduce the information about the firm and may lead to an increase in forecast error of the remaining analysts. In this case, it will be impossible to infer whether the change in forecast error is driven by information or by competition. Another concern with the use of brokerage house mergers and closures is that both are likely to have a limited effect on star analyst coverage. By definition, star status is only awarded to a distinct subsample of analysts, and the intersection of this already extremely small sample with a rare event such as mergers or closures yields a sample too small for any statistical inference. For example, using the data set of brokerage house mergers and closures of Derrien and Kecskés (2013), merely 150 stocks lose star analyst coverage. Even if half of these stocks switch from multi- to single-star, we are still left with a sample too small. We thank the authors for providing us with their data.

A major concern with using demotion as an instrumental variable is that the demotion may represent a decrease in the quality of peers covering the same stock, which spills over to the accuracy of the remaining star. While such deterioration in information environment would predict an increase in forecast errors, the timing of this increase is different from the one we examine. We rely on the fact that analysts' rankings in year t is determined by their performance up to the beginning of that year. Thus the deterioration in the quality of a star demoted in October during year t has already been observed by the I/I rankers at the beginning of the year, but the demotion is not yet public. We compare the error of reigning stars in their year t forecast to the error in their year t+1 forecast. Our competition argument suggests that in year t the demotion is not yet known, and thus both rivals will allocate their effort to multi-star stocks. After the demotion, the remaining star can afford to reduce effort in stocks in which he/she is no longer facing competition, leading to an increase in his/her own forecast error. By contrast, the information environment story suggests there should not be a fundamental difference between years t and t+1 as the decrease in star quality had already happened by the beginning of year t.

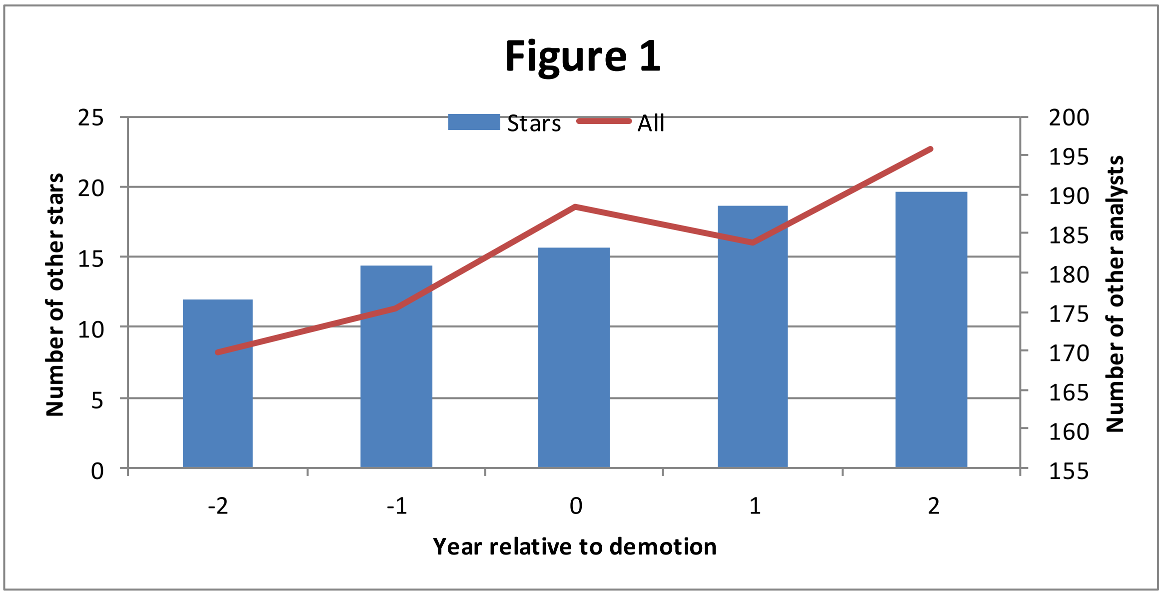
Accordingly, we examine the accuracy of star analysts in the last year during which they face direct competition with other stars and compare it to their own accuracy following the demotion of all their competitors. Therefore, this exercise examines the effect of competition on accuracy when quality remains unchanged. Our instrumental variable meets the exclusion restriction, as it is uncorrelated with the information environment of the firm, other than through the competition channel.[17] Furthermore, our instrumental variable allows us to contrast stocks that switch from multi-star to single-star and stocks that shrink in star coverage and yet remain multi-star stocks.

Another possible concern is that star analysts may be demoted when some stocks in their portfolio fall out of interest. If so, we would expect analyst performance in stocks with higher star coverage to play a larger role in the rankings. A star analyst, however, typically covers 10–15 stocks, and so the probability that most stocks in a portfolio of that size would

[17] While we have no reason to expect that the stocks that experience a drop in star-analyst coverage are also the ones that cause the demotion, we still confirm that a drop in star coverage is uncorrelated with observable proxies for the information environment. Since a firm's information environment is unobservable, we examine variables used in the literature that are likely to be correlated with changes in the information environment. These variables include the change in the number of analysts covering the firm (McNichols and O'Brien (1997)), the change in firm earnings (Basu (1997)), and the change in market value (Chang, Dasgupta, and Hilary (2006)). We find no apparent relation between the change in the number of star analysts that cover a stock and changes in our proxies for information environment.

move in the same direction (and in the same period) in terms of institutional investor interest is extremely low. We reiterate that the I/I asks survey respondents to rank analysts within their industry and hence any industry-wide shocks to the information environment should affect all competing analysts in the same way.

To verify that demotion is uncorrelated with an individual stock–or a small subset of stocks out of many in an analyst's portfolio–we examine analyst coverage and institutional interest in stocks covered by demoted stars. If loss of interest by institutional investors is the driving force behind a demotion, we should observe a decrease in institutional investor interest in stocks covered by the demoted star around the year of demotion. Similarly, we would expect analysts to abandon coverage in response to a loss of interest from institutional investors. Figure 1 looks at the portfolios of demoted stars, from two years before the demotion to two years after the demotion. Year 0 represents the last year in which the analyst was selected as star. For every stock a demoted star analyst covers, we count the number of *other* stars who cover it in the same year. By not including the analyst in question, we make sure that we avoid a mechanical drop in the total number of stars post-demotion. We then sum the number of other stars for the entire portfolio of the demoted star. The bars in Figure 1 represent this number. We can now examine how the number of star analysts (other than the demoted star) changes around the year of demotion.



If stars are demoted primarily because they cover stocks that have fallen out of interest, then we should see a drop in the number of other stars leading to the demotion of the analyst in question. Going from years -2 and -1 to year 0, we see a slight increase—rather than a decrease—in the number of other stars covering the same stocks as the demoted star.

We choose to focus on demotion rather than on promotion, as the former is less predictable. Star analysts may be able to predict who will be promoted through the rankings and compete with them. Our unreported results show that analysts are more likely to become stars if they are affiliated with a large brokerage house and if they cover more star-covered stocks in the first year of their career. Arguably, star analysts are even better equipped to identify potential competitors, by taking into account the overall level of their work (such as recommendations and the quality of other reports). Hence, reigning stars are likely to increase their effort (and thus improve their forecast accuracy) as soon as they identify up-and-coming stars who also cover the stock. Our finding (cf. Table 3 Model 4) that the accuracy of a star analyst in a single-star stock is higher when facing a future star supports this conjecture. Stars are likely to increase effort in a single-star stock as soon as the promotion of an ordinary analyst covering the same stock is expected. If so, there would be no subsequent increase in accuracy when the initiation in direct competition actually materializes. In contrast, an unexpected termination in direct competition should result in a subsequent drop in accuracy.

We start by dividing the sample into three groups according to the change in star analyst coverage. Evidently, the number of star analysts that cover a stock can decrease, increase, or remain unchanged relative to the previous year. For each stock a star analyst covers, we calculate the change in its forecast error from the preceding year. For every firm-year, we then calculate the average difference in forecast error across all star analysts covering the firm between the year of portfolio formation and the subsequent year.

(Insert Table 4 about here)

The results are included in Table 4. The first three columns present the average forecast error in the year of portfolio formation, the average forecast error one year after portfolio formation, and the difference in forecast error between the two years. The first row presents the forecast error among stocks in which the level of star coverage remains unchanged. With no change in the number of star analysts, the competition between star analysts is unlikely to change materially and hence there should be no substantial difference in the average forecast error between the two consecutive years. Results displayed in Table 4 confirm the abovementioned argument by showing that the difference in the forecast error between year t—the year of portfolio formation—and the subsequent year is small and insignificant. The next row presents the results for stocks that experience an increase in star coverage. As previously argued, star analysts are likely to exert more effort as soon as they are able to detect up-and-coming analysts that may jeopardize their star status. Hence star analysts are likely to exert more effort into stocks before they become multi-stars. Indeed, our results show that stocks that experience an increase in star coverage exhibit a very slight decrease in forecast error (-0.004).

Our main treatment group consists of stocks that experience a decrease in star coverage. Results show that the average forecast error in these stocks is 0.28 in the year of portfolio formation. The forecast error increases materially to 0.31 in the following year.[18] This difference, close to 0.03, is significant at the 5% level. In the next two rows, we divide all stocks that experience a decrease in star coverage into two subgroups. In the first subgroup we include stocks that remain multi-star stocks even after the decrease in star-analyst coverage (e.g., from three star analysts to two). In the second subgroup we include stocks that switch from multi-star to single-star stocks (e.g., from two star analysts to one). We repeat the tests for these two groups separately. If the demotion of rival stars is not an exogenous shock, then the forecast error of the remaining stars is expected to rise in all stocks that experience a decrease in star coverage regardless of whether they lose multi-star status. The results show that firms that shrink in star coverage but remain multi-star stocks experience a small and insignificant decrease of 0.024 in their average error. Stocks that lose their multi-star status therefore drive the entire increase in forecast error in all firms that experience a drop in star coverage. The average forecast error in these stocks increases substantially by roughly one-third (0.10), and this increase is significant at the 1% level.

We then conduct a difference-in-difference analysis by using firm characteristics to match each firm that experiences a change in star coverage with the most similar firm that experiences no change in star coverage (row 1 in the Table). This allows us to compare stocks that experience a shock to the competition between star analysts to similar stocks that experience no such shock. We match each stock sequentially, according to the year of the forecast, industry (F&F 12 industries), and size. Results of this matching analysis are presented in the last three columns.

Focusing on our main treatment group (last three rows), the results of the matching analysis are similar to those in the third column. For the entire portfolio of stocks that

[18] If less accurate stars were more likely to be demoted, we would expect the average error to drop. This is because the forecast error of the demoted star is included in the average error in year t, but is no longer included in year t+1. Therefore, this would only go against finding an increase in the average error of those stars who managed to remain stars in the following year.

experience a decrease in star coverage, the difference-in-difference in forecast error is positive (0.036), but statistically insignificant. Again, stocks that lose their multi-star status as result of a decrease in star coverage drive the results. For these stocks, the difference-in-difference in forecast error is 0.12 and significant at the 1% level. The next column examines difference-in-differences in forecast error, but only for stocks that are larger than the median NYSE size in the year of portfolio formation. We largely control for heterogeneity in size by comparing the forecast error of each stock to the forecast error in the subsequent year. However, it may be that the increase in forecast error is limited to relatively small firms whereas large, heavily covered firms are hardly affected. Results do not support this conjecture, as the difference-in-differences in forecast error among large firms decreases only slightly (0.10) and remains significant at the 5% level.

As previously mentioned, our instrumental variable allows us to test whether the change in forecast error is driven by information rather than by competition. In particular, it allows us to disengage from cases in which the former star no longer continues to cover the firm. A star analyst covering the stock could decide to drop its coverage or may no longer be included in the I/B/E/S database (e.g., brokerage house mergers and closures or the analyst's transition to a corporate executive position). This drop in star coverage may reduce the information about a firm and spill over to increase the forecast error of the remaining stars. While many demoted analysts continue to cover the firm in the year after the demotion, we still restrict our analysis to stocks in which the recently demoted star analyst continues to cover the firm. Results in the last column are consistent with our previous findings and show that stocks that switch from multi-star to single-star experience a large increase in forecast error.

In order to ensure the robustness of our results, we examine alternative matching criteria that add (in conjunction with forecast year, industry, and size) either the number of analysts, profitability, or forecast error in the previous year.[19] In all of these matching specifications, the difference in the differences in forecast error over time between the treatment and control group is positive and statistically significant. Among stocks that experience an increase in star coverage, the difference-in-differences in forecast error is negative and, in some cases, significant. While this result is consistent with our competition

[19] We also match by industry and number of analysts; industry and earnings; and size and number of analysts. In all of these specifications, the difference-in-differences in forecast error is positive and statistically significant.

argument, we note that it is the control group that drives it. Furthermore, this result is sensitive to the matching criteria used. Thus, we take this result with a grain of salt.

Similarly, the difference-in-differences results show a decrease in forecast error for stocks that lose star coverage but retain multi-star status. While we do not provide an explanation for this result, we note that it is partially driven by the matching scheme.

2.3 Competition among stars and the Information Environment of the Firm

The results in Panel A of Table 4 find a significant increase in the forecast error of star analysts when stocks lose multi-star status. Given the importance of star analysts, one should expect that this deterioration in star analyst accuracy would have a broad effect on the firm's information environment. If so, our instrumental variable (a shift in a firm's status from multi-star to single-star sort) can then be utilized throughout the finance literature as an exogenous shock to a firm's information environment. Our instrumental variable has a clear advantage over other instruments commonly used in the existing literature, such as brokerage house mergers and closures. While the drop in analyst coverage due to brokerage house mergers and closures typically affects small stocks covered by five analysts or less (e.g. Derrien and Kecskés (2013) and Kelly and Ljungqvist (2012)), the loss of multi-star status affects firms in general, and large firms in particular.

In order to test the effect of competition between stars on the information environment of the firm, we ask whether the loss of competition between star analysts has a broader effect on the overall contribution of the analyst community to the firm's information environment. We expect the competition between star analysts to affect the firm's information environment for two reasons. First, it is likely that the higher effort star analysts exert in multi-star stocks generates more information in general. Second, the higher accuracy of star analysts in multi-star stocks than in single-star stocks is expected to spill over to that of ordinary analysts who tend to herd around stars. In Panel B of Table 3, we consider the overall accuracy of all analysts, including both stars and ordinary ones, and thus the forecast error is the absolute difference between the actual earnings and the average prediction of all analysts. We employ the same difference-in-differences approach as in Panel A of Table 4, and study changes in all analysts' forecast error covering the firm.

The results show that the average forecast error of all analysts increases materially in stocks that experience a decrease in star coverage. This increase in overall error in analyst forecasts is attributed strictly to stocks that lose their multi-star status. The difference-in-differences in overall analyst forecast error is highly significant, although 25% smaller (0.09 vs. 0.12) relative to that of star analysts alone. Focusing only on large firms or on stocks in which the demoted star remains active, as shown in Panel A, barely changes our results. By requiring that the demoted star remains active, we mitigate any concern that the firm becomes more complex to analyze, which may drive not only an increase in overall forecast error, but also abandonment by stars. Our results show that when a multi-star stock becomes a single-star stock, merely due to the demotion of one of the stars covering it, the overall contribution of the analyst community to the firm's information environment deteriorates significantly. Hence, the competition between star analysts has a broad effect on the firm's information environment.

2.4 Analysis of possible alternative explanations

2.4.1 The intensity of star coverage

The literature suggests additional channels through which competition among analysts can affect their accuracy. Hong and Kacperczyk (2010) argue that competition makes it harder for a firm to suppress unfavorable information. The authors propose two possible explanations for this conjecture. First, a larger number of analysts increases the total cost the firm needs to incur in order to suppress unfavorable information. Second, a larger number of analysts increases the probability that (at least) one of the analysts covering the firm will not surrender to any hypothetical pressure to suppress unfavorable information. To support their conjecture, Hong and Kacperczyk (2010) report that a decrease in the number of analysts increases optimism bias in firms that have experienced a negative earnings surprise (i.e., when realized earnings turn out to be lower than the analyst's forecast).

Both channels may have a strong effect in the presence of star analysts. Star analysts are likely to be the most expensive to solicit, and the incentive to maintain their star status is likely to hinder their bias. For example, a firm covered by a single star analyst can suppress unfavorable news by offering future deals for the brokerage house. A firm covered by multiple stars, however, may find difficult to provide a similar incentive to multiple brokerage houses. It is therefore possible that the withholding of negative information drives the higher accuracy in multi-star stocks. In contrast, our empirical results (not reported) show that the higher accuracy in multi-star stocks also prevails when there is a positive earnings surprise. Thus, the withholding of negative information is unlikely to be the sole driving force behind the higher accuracy in multi-star stocks.

2.4.2 The I/I rankings as a signal of institutional investors interest

Another possible explanation is that institutional investors signal their interest in certain firms using the ranking. According to this explanation, when a stock loses interest from institutional investors, the analysts that cover it are less likely to be chosen as stars. Thus, a stock changing its status from multi-star to single-star is a signal of a drop in interest from institutional investors. It is this drop in interest rather than drop in competition that drives the increase in forecast errors.

Importantly, the above explanation suggests that stars are selected based on their portfolio choice rather than on their research output. This explanation is at odds with most existing literature on the determinants of analyst rankings. It also contradicts our own empirical results that show that the number of multi-star stocks the star covers is uncorrelated with subsequent rankings (see Table 6). Furthermore, the lack of interest argument suggests that the portfolio of new star analysts should be less correlated with the portfolio of demoted star analysts. We examine the number of stocks that are covered by both analysts and compare it to the average of all the star analysts from the same industry. Our unreported results show that in both subsamples the number of overlapping stocks is virtually the same – just above three.

3 Star competition and the I/I rankings

3.1 Success in multi-star stocks and promotion on the I/I rankings

Our results so far suggest that star analysts are more accurate when competing against other stars than when such competition does not exist. We interpret this finding as supportive of the argument that star competition leads to higher effort, that in turn leads to better output. In this section, we examine whether success in star competition is correlated with better performance in the most prestigious analyst ranking, the I/I annual rankings. The possible determinants of the I/I rankings have been the subject of much debate among academics and practitioners alike. While some research argues that stars are more talented than ordinary analysts (e.g. Stickel (1992), Leone and Wu (2007), Gokkaya and Liu (2017)), others suggest that the competition is mainly a beauty contest (Emery and Li (2009)). In recent years surveys of I/I rankers show that the rankings are based on multi-dimensional performance factors in which forecast accuracy plays a relatively minor role.[20]

Within the scope of this paper, we do not argue that star competition is the mechanism behind the I/I rankings, nor do we suggest that accuracy is the sole–or even the most important–factor in analyst rankings. Survey participants surely use other soft cues, such as industry knowledge and responsiveness, which make a good analyst. We simply assume–in the spirit of Yin and Zhang (2014)–that such qualitative features are highly correlated with the analyst's ability and/or opportunity to generate forecasts that are more accurate. It is this correlation that motivates a testable implication derived from the notion of star competition–that the best star is more likely not only to generate accurate forecasts but more broadly to get promoted in subsequent rankings.

Our star competition argument, as well as our previous empirical results, suggest that star analysts exert more effort in multi-star stocks than in single-stars stocks. Furthermore, it also suggests that stars analysts' performance in multi-star stocks should be compared to other stars rather than the entire analyst community. Hence, we measure whether being the most accurate star analyst in a multi-star stock has an economically significant effect on success in the I/I rankings. For this purpose, we create a binary variable *win*, to which we assign the value of 1 if the star analyst is closer to the actual earnings than all other star analysts—that is, his/her forecast error is the smallest among all the star analysts covering the stock. We then count the total number of wins that an analyst accumulates in a given year, which we refer to as *No. of wins*.

Arguably re-selection as a star could be considered the simple goal of a star analyst. However, measuring success as maintaining star status is too coarse. This is because maintaining star status is not only influenced by success in the current year, but also by one's current place in the rankings. That is, a higher ranking substantially decreases the probability that an analyst will lose star status. Table 5 illustrates this point using a simple transition matrix. The rows represent the ranking of the analyst in year *t* and the columns represent the ranking at year *t + 1*. The results show that during our sample period, the probability of an analyst ranked in the highest position to be demoted out of the first three places is close to 12%. The probability of demotion more than doubles for an analyst ranked in second place,

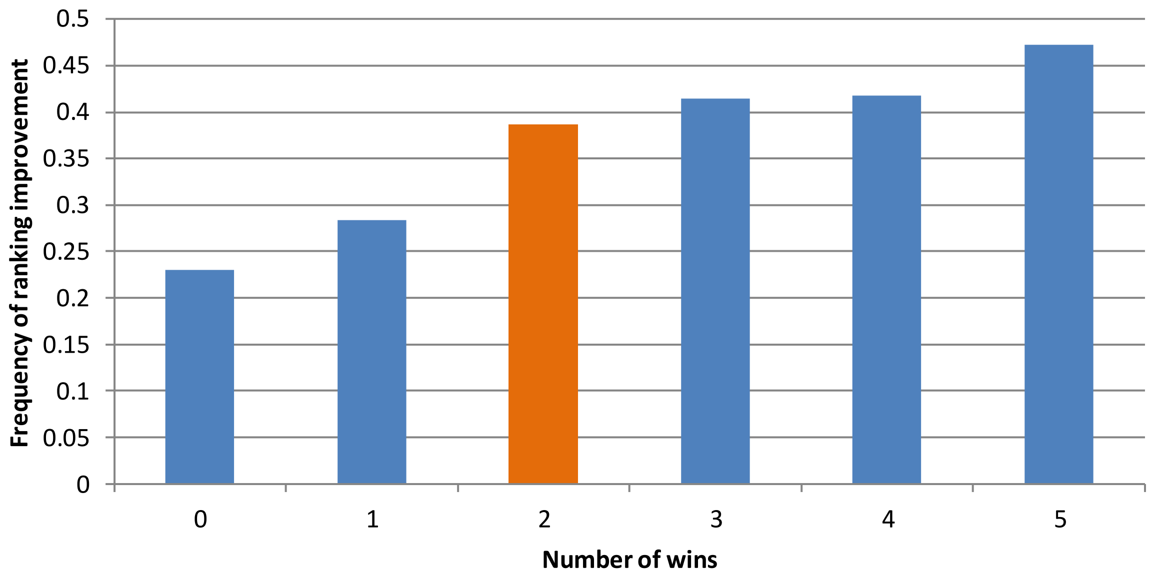
[20] For example, in 2009 and 2010 surveys, forecast accuracy was ranked in 11th and 12th place respectively as a criterion to rank analysts.

and an analyst ranked third faces a probability of more than 40% of not being selected into the top three places in the subsequent year. That is, an analyst ranked in the third place is four times more likely to lose star status in the subsequent year than one ranked in first place.

(Insert Table 5 about here.)

Results of Table 5 demonstrate that current ranking is crucial in maintaining star status. Therefore, we do not define success in the I/I rankings as maintaining star status but rather by promotion in the I/I rankings. A *ranking improvement* takes place when a star that was ranked in second or third place moves up, or when an analyst ranked in the highest position remains in that position in the subsequent year.[21] To illustrate the relationship between the accuracy of star analysts in multi-star stocks and their promotion in the I/I rankings, Figure 2 plots the frequency of ranking improvement by number of wins.

Figure 2



[21] Our notion of improvement includes analysts ranked in the highest position who manage to remain in the top place, which is consistent with the incentive to maximize the probability of retaining star status. Alternatively, we use a more restrictive definition of actual improvement by dropping analysts ranked first in year *t* since they technically cannot improve their ranking. After dropping all analysts ranked first, our sample decreases by roughly one-third, and the proportion of ranking improvement decreases to 21.6%. The results remain qualitatively the same as in Table 6 although with lower significance.

The probability of improving one's ranking substantially increases with every additional win and more than doubles from 0 to 5 wins. Importantly, stars that accumulate more wins than the median number of wins (2 in our sample) are 50% more likely to be promoted in the rankings than those who did not.

Table 6 uses a multivariate analysis to formalize the statistical significance of this big economic effect. This allows us to account for the possibility that the number of an analyst's *wins* is merely correlated with the number of high-interest, or central, stocks he/she covers. According to this reasoning, institutional investors—a sizable proportion of the participants in the I/I survey—are interested in a particular set of stocks and nominate the analysts that cover them. We explore this possibility in several ways. First, we control for both the *level* and the *change* in institutional ownership of the stock, as proxies for interest. We also include the number of stocks in which an analyst competes against other star analyst(s) (multi-star stocks) as another possible proxy for centrality.

In Table 6, we focus on the success in star competition leading to promotion in the I/I rankings. We define a ranking improvement and the number of wins as shown previously in Fig. 1. The main independent variable is *number of wins* and the control variables are similar to Table 2. Given the annual frequency of I/I rankings, we aggregate all forecasts made by each analyst in each year with a simple mean. Our sample includes 1,905 analyst-years, of which 33% experience a ranking improvement in the subsequent year.

(Insert Table 6 about here.)

In Model 1, the main independent variable is mean relative accuracy, which we define as follows:

$$Relative\ accuracy_{i,j,t} = 1 - \frac{Error_{i,j,t} - MIN\left(Error\right)_{j,t}}{MAX\left(Error\right)_{j,t} - MIN\left(Error\right)_{j,t}},$$

where i is the analyst, j is the firm, and t is the year. We then calculate the mean (simple average) across all stocks the analyst covers in each year. Note that the accuracy is normalized relative to all analysts covering the firm (whether stars or non-stars) and thus it inherently controls for firm-specific differences. The results of Model 1 show that the coefficient of mean relative accuracy is positive (0.93) and significant at the 5% level. Due to the loss of information in aggregation, the insignificant results for most of our control variables are to be expected. Still, the negative coefficient of the binary variable *low coverage* indicates that the probability of promotion is relatively low for analysts who cover few firms, which is consistent with Emery and Li (2009). A likely explanation is that a broader coverage portfolio is interpreted as higher confidence in the analyst's ability by his/her employer and thus results in a higher probability of promotion. The negative coefficient of *brokerage size* indicates that once an analyst from a small brokerage house has already proven to be successful in becoming a star, he/she is more likely to enjoy a subsequent ranking improvement. A possible explanation is that I/I rankers favor analysts from small houses given the high hurdle they must overcome in order to become stars in the first place.

Model 2 adds the *number of wins* and finds that its coefficient is positive (0.10) and highly significant. This result is consistent with our argument that the success in head-to-head competition against other analysts is likely to signal the ability of the star as reflected in the next year's rankings. An alternative explanation for the strong relation between the number of wins and promotion is that multi-star stocks are more important to institutional investors, and institutions nominate analysts who cover more of these stocks. To account for this possibility, we try to control for institutional interest in a stock using three proxies. In Model 3, we add the proportion of shares held by institutional investors (IO) as an explanatory variable (Gompers and Metrick (2001)). The IO coefficient is positive but statistically insignificant. Importantly, the coefficient of *number of wins* is unaffected by the addition of IO and remains 0.10. The level of institutional ownership can be viewed as the long-term institutional interest. Changes in short-term institutional interest may also be correlated with multi-star status. We therefore use the change in institutional ownership around each forecast as a proxy for short-term interest (Yan and Zhang (2007)). Specifically, we measure the change in institutional ownership between six months before and six months after each earnings forecast.[22] We then compute the absolute value of the change in institutional ownership (Δ_IO), and then average Δ_IO in the analyst portfolio level.[23] Results in Model 4 show that the coefficient of *Δ_IO* is positive and significant, suggesting that the probability of promotion increases when the analyst's portfolio attracts more short-term interest from

[22] We examine several alternative windows to examine the predicting ability of Δ_IO. Our findings suggest a U-shaped relation as Δ_IO loses its statistical significance when we reduce the window around the forecast announcement date to six months and when we increase it to two years.
[23] We use the absolute value, as institutions are likely to increase their interest regardless of whether they are buying or selling.

institutional investors. However, the coefficient of *number of wins* is not affected by the inclusion of the change in institutional ownership.

In Model 5 we use a different approach. Rather than trying to proxy for institutional interest using institutional ownership, we assume that star coverage proxies for institutional investor interest. If stars are selected based on the interest of institutional investors in the stocks they cover, then the number of star analysts covering a stock should be correlated with institutional investor interest. Therefore, the total number of multi-star stocks that a star analyst covers would subsume the predictive power of *number of wins*. Although the coefficient of the total number of multi-star stocks is positive, it amounts to less than its standard error. In contrast, the coefficient of number of wins hardly changes (0.09) and remains positive and highly significant. These results suggest that the number of multi-star stocks merely facilitates a larger number of opportunities to outperform other stars.

Finally, in Model 6 we examine the relative importance of institutional ownership and number of wins by normalizing these variables to values between 0 and 1, with the same methodology used for the rest of the control variables. We do so by normalizing the value of *No. of wins, IO, and Δ_IO* relative to *existing* star analysts, so that

$$Normalized\ wins = \frac{wins_{it} - MIN(wins)_t}{MAX(wins)_t - MIN(wins)_t},$$

where *wins* is the number of wins of analyst *i* in year *t*, and *MAX (MIN) wins* is the maximum (minimum) number of wins among star analysts in the same year. The results show that the relative importance of *number of wins* is more than double that of institutional ownership. Altogether, our evidence suggests that star analysts that do well in star competition are also likely to do well in the subsequent I/I rankings, supporting our hypothesis of stars exerting more effort in multi-star stocks.

3.2 Competition with other stars vs. with the entire analyst community

We next examine the importance of success in multi-star stocks relative to non-multi-star stocks. Previous literature on analyst rankings has focused on forecast accuracy relative to the entire analyst community, rather than relative to existing stars (e.g. Emery and Li (2009) and Bradley, Gokkaya and Liu (2017)). Since the two measures of analyst success are clearly correlated, we seek to distinguish our measure—i.e., success relative to existing stars—from overall accuracy relative to all analysts, whether stars or not. We aim to show that success relative to stars is more correlated with promotion in the I/I rankings compared with success against ordinary analysts. To address this issue, we create another binary variable, *ibes win*, to which we assign the value of 1 if the analyst is the most accurate in the entire I/B/E/S universe, including both stars and ordinary analysts. We then count the total number of I/B/E/S wins that an analyst has accumulated in a given year, which we refer to as *No. of top1*. Our main goal is to compare the importance of performing well relative to stars (*No. of wins*) to that of performing well relative to all analysts (*No. of top1*).

In Table 7, we examine the incremental effect of performing well relative to the entire analyst community on the promotion of existing star analysts. In Model 1, our results show that the coefficient of *No. of top1* is positive and highly significant. This suggests that doing well against the entire analyst community is correlated with success in the I/I rankings.

(Insert Table 7 about here.)

In Model 2, we add the variable *No. of wins* (the number of stocks in which the analyst is the most accurate star among existing stars) back to the regression and we find that the coefficient of *No. of top1* drops by almost half and becomes insignificant. In comparison, the coefficient of *No. of wins* remains roughly the same as in Panel A (0.096) and significant at the 1% level. The results of this regression supports our main argument and suggests that the main reason for the success of the *No. of top1* variable is likely to be because doing well against other stars increases your chances to finish in the top spot among all analysts.

We use several robustness tests for these results. We change the definition of Top 1 to Top 3 or finishing in the top 10% of analysts that cover a stock. In all these definitions the coefficient of *No. of wins* remain positive and highly significant. We also separate between doing well in multi-star stocks and doing well in single-star stocks by dividing the variable *No. of top1* to two. Our results suggest that finishing in the first place (among all analysts) in multi-star stocks is not correlated with subsequent promotion whereas finishing in the first place in single-star stock is weakly correlated with future promotion. However, when we normalize both variables the coefficient of *No. of wins* is more than four times larger than that of finishing in first place in single-star stocks.

Finally, while our results are consistent with the notion that talented stars are likely to both win the star competition and be promoted in the I/I rankings, another possible explanation exists. This alternative explanation suggests that the I/I rankers use the head-to-head competition in order to rank star analysts. We note that this explanation is at odds with both the rankers' self-reported reasoning for their own ranking (e.g. and I/I survey[24] and Brown et al. (2015)). However, if some rankers use the head-to-head competition as a shortcut to estimate the abilities of stars it would provide stars with another reason to perform well in multi-star stocks. Succeeding in the I/I rankings is a common goal of both analysts and their brokerage houses, as it guarantees higher compensation for the analysts and more business for their brokerage house (e.g. Groysberg, Healy, and Maber (2011) and Clarke, Khorana, Patel, and Rau (2007)). Thus, although we have concentrated our discussion on non-monetary incentives for analysts to engage in stars competition, monetary incentives might also be a factor.

4 Conclusions

In this paper we study the incentives and strategic behavior of star analysts resulting from the influential *Institutional Investor* (I/I) magazine rankings. We argue that the competition between star analysts improves the information environment of firms because of the ambition to outperform other stars. We suggest that, similarly to top professional athletes, top analysts also see other top analysts as their main competitors. Our findings indicate that these incentives lead to more accurate earnings forecasts of star analysts on stocks in which they compete with other stars, compared with their forecasts in stocks in which they are the only star. Our findings line up with the literature that argues in favor of star analysts' outstanding ability. We show, however, that this ability is mainly deployed in *multi-star stocks*, which are the most important for the analysts.

The relevance of this study stretches well beyond the I/I tournament and has implications for various fields in finance. Market participants, including both institutional investors and corporate executives, attribute high importance to star analysts' forecasts and recommendations. If the I/I rankings are a beauty contest, as deemed by Emery and Li (2009), then such rankings may lead to sub-optimal decisions. Their findings suggest that investors, managers, and other analysts place their trust in a bunch of gifted salesmen. By highlighting the importance of a head-to-head competition between star analysts, this paper provides evidence consistent with superior ability of star analysts. Future research can extend much broader effects of head-to-head competition between stars. Our findings suggest that

[24] http://www.integrity-research.com/what-the-buy-side-wants/

multi-star stocks may well feature better monitoring and less information asymmetry, higher corporate investment and financing, and a lower cost of capital. We also note that our head-to-head competition brings closer the empirical analyst literature and theoretical models that primarily concentrate on a two-player setting rather than multiple player (e.g. Aharoni, Einhorn and Zeng 2017).

Finally, we introduce a novel methodology–namely, the use of loss of *multi-star* status due to the loss of star certification by some analysts as an instrumental variable—to rule out endogeneity concerns. Future research in both accounting and finance can employ our instrumental variable to tease out the effect of analysts on firms. Early studies on this topic largely remained silent regarding endogeneity concerns, whereas recent studies that try to control for endogeneity (typically using brokerage house closures and mergers) have been limited to relatively small stocks. Our instrument pertains to star-covered stocks–the largest and most important stocks in the overall investment community–and can serve as a springboard in identifying the key role analysts play in financial markets and, in particular, in stocks that garner the most attention in these markets.

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Table 1: Summary Statistics

We use *Institutional Investor* (I/I) rankings published between 2002 and 2015. All analysts ranked in the first three places in the previous year are considered to be stars. We divide all firm-years into three groups: (1) stocks not covered by any star analyst (No star analyst), (2) stocks covered by a single star analyst (Single-star analyst), and (3) stocks covered by more than one star analyst (Multi-star stocks). *Size* is the natural logarithm of the market value at the end of the month before the first forecast of the fiscal year. *Large firms* are larger than the median NYSE size. *Proportion small* is the proportion of stocks in the lowest size quintile (NYSE cutoff points). *Average EPS* is the simple average of EPS among all stocks in the portfolio. *Proportion negative EPS* is the proportion of firms with positive EPS. *No. Analyst* is the number of analysts that cover that firm in a given fiscal year. *Δanalysts* is the change in the number of analysts compared with the previous year. Finally, *Abs error* is the average absolute error of the analyst, calculated as the difference between the analyst's forecast and the realized earnings.

Panel A: Firm-years

		No Star Stocks	**Single-Star Stocks**	**Multi-star Stocks**
1	**No. of firm-years**	20,888	5,344	6,204
2	**Large firms**	2,874	2,341	4,815
3	**Size (log)**	13.01	14.28	15.60
4	**Proportion small**	0.56	0.19	0.04
5	**Institutional ownership**	0.60	0.73	0.75
6	**Median EPS**	0.59	1.15	1.90
7	**Proportion negative EPS**	0.27	0.15	0.07
8	**No. Analysts**	7.17	12.35	20.36
9	**Δanalysts**	0.35	0.66	0.96
10	**Absolute error**	0.48	0.39	0.26

Panel B: Analyst-years

		No Star Stocks	**Single-Star Stocks**	**Multi-star Stocks**
10	**No. of firms covered by star**	---	5.22	7.10
11	**No. of initiations per year (stars)**	---	0.67	1.15
12	**No. of abandonments per year (stars)**	---	0.27	0.32

Table 2: Star Competition and Forecast Errors

The table presents the accuracy of star analysts. We define a star analyst as an analyst ranked in (all top three places in) the I/I rankings. The dependent variable is forecast error, defined as the absolute difference between the analyst's EPS forecast and the realized EPS scaled by the realized EPS. Throughout, we use only the earliest forecast each year for each firm. *Multi-star* is a binary variable to which we assign the value of 1 if two or more star analysts cover the firm. *Firm size* is the market value of equity. *No. analyst* is the total number of analysts that cover the firm. *Days elapsed* is the number of days elapsed since the previous forecast on the same firm by any analyst. *Forecast horizon* is the number of days until the end of the fiscal year. *Order* is the (ordinal) timing in which the analyst announces. *Broker size* is the number of analysts employed by the brokerage house. *General experience* is the number of years the analyst has been in I/B/E/S files, whereas *Firm experience* is the number of years the analyst has been covering the firm. *IO* is the proportion of shares held by institutional investors, while *delta IO* is the change in IO between six months before and six months after the forecast date. Control variables are normalized to be between 0 and 1. We exclude from the analysis firms below the NYSE size median, except in Model 3, which includes only the highest size quintile. Model 4 drops all initiations made after becoming a star All standard errors are clustered by firm. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Model 1	**Model 2**	**Model 3**	**Model 4**
Multi-star	-0.0456***	-0.0509***	-0.0469**	-0.061**
	(-0.0162)	(-0.0166)	-0.0208	(0.026)
Firm size		-0.557***	-0.274	-0.755**
		(-0.1690)	-0.239	(0.315)
No. of analysts		0.190**	0.122	0.152*
		(-0.0773)	-0.0861	(0.086)
Days elapsed		-0.00572	-0.00684	0.002
		-0.014	-0.0145	(0.015)
Forecast horizon		0.152***	0.106***	0.186***
		-0.0236	-0.0246	(0.025)
Order		0.0344	0.00767	0.053
		-0.0237	-0.0241	(0.043)
Broker size		0.00546	0.0350*	0.046*
		-0.02	-0.02	(0.041)
General experience		-0.0452	-0.0426	-0.043
		-0.0424	-0.0482	(0.048)
Firm experience		0.0390**	0.0207	0.051
		-0.0163	-0.0208	(0.041)
delta_IO		-0.031	0.0448	0.049
		-0.0639	-0.066	(0.066)
Institutional ownership		-0.105	-0.181	-0.181
		-0.0793	-0.135	(0.135)
Constant	0.0692	0.294*	1.115***	0.548**
	-0.0852	-0.154	-0.238	(0.238)
Year fixed effects	Yes	Yes	Yes	Yes
Analyst fixed effect	Yes	Yes	Yes	Yes
Firm fixed effect	Yes	Yes	Yes	Yes
N	18,157	16,568	8,951	11,553
adj. R-sq	0.345	0.339	0.342	0.342

Table 3: cross sectional differences and star competition

This table examines alternative explanations that may drive for the lower forecast error in multi-star stocks. These broadly include the notion that the differences are driven by cross sectional differences in stocks and cross sectional differences in the ability of analysts. Control variables include all controls as in Table 2 and also year and firm fixed effects. We call career-star those analysts that at some point in their careers are selected as stars (top three places in the I/I ranking).In Model 2 (3), we limit the sample to stocks that shift from multi-star to single-star sort or vice versa at least once (three times) during our sample period. In Models 4–5 we include the number of career stars as an additional control variable. We include only stocks that are larger than the NYSE size median, as in Table 5. All standard errors are clustered by firm. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively

	Model 1	**Model 2**	**Model 3**	**Model 4**
Multi-star	-0.051***	-0.050**	-0.048***	-0.103***
	(0.017)	-0.0253	(0.016)	(0.038)
Firm size	-0.591***	-0.760***	-0.5485***	-0.543***
	(0.211)	-0.293	(0.168)	(0.168)
No. of analysts	0.178*	0.111	0.205***	0.209***
	(0.094)	(0.175)	(0.078)	(0.079)
Days elapsed	-0.006	-0.035	-0.006	-0.007
	(0.018)	-0.0237	(0.014)	(0.014)
Forecast horizon	0.145***	0.093*	0.153***	0.151***
	(0.029)	(0.049)	(0.024)	(0.024)
Order	0.0394	-0.011	0.035	0.034
	(0.030)	(0.050)	(0.024)	(0.024)
Broker size	-0.006	-0.004	0.0043	0.0031
	(0.024)	(0.037)	(0.024)	(0.023)
General experience	-0.076	-0.151*	-0.045	-0.045
	(0.052)	(0.083)	(0.042)	(0.042)
Firm experience	0.052**	0.0609*	0.037**	0.036**
	(0.021)	(0.036)	(0.016)	(0.016)
delta_IO	0.056	-0.012	-0.028	-0.029
	(0.075)	(0.107)	(0.064)	(0.064)
Institutional ownership	-0.0569	-0.0473	-0.1062	-0.1015
	(0.080)	(0.122)	(0.079)	(0.079)
No. of career-stars			-0.004	-0.017**
			(0.003)	(0.007)
BG * No. of career-stars				0.015**
				(0.007)
Constant	0.452	0.27	1.541	1.581***
	(0.297)	(0.607)	(0.171)	(0.173)
Year fixed effects	Yes	Yes	Yes	Yes
Analyst fixed effect	Yes	Yes	Yes	Yes
Firm fixed effect	Yes	Yes	Yes	Yes
N	11,124	4,394	16,568	16,568
adj. R-sq	0.335	0.328	0.4147	0.415

Table 4: Changes in Star Coverage and Forecast Error

The table presents the relationship between the forecast error of star analysts and the change in the number of star analysts covering the firm. We start by calculating the average forecast error of star analysts that cover a firm in both the year of portfolio formation and the subsequent year. We then divide all stocks covered by star analysts into three groups: (1) stocks that experienced a decrease in the number of star coverage, (2) stocks that experienced no change in star coverage, and (3) stocks that experienced an increase in star coverage relative to the previous year. The third group (stocks that experienced a decrease in star coverage) is further divided into two subgroups: stocks that remain multi-star stocks and multi-star stocks which become single-star stocks, merely due to the demotion of rival stars. Note that we include only stocks covered by at least one star analyst in the year of portfolio formation and in the subsequent year. The first column presents the mean forecast error in the year of portfolio formation. The second column presents the mean forecast error in the subsequent year. The third column presents the change in forecast error from the year of portfolio formation to the subsequent year. The next three columns present the difference-in-difference analysis. Each firm in our treatment group (firms that experience a change in star coverage) is matched with a similar firm from the subsample in which star coverage remains unchanged. Our matching criteria are industry (Fama & French 12 industries) and size. The fourth column presents the difference-in-difference analysis for the entire sample. The fifth column presents a similar analysis but only in stocks that are larger than the median NYSE size at the year of portfolio formation. Finally, the last column presents the difference-in-difference analysis when we only include cases in which the demoted star analyst continues to cover the firm. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Forecast Error of Star Analysts

	Error in year t	**Error in year t+1**	**Diff**	**Diff-in-diffs analysis**		
				All firms	**Large firms**	**Ex-star coverage**
Stable star coverage (n=3,597)	0.288	0.290	0.002 (0.309)			
Increase in star-analyst coverage (n=1,890)	0.276	0.280	-0.004 (-0.354)	-0.033* (1.870)	-0.047** (2.760)	-0.002 (0.009)
Decrease in star-analyst coverage (n=1568)	0.281	0.312	0.031** (2.036)	0.036 (1.526)	0.007 (0.386)	0.298 (1.091)
Remain multi-star (n=869)	0.240	0.216	-0.024 (-1.371)	-0.041** (2.157)	-0.043** (2.327)	-0.046** (2.014)
Switch to single-star (n=699)	0.331	0.437	0.106*** (3.440)	0.123*** (3.370)	0.097** (2.380)	0.124** (2.117)

Panel B: Forecast Error of All Analysts

	Error in year t	**Error in year t+1**	**Diff**	**Diff-in-diffs analysis**		
				All firms	**Large firms**	**Ex-star coverage**
Stable star coverage (n=3,597)	0.240	0.234	-0.007 (-0.918)			
Increase in star-analyst coverage (n=1,890)	0.232	0.226	-0.012 (-1.062)	-0.008 (-0.511)	-0.015 (-1.070)	0.014 (0.822)
Decrease in star-analyst coverage (n=1568)	0.227	0.248	0.021** (1.757)	0.024 (1.399)	-0.001 (-0.034)	0.168 (0.822)
Remain multi-star (n=869)	0.191	0.172	-0.019* (-1.661)	-0.027 (-1.415)	-0.040** (-2.224)	-0.034* (-1.779)
Switch to single-star (n=699)	0.267	0.343	0.074*** (3.188)	0.089*** (2.820)	0.097** (2.380)	0.085** (2.376)

Table 5: Transition Matrix

The table presents the frequency of changes in I/I rankings during our sample period. The rows represent the ranking of the analyst in year t, whereas the columns represent the ranking at year t+1. Rankings 1, 2, and 3 correspond to the first, second, and third place on the I/I All-American Research Team. Ranking 4 represents runner-ups, and Ranking 5 represents analysts that are not included in the I/I rankings.

	Ranking (t+1)					
	1	**2**	**3**	**4**	**5**	**Total**
Ranking(t)						
1	588	108	39	32	66	**833**
	(70.59)	(12.97)	(4.68)	(3.84)	(7.92)	**(100)**
2	126	359	129	82	106	**802**
	(15.71)	(44.76)	(16.08)	(10.22)	(13.22)	**(100)**
3	53	143	252	207	134	**789**
	(6.72)	(18.12)	(31.94)	(26.24)	(16.98)	**(100)**
4	28	129	233	609	532	**1531**
	(1.83)	(8.43)	(15.22)	(39.78)	(34.75)	**(100)**
Total	**795**	**739**	**653**	**930**	**838**	**3955**
	(20.1)	**(18.69)**	**(16.51)**	**(23.51)**	**(21.19)**	**(100)**

Table 6: Success in Multi-star Stocks and Promotion of Existing Stars

The table presents the relation between star analyst accuracy in multi-star stocks and the probability of promotion in the I/I rankings. The dependent variable is binary, and we assign it the value of 1 if the star analyst (ranked in the first three places) improves his/her ranking or remains in first place. The variable *No. multi-star stocks* counts the number of stocks covered by more than one star analyst. The variable *No. of wins* counts the number of wins in multi-star stocks. A win is defined as a stock in which the star analyst is closer to the actual earnings than all the other star analysts covering the stock. All other control variables are normalized to take a value between 0 and 1. *IO* is the proportion of shares held by institutional investors, while *delta IO* is the change in IO between six months before and six months after the forecast date. *Firm size* is the market value of equity. *No. analyst* is the total number of analysts that cover the firm. *Days elapsed* is the number of days elapsed since the previous forecast on the same firm by any analyst. *Forecast horizon* is the number of days until the end of the fiscal year. *Order* is the (ordinal) timing in which the analyst announces. *Broker size* is the number of analysts employed by the brokerage house. *General experience* is the number of years the analyst has been in I/B/E/S files, whereas *Firm experience* is the number of years the analyst has been covering the firm. Given that the basic measure is analyst-years rather than individual forecasts, we aggregate all the independent variables across all stocks in a certain year. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**
Mean relative accuracy	0.933**	0.554	0.581	0.611	0.712	0.624
	(0.402)	(0.412)	(0.413)	(0.422)	(0.435)	(0.422)
No. of wins		0.102***	0.103***	0.106***	0.0867***	
		(0.0205)	(0.0206)	(0.0207)	(0.0290)	
Institutional ownership			0.866	1.205*	1.323**	
			(0.624)	(0.643)	(0.657)	
Δ_IO				3.987**	4.064**	
				(1.820)	(1.825)	
No. of multi-star stocks					0.0127	
					(0.0131)	
Normalized wins						1.421***
						(0.287)
Normalized IO						0.642*
						(0.340)
Normalized Δ_IO						0.634*
						(0.338)
Mean size	0.839	0.971	1.287*	1.801**	1.768**	1.690**
	(0.710)	(0.718)	(0.757)	(0.802)	(0.805)	(0.793)
Mean no. analyst	0.458	0.709	0.658	0.767	0.783	0.734
	(0.553)	(0.560)	(0.564)	(0.570)	(0.571)	(0.569)
Mean days elapsed	-0.123	-0.0912	-0.0878	-0.134	-0.138	-0.137
	(0.512)	(0.517)	(0.515)	(0.522)	(0.523)	(0.524)
Mean forecast horizon	-0.226	-0.194	-0.248	-0.412	-0.395	-0.405
	(0.711)	(0.719)	(0.722)	(0.734)	(0.735)	(0.733)
Mean order	-0.809	-0.925	-0.957	-1.069	-1.062	-1.063
	(0.686)	(0.692)	(0.693)	(0.702)	(0.703)	(0.701)
Mean brokerage size	-0.424*	-0.515**	-0.501**	-0.459*	-0.463*	-0.453*
	(0.234)	(0.237)	(0.237)	(0.239)	(0.239)	(0.239)
Mean general experience	0.626	0.562	0.581	0.392	0.367	0.419
	(0.401)	(0.405)	(0.406)	(0.412)	(0.413)	(0.411)
Mean firm experience	-0.594	-0.566	-0.595	-0.321	-0.309	-0.381
	(0.366)	(0.371)	(0.372)	(0.385)	(0.385)	(0.383)
Low coverage	-1.251***	-0.985***	-0.991***	-1.026***	-0.978***	-1.014***
	(0.157)	(0.167)	(0.167)	(0.171)	(0.178)	(0.172)
Constant	-1.381	-1.739	-2.555**	-3.388**	-3.612***	-2.623**
	(1.110)	(1.126)	(1.275)	(1.346)	(1.369)	(1.229)
N	1,914	1,914	1,914	1,905	1,905	1,905

Table 7: Success in Multi-star and non-Multi-star Stocks and Promotion of Existing Stars

The table presents the relation between star analyst accuracy in multi-star and non-multi-star stocks and the probability of promotion in I/I rankings. The dependent variable is binary, and we assign it the value of 1 if the star analyst (ranked in the first three places) improves ranking or remains in first place. Given that the basic measure is analyst-years rather than individual forecasts, we aggregate all the independent variables across all stocks in a certain year. The variable *No. multi-star stocks* counts the number of stocks covered by more than one star analyst. The variables *No. of wins* and *No. of top1* count the number of wins in multi-star stocks and the number of I/B/E/S wins in non-multi-star stocks, respectively. All other control variables are normalized to take a value between 0 and 1. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Model 1	**Model 2**
Mean relative accuracy	0.672	0.503
	(0.423)	(0.428)
No. of top1	0.146***	0.0693
	(0.0418)	(0.0462)
No. of wins		0.0926***
		(0.0227)
Institutional ownership	1.216*	1.290**
	(0.643)	(0.648)
Δ_IO	4.042**	4.166**
	(1.816)	(1.826)
Mean size	1.846**	1.923**
	(0.8)	(0.808)
Mean no. analyst	0.866	0.905
	(0.573)	(0.577)
Mean days elapsed	-0.166	-0.139
	(0.521)	(0.523)
Mean forecast horizon	-0.084	-0.246
	(0.737)	(0.743)
Mean order	-0.791	-0.98
	(0.699)	(0.705)
Mean brokerage size	-0.395*	-0.459*
	(0.237)	(0.24)
Mean general experience	0.458	0.391
	(0.409)	(0.412)
Mean firm experience	-0.378	-0.328
	(0.382)	(0.385)
Low coverage	-1.170***	-1.004***
	(0.166)	(0.172)
Constant	-3.637***	-3.741***
	(1.358)	(1.37)
N	1,905	1,905