

Competition among Star Analysts and the Information Environment of the Firm^{*}

Gil Aharoni
University of Melbourne

Joshua Shemesh
University of Melbourne

Fernando Zapatero
University of Southern California

November 15, 2014

ABSTRACT

We find that direct competition among star analysts plays a key role in their forecast accuracy. When two or more star analysts cover the same stock (battleground stock), star analysts are roughly 20% more accurate than when they are the only star covering a firm. Using a novel exogenous shock to star analyst coverage, our results suggest that the higher accuracy is not driven by star analysts' ability to pick stocks with a better information environment. We also document that the annual rankings of the Institutional Investor magazine are mainly based on star analysts' performance in battleground stocks. Overall, our findings unveil the important role of competition among star analysts in covering the largest firms.

^{*} We thank Eti Einhorn, Jordan Neyland, Jianfeng Shen, and conference participants in the 2013 Borsa Istanbul Finance & Economics Conference, the FIRN 2013 Annual Meeting, the 2013 Australian Banking & Finance Conference, and seminar participants from Tel Aviv University, the University of Melbourne, and the University of Southern California for helpful comments. Any existing errors are our sole responsibility.

1 Introduction

The question whether analysts affect the firms that they cover has been in the centre of the academic debate. One of the findings that emerge from this literature is that there is a positive relation between analyst coverage and what can generally be referred to as the transparency of the information environment of the firm. Recent evidence suggests that a decrease in analyst coverage is correlated with an increase in analyst optimism (Hong and Kacperczyk (2010)), an increase in earnings management (Yu (2008) and Lindsay and Mola (2014)), an increase in information asymmetry (Kelly and Ljungqvist (2012) and Chang, Dasgupta and Hilary (2006)) and a decrease in monitoring firm activity (Chen, Harford and Lin (2013)). Irvine (2003) shows that a firm's stock liquidity improves with initiations of analyst coverage. Derrien and Kecskés (2013) document that a decrease in analyst coverage leads to a decrease in corporate investment and financing. They suggest that a decrease in analyst coverage increases information asymmetry and thus increases the cost of capital.

Our paper adds to this literature by examining the effect of competition among star analysts on another aspect of information environment—the ability to estimate the firm's future earnings. Previous papers document that analysts that are selected to the All-American team by the Institutional Investor magazine (I/I) are much more influential than non-star analysts.¹ We suggest that the special status of star analysts leads the investment community as a whole to treat them as a separate group from all other analysts. As such, star analysts are not compared against the entire analyst community, but primarily against other star analysts. According to this premise, the portfolio of stocks that a star analyst covers can be split into two groups, depending on whether or not the same stocks are covered by other star analysts. We refer to stocks that are covered by more than one star analyst as battleground stocks and document that star analysts are more accurate in forecasting earnings of battleground stocks than of stocks that they cover as a single star. Using a novel exogenous shock to star analyst coverage, we argue that the higher accuracy is unlikely driven by the reverse causal argument, according to which star analysts self-select into stocks with better information environment. Furthermore, our results also suggest that

¹ Previous papers document that star analysts are more accurate (Stickel (1992)), their recommendations are more influential (Loh and Stulz (2011) and Fang and Yasuda (2013)), have stronger effect on information asymmetry (Kelly and Ljungqvist (2012)), and are more influential in reducing earnings management (Yu (2008)).

the competition among star analysts plays an important role in the I/I rankings. Specifically, doing well in battleground stocks relative to other star analysts carries much more weight in the I/I rankings than doing well relative to ordinary analysts.

This study measures the effect of competition among the most influential analysts covering the most important stocks. More than half of all battleground stocks are in the highest size quintile. Conversely, most existing papers report that analysts mainly affect relatively small stocks that are covered by five analysts or less. The existing evidence is consistent with the notion that analyst coverage predominantly affects the information environment of smaller stocks, while large firms are hardly affected. We show that star analyst accuracy among the largest firms is strongly dependent on the competition among star analysts. Another novelty of our setting is that we compare between stocks in which competition among stars exists to those in which there is no such competition. Most of the literature examines changes in the level of competition (changes in the number of analysts) and their effect on the information environment. We find that the presence of competition with other stars plays a significant role in star analyst accuracy, whereas the intensity of competition plays a minor role if any. The latter result is consistent with Lindsay and Mola (2014) that show similar findings regarding the effect of (mainly) ordinary analysts on earnings management. Our findings also highlight the importance of star analysts in the financial markets. The average battleground stock is covered by more than 20 ordinary analysts. Yet, the presence of one other star analyst reduces the forecast error by more than 20%. This finding is consistent with other papers that emphasize the strong influence of star analysts (e.g. Loh and Stulz (2011)).

We proceed as follows. First, we identify the battleground stocks, defined as stocks that are covered by at least two star analysts during the same year. Our findings show that, on average, roughly half of the stocks in a star analyst's portfolio are battleground stocks. Next, we examine whether competition among stars affects the information environment of the firm. To study this, we measure the accuracy of star analysts' forecasts in battleground stocks and compare it with their accuracy in single-star stocks. We find that star analysts are more accurate in battleground stocks. Our results show that, after controlling for common factors that have been shown to affect analyst accuracy, the average forecast error in battleground stocks is about 20% lower than that in single-star stocks.

As many of the papers in the analyst literature, our paper is subject to an endogeneity problem. In our case the reserve causal argument is that analysts prefer to cover stocks with better information environment.² Because star analysts are more talented in finding these stocks (and/or have a higher motivation to do so) than ordinary analysts, they self-select into stocks with better information environment, suggesting a negative relation between forecast errors and the number of stars. We therefore require an exogenous shock to star analyst coverage in order to distinguish between the two competing explanations.³ We suggest that a decrease in the number of star analysts that cover the stock due to the loss of star status can serve as such a shock. It is unlikely that star analysts are being selected according to *changes* in the characteristics of the stock they follow. Because analysts compete for star status within industries, any market- or industry-wide shock is likely to affect all competing analysts similarly. Any *differences* in the changes in information environment across competing stars are likely to be idiosyncratic. Since the median star analyst follows as many as 11 firms, any idiosyncratic changes in information environment are expected to be mitigated in the analyst level.⁴ Using the decrease in the number of star analysts that cover the stock due to the loss of star status, we show that when a battleground stock becomes a single-star stock, the forecast error of the remaining star analyst increases by roughly one third. This increase in forecast error is unique to firms that lose battleground status as it is not matched by stocks that experience a drop in the number of stars but remain battleground stocks. We also show that the higher accuracy in battleground stocks remains even when we limit the sample to stocks that switch from battleground to single-star at least once during the sample period. We use several additional tests to try to distinguish between the competition motive and the alternative causal argument. These tests broadly favor the competition story over the self-selection argument.

² Papers that document the tendency of analysts to choose stocks with better information environment include: Lang and Lundholm (1996), McNichols and O'Brien (1997), Francis, Hanna, and Philbrick (1997), and Bushman, Piotroski, and Smith (2003)).

³ The two widely used shocks are brokerage house mergers and closers (Hong and Kacperczyk (2010), Kelly and Lundquist (2012)). These are inadequate to our purpose as they mainly relate to the loss of ordinary analyst coverage. Derrien and Kecskes sample less than 10% (roughly 100 firms) of all firms that lost coverage are related to star analysts. We would like to thank the authors for providing us with this information.

⁴ We examine this assumption by testing whether demotion from star status is correlated with a decrease in analyst coverage, market value or earnings. We find no relation between these variables, all of which are likely to proxy for deterioration in the information environment, and demotion.

Our results so far indicate that the forecast error in battleground stocks is lower than in single-star stocks. While we relate these findings to the effect of competition it may be driven by other factors. For example, it may be that brokerage houses, in an attempt to try to maintain their prestige, divert more resources to stocks that are covered by their star analysts. This information-based explanation can account for most of our empirical results as it suggests a decrease in forecast errors in the time that a star analysts is reigning compared with other times in her career.⁵ In the second part of our work we try to identify the exact mechanism that is behind our results. We do so by identifying an incentive that leads star analysts to pay special attention to stocks that are covered by other star analyst(s).

Arguably, the most important organized competition for star analysts is the I/I ranking that awards the most prestigious star status. I/I star status has been shown to have a substantial effect on both analyst compensation and the brokerage house ability to attract new clients (e.g., Groysberg, Healy, and Maber (2011), Clarke, Khorana, Patel, and Rau(2007)). We find that success in battleground stocks is associated with higher probability of being promoted in the I/I rankings.⁶ Furthermore, consistent with the notion that star analysts are mainly compared to other star analysts, we find that the important determinant is the performance in battleground stocks relative to other stars, while performance relative to ordinary analysts plays only a minor role. Thus, our results suggest that star analysts are being ranked by I/I mainly according to their performance in battleground stocks. While not excluding other possible explanations, this incentive is likely to contribute to the lower forecast error observed, as it induces star analysts to strategically devote more effort to battleground stocks.

The rest of the paper is organized as follows. In Section 2, we discuss the data and methodology. In Section 3, we study the forecast accuracy in battleground versus other stocks, and we explore whether the higher accuracy might be due to the selection of more predictable stocks by star analysts. In Section 4 we analyze the relation between success in

⁵ The only empirical finding that seems inconsistent with this explanation is that the effect of an increase in the number of star analysts is limited to an increase from one to two and does not persist for higher numbers.

⁶ The I/I rankings are based on a questionnaire sent out to thousands of professionals in hundreds of institutions on an annual basis. The survey respondents do not receive any type of compensation, and so it seems reasonable to assume that they use “rules of thumb” that allow them to respond to the survey in a limited amount of time while providing adequate answers.

battleground stocks and promotion in the I/I rankings. We close the paper with some conclusions in Section 5.

2 Data, Methodology, and Summary Statistics

2.1 Data and Methodology

Our data is drawn from two 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 2002–2011 because many papers show that the nature of analyst estimates changed materially after the Fair Disclosure regulation was adopted. Throughout the paper, we concentrate on the earnings per share (EPS) forecast for the next fiscal year. Analysts' rankings are drawn from the files of I/I.

We determine the star status according to the I/I rankings, which are also known as the "All-American Research Team." As mentioned above, I/I proclaims the top three analysts in various industries and sectors on an annual basis. In this paper, we define stars as those who are in the first, second or third place (an additional runner-up may also be chosen). The vast majority of analysts included in the All-American 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. Throughout our sample period, we have 1,184 unique star analyst-year observations.

In this paper, we want to study the effects of the competition among star analysts, and so we divide all stocks in the I/B/E/S universe according to the number of star analysts who cover each stock. Of the 20,293 firm-years in our sample, 63.5% are not covered by any star analyst, while the rest are split almost evenly between stocks that are covered by a single star analyst and those that are covered by two or more star analysts (3,749 and 3,663, respectively). 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 realized earnings. 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 for which the forecast error is larger than 4. We follow Clement and Tse (2005) in defining and

normalizing the control variables, and we normalize all variables to a value between 0 and 1 using the following formula, in which analyst i covers firm j at year t :

$$Characteristic_{ijt} = \frac{RawCharacteristic_{ijt} - RawCharacteristic\ min_{jt}}{RawCharacteristic\ max_{jt} - RawCharacteristic\ min_{jt}}.$$

As noted by Clement and Tse (2005), applying this normalization to every variable allows us to examine their relative importance by directly comparing their coefficients.

Our focus is on the competition between existing stars, and so we require that the analyst achieve star status one year prior to her forecast's fiscal year end. We then examine the relation between the accuracy of star analysts and their ranking in the subsequent year. For every firm that an analyst covers, we include in our study only the earliest announcement in each year. We focus on the earliest announcement rather than on the last for two main reasons. First, the earliest forecast is arguably the most challenging because the forecast horizon is the longest. Second, the previous literature shows that analysts' forecasts are likely to cluster toward the end of the fiscal year, and hence later announcements carry less information about 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 fiscal year's end.⁷

2.2 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 "battleground" stocks). In Table 1 we present summary statistics of accounting variables, market performance and analyst coverage for each category.

⁷ We note that I/I respondents are required to send back their questionnaires between March and May, and so for firms with a fiscal year end other than December, the actual EPS is not yet available when the survey closes. This suggests that in some cases the respondents need to estimate the winner (possibly based on revisions in analysts' forecasts and quarterly earnings). Such measurement errors in our dependent variables is generally expected to bias the regression coefficients toward 0, and thus they work against finding a relation between the dependent and independent variables. Nevertheless, we can report that when we exclude these firms (roughly 20% of all forecasts) our main results hold.

(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 those covered by more than one star analyst (i.e., battleground stocks). The second row presents the number of large firms. Throughout the paper, we refer to firms in the top two size quintiles of the New York Stock Exchange (NYSE) as large firms. We find that close to 80% of all large firms are covered by at least one star analyst, and that over 50% of all large firms are battleground stocks. Focusing on firm size, our results show that battleground stocks are larger than those that are covered by a single star analyst, which are in turn larger than those that are not covered by any star analyst. Importantly, the proportion of small firms (the lowest NYSE size quintile) in battleground stocks is only 3%.

Battleground stocks are also more profitable than other stocks. The proportion of firms with negative net income among battleground stocks is only one fifth of the proportion of firms covered by a single star analyst. Analyst coverage increases with the number of star analysts that cover the stock. The average number of analysts that cover stocks with no star coverage is less than 7, but this number increases to 11.5 for stocks with single-star coverage and further increases to 18.5 for battleground stocks. Furthermore, while analyst coverage increases throughout our sample period, as evidenced by the change in the number of analysts (compared with the previous year), battleground stocks experience the sharpest increase. The average increase in coverage for battleground stocks is almost twice the increase for stocks covered by a single star analyst (1.05 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 battleground stocks. Finally, the last three rows present data regarding the coverage choice of star analysts. A star analyst covers an average of 12.3 stocks, and close to 60% of them are battleground stocks. 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 of the initiations take place within two years after the analyst becomes a star. The last row reports the number of firms that are dropped. 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.

3 Forecast Accuracy in Battleground Stocks

Recent literature focuses on the effect of financial analysts on the firms that they cover. Some researchers suggest that analysts may damage the transparency of the information environment, either because they bias their reports or because they put pressure on managers to meet earnings targets (e.g. Michaeli and Womak (1999), Bartov, Givoly and Hayn (2002)). Despite these concerns, most of the evidence suggests that analyst coverage improves the information environment of the firm by monitoring opportunistic behavior of managers (Jensen and Meckling (1976)) and/or reducing information asymmetry (e.g. Chang Dasgupta and Hilary (2006)). Hong and Kacperczyk (2010) report that a decrease in the number of analysts covering a firm leads to an increase in the optimism bias. Both Yu (2008) and Lindsey and Mola (2014) find that the number of analysts covering a firm is negatively related to earnings management. Kelly and Ljungqvist (2012) provide evidence that analyst coverage reduces information asymmetry by showing that a decrease in analyst coverage leads to a decrease in prices and uninformed demand. Building on this finding, Derrien and Kecskes (2013) show that a decrease in analyst coverage leads to a decrease in corporate investment and financing. They interpret this result as consistent with an increase in information asymmetry. Chen, Harford and Lin (2013) provide further evidence on the monitoring role of analysts by showing that analyst coverage reduces CEO compensation and leads to better acquisition decisions.

Importantly, most of the existing papers report that analysts have the strongest effect on relatively small stocks that are covered by five analysts or less. This result is not surprising as these papers typically employ the change in the number of analysts following brokerage house mergers or closers as proxy for a change in the information environment. Naturally, stocks with initial low analyst coverage are affected more strongly by a decrease in analyst coverage. This may lead to the conclusion that changes in analyst coverage are less important in large firms. We thus focus entirely on changes in the coverage of arguably the most influential analysts—star analysts—who typically cover very large firms.

Specifically, we study whether competition among star analysts improves the information environment of the firm they cover by examining the forecast error of star analysts themselves.

3.1 *Battleground and Star Analyst Accuracy*

Our univariate analysis in Table 1 shows that the average forecast error in battleground stocks is smaller than in single-star stocks. It also suggests that battleground stocks are larger and more profitable and that they enjoy higher analyst coverage than single-star stocks. It is therefore vital to establish that the smaller error is not solely driven by the different characteristics of battleground stocks. To investigate this question further, we perform a series of tests at the forecast level in which we control for common factors that have been shown to affect analyst accuracy. The dependent variable is the forecast error, defined as the absolute difference between the forecast and realized earnings, scaled by the realized earnings. The main independent variable is the binary variable *battleground*, to which we assign a value of 1 if the stock is covered by more than one star analyst and 0 otherwise. Our analysis, as represented in Table 2, is focused on the effect of competition on star analyst accuracy. Accordingly, only forecasts that are made by star analysts are part of our regression estimations—that is, we include only stocks that are covered by at least one star analyst. In order to mitigate the problem of large differences between small and large stocks, we drop all firms that are in the lowest-size quintile (NYSE cutoff points) from our analysis. Table 1 shows that less than 3% of all battleground stocks are in the lowest-size quintile, so we are unlikely to lose many observations. There are a total of 12,149 forecasts made by star analysts during our sample period. Control variables include the number of days elapsed since the previous forecast of the analyst (*days elapsed*), the number of days remaining until the announcement of the annual report (*forhorizon*), 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 (*generalexp*) 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 in covering the firm (*firmexp*), measured by the number of years that the analyst has covered the firm. All control variables are normalized to take a value between 0 and 1.

(Insert Table 2 about here.)

Model 1 in Panel A of Table 2 examines the univariate relation between forecast error and battleground status. Consistent with the results shown in Table 1, battleground status has a negative and significant relation with analysts' forecast error. In Model 2, we add the control variables as well as ranking fixed effects. The latter ensures that our results are not driven by the possibility that battleground stocks are mainly covered by star analysts of higher rankings. The coefficient of the number of analysts is negative and significant, as expected from its high correlation with firm size. Consistent 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 in some specifications it is significant, suggesting that relatively earlier announcements are more accurate. A possible explanation for this result is that some analysts who announce later than others deviate from the consensus in order to stand out in case they manage to perform better than their competitors (Bernhardt and Kutsoati (2004)). Most importantly, the coefficient of the battleground dummy is hardly affected (from -0.055 to -0.063) and remains highly significant after the inclusion of controls.

In Model 3, we add firm fixed effects to account for firm heterogeneity. In essence, firm fixed effects limit the effect of cross-sectional differences between firms, which in our context may affect how easy it is to forecast the firm's earnings. Our results show that the coefficient of the *battleground* binary variable decreases only slightly from -0.063 to -0.043 and remains statistically significant at the 1% level. Notably, this is the weakest of our results, yet even so it remains economically significant: a decrease of 0.043 in absolute error accounts for roughly 15% of the average error of star analysts. In Models 4 and 5, we add analyst fixed effects, which control for the identity of the analyst. This is to make sure that battleground stocks are not only covered by very few distinct individuals. In Model 4, we estimate the regression without firm fixed effects, whereas in Model 5 we include firm fixed effects. Both tests examine the forecast error of specific analysts in battleground stocks in comparison with their forecast errors in non-battleground stocks. The results show that for both models the coefficient of the binary variable *battleground* is negative and highly

significant. In fact, in both models the coefficient of *battleground* increases slightly to around 0.05 compared with 0.04 in Model 3.

One possible explanation for the lower forecast error in battleground stocks may be that star analysts condition their information on previous announcements made only by other star analysts and not by the entire analyst community. In this case, star analysts who announce later than other star analysts will have more information in battleground stocks. In order to examine this possibility, we concentrate only on the earliest forecast in each battleground stock by *any* star analyst. For that purpose, we exclude from the sample all forecasts by star analysts after observing previous forecasts by other star analysts. In this subsample, star analysts do not have at their disposal previous announcements by other star analysts. Thus, if the conditional information story is the main driving force behind our results, performance in battleground stocks should be indistinguishable from that in non-battleground stocks in this subsample. In contrast, if higher effort is the driving force behind the higher accuracy in battleground stocks, then our results should hardly change in this subsample. Our results are reported in Model 6, and they favor the special attention over the conditional information explanation. When we contrast the accuracy of star analysts in non-battleground stocks with that in only the earliest announcement among all star analysts in each battleground stock, the coefficient of *battleground* slightly increases (in absolute value) and remains highly significant.

In Panel B of Table 6, we limit the sample to include only large stocks that are in the top two quintiles (NYSE cutoff points). Focusing on large stocks has two advantages. First, it limits the effect of cross-sectional differences between small and large stocks. Second, it focuses the empirical analysis on the same stocks that are likely to be most important to I/I respondents, most of whom are money managers. The results show that the coefficient of the binary variable *battleground* does not decrease (in absolute value) and in some models increases by up to 50%. We note that the negative coefficient of *battleground* accounts for roughly 20% of the average forecast error of stocks in the highest two quintiles (0.34). We also note that, in comparing Panel B with Panel A, the coefficient of *No. analysts* becomes insignificant in some specifications. This was expected because in limiting the sample to include only large stocks we are mostly left with similar stocks in terms of their high coverage.

We conduct various robustness tests. First, we repeat the tests shown in Table 6 while defining a star analyst as ranked first or second but not as third place in the I/I rankings. The results (unreported) show only minor differences from Table 6. The coefficient of *battleground* is negative and significant in most specifications. We also repeat these tests while using the market value of equity as an alternative to the number of analysts in controlling for firm centrality. While this leads to a slightly higher r-square in the regression, the coefficient of *battleground* remains negative and significant. We also include industry fixed effects (both Fama-French 12 industries and two-digit SIC codes), but this does not affect our results materially either. Finally, we change the dependent variable from the absolute difference to the square of the difference between the forecast and the realized earnings (scaled by the realized earnings in both cases). Our unreported results show that the coefficient of *battleground* is significant in all 12 specifications of Panels A and B.

3.2 *Reverse Causality*

Our results so far suggest that star analysts have a lower forecast error in battleground stocks relative to stocks that involve no direct competition between star analysts. It is possible that the effect of competition leads star analysts to allocate more effort to battleground stocks, which would explain the smaller error. The smaller error, however, may also arise from the coverage choice of star analysts. The existing literature shows that analysts tend to cover firms with a better information environment (e.g., Lang and Lundholm (1996), McNichols and O'Brien (1997), Francis, Hanna, and Philbrick (1997), and Bushman, Piotroski, and Smith (2003)). Hence, the alternative causal argument suggests that, like other analysts, stars actively choose stocks that are easier to predict. Notably, we have already established that the higher accuracy in battleground stocks is not sensitive to the inclusion of the total number of analysts as a control. However, it is possible that star analysts (and those that aspire to be stars) are more aggressive in seeking stocks with better information environments. It may also be that star analysts are more talented in recognizing

changes in a firm's information environment.⁸ Both of these assumptions are likely to lead to a positive correlation between battleground status and forecast accuracy.

The inclusion of firm fixed effects ensures that our results are not driven by cross-sectional differences in the information environments. In essence, firm fixed effects account for heterogeneity in the complexity of forecasting a firm's earnings. A firm's information environment, however, may also be time varying, and thus, the self-selection argument may still hold. The endogeneity of coverage choice outlined above has already been acknowledged in the literature on changes in analyst coverage and their effect on the firm. In order to differentiate between the hypothesis that analyst coverage affects the firm and the alternative one that analysts self-select into firms with certain characteristics, researchers have used instrumental variables. Two such variables are brokerage house mergers (Hong and Kacperczyk (2010)) and brokerage house closures (Kelly and Ljungqvist (2012)), as both represent an exogenous negative shock to analyst coverage.⁹ These papers document that a decrease in analyst coverage is largely associated with a deterioration of the information environment of the firm.

For our research question, however, the use of brokerage house mergers and closures is not appropriate as both mergers and closures are not likely to have a broad effect on star analyst coverage. For example, using the dataset of brokerage house mergers and closures of Derrien and Kecskes (2013), merely one hundred stocks lose star analyst coverage. We therefore introduce a novel instrumental variable in order to separate between the two alternative stories—the decrease in the number of star analysts that cover a stock due to the loss of star status. We argue that the loss of star status is unlikely to be correlated with changes in the information environment. Analysts are ranked in the I/I rankings within specific industries, with roughly 65 industries in total. For this reason, any market- or industry-wide shock is likely to affect all competing analysts similarly. As such, any remaining differences in the changes in the information environment of competing star analysts are likely to be driven by idiosyncratic shocks. Taking into account that the median

⁸ This strategy, however, is unlikely to improve their relative accuracy. Still, it is possible that more talented analysts seek less-noisy stocks because success in such stocks will be attributed to their ability rather than to luck.

⁹ Other instrumental variables used include an inclusion in the S&P 500 index (Yu (2008)) and loss of coverage due to death of analysts in 9/11 (Kelly and Ljungqvist (2012)).

star analyst covers as many as 11 stocks, any idiosyncratic changes in the information environment are expected to be substantially mitigated in the analyst level. We confirm in the data that the loss of star status is uncorrelated with observable proxies for the information environment.¹⁰

Next, we examine whether changes in star analyst coverage are related to changes in forecast accuracy. Specifically, we examine whether there is an increase in forecast error when a stock switches from battleground to single-star sort. We choose to focus on the termination of battleground status, rather than on the initiation of one, as the former is less predictable. Star analysts may be able to predict who will be promoted through the rankings and challenge their position. Reigning stars will therefore gradually increase their effort (and thus improve their forecast error) accordingly. In contrast, the loss of star status is more unexpected and should thus have a stronger effect. 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 difference in its forecast error between the year of portfolio formation and the preceding year. Then, for every firm-year, we calculate the average difference in forecast error across all star analysts covering the firm. Hence, in order to be included in this test a stock needs to have star coverage in both the year of portfolio formation and the preceding year, and the star analyst needs to cover the firm over these two years.

(Insert Table 3 about here)

Results are presented in Table 3. The first three columns present the average forecast error one year prior to portfolio formation, the average forecast error in the year of 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

¹⁰ Since the information environment of the firm is unobservable, we examine variables 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, the change in firm earnings and the change in market value. We find no apparent relation between the number of star analysts that cover a stock and our measures for information environment.

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 material difference in the average forecast error between the two consecutive years. Results of Table 3 confirm the above argument by showing that the difference in the forecast error between one year prior to portfolio formation and the subsequent year is small and insignificant. The next row presents the results for stocks which experience an increase in star coverage. As previously argued, star analysts are likely to put 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 put more effort into stocks before they become battleground ones. Indeed, our results show that these stocks had a very slight decrease in forecast error (-0.007).

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 0.26 one year before the portfolio formation. The forecast error increases materially to 0.31 in the year of portfolio formation. This difference of, close to 0.05, 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 in which only one star analyst remains—meaning stocks that switch from battleground to single-star stocks (e.g. from two star analysts to one). In the second subgroup we include stocks that remain battleground stocks even after the decrease in star analyst coverage (e.g. from three star analysts to two). We repeat the tests for these two groups separately.¹¹ The results show that almost the entire increase in forecast error is driven by stocks which lose their battleground status. The average forecast error in these stocks increases by roughly one third (0.10), and this increase is significant at the 1% level. In contrast, stocks that remain battleground stocks experience a small and insignificant increase of 0.007.

Results in the third column can be viewed as the first step in a difference-in-difference analysis. In order to complete the second step, we match each firm that experiences a change in star coverage with the most similar firm in which star coverage remains unchanged (Row 1 in the Table). This allows us to compare stocks that experience a

¹¹ Notably, the forecast error of the second group (stocks that remain battleground ones) is lower than the first group one year before portfolio formation. This is to be expected as stocks that lose star coverage and remain battleground stocks are larger than stocks that lose battleground status.

shock to the competition among star analysts to similar stocks which 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 result of the matching analysis are similar to the ones in the third column. For the entire portfolio of stocks that experience a decrease in star coverage, the difference-in-difference in forecast error is positive (0.066) and significant at the 5% level. Again, the results are driven by stocks that lose their battleground status as a result of a decrease in star coverage. For these stocks the difference-in-difference in forecast error is 0.11 and significant at the 1% level. The next column similarly examines difference-in-differences in forecast error, but only for stocks that are larger than 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 previous 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-difference in forecast error among large firms decreases only slightly (0.08) and remains significant at the 10% level.

We note that a stock can switch from battleground to single-star sort not strictly because a star analyst covering it loses her star status in the I/I rankings. It is also possible that a star analyst covering the stock either decided to drop its coverage or is no longer included in the I/B/E/S database (e.g. transitioned to become a corporate executive). The last column presents the results for stocks in which the recently demoted star analyst continues to cover the firm. The motivation behind this test is twofold. First, although our previous results (cf. Table 1) show that stars rarely drop coverage, we still need to ensure that change in forecast error is independent of any decision of the star analyst. Second, we want to test whether the change in forecast error is driven by information rather than by competition. A plausible explanation for an increase in forecast error among stocks that experience a decrease in star coverage is that the loss of a star reduces the information about a firm and thus leads to an increase in forecast error. We mitigate both these concerns by requiring that the ex-star analyst continues to cover the firm. Results in the last

column are consistent with our previous findings by showing that stocks that switch from battleground to single-star ones experience a large increase in forecast error.¹²

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

Next, we take a different approach in order to separate between the two alternative stories. We examine several observable implications of the assumption that star analysts self-select into stocks with better information environment. We first note that if star analysts were to select firms with better information environments, one would expect them to constantly change their stock coverage in response to changes in the information environments of the firms. In practice, however, Clarke, Khorana, Patel, and Rau (2007) report that the coverage choice of star analysts is very sticky. Even star analysts who change their brokerage houses replace only two stocks per year on average. Our previous results (cf. Table 1) also highlight the fact that star analysts hardly modify their coverage portfolio. Star analysts drop 0.6 stocks per year on average, which accounts for 5% of the number of firms in their portfolio. Furthermore, slightly more than half of all star analysts do not drop any large stock throughout the entire period during which they maintain star status.

In Table 4, we examine other implications of the assumption that star analysts self-select into stocks with better information environment, and examine whether they hold in the data. We start by posing the question whether star analysts are only able to identify firms with better information environments during their reign, or whether they are able to select such stocks before they obtain star status. We formally test this question by examining whether our results hold when we exclude from the sample all stocks in which

¹² We conduct several robustness tests by changing the matching criteria to industry and number of analysts, industry and earnings and size and number of analysts. In all these specifications the difference-in-difference in forecast error is positive and statistically significant.

coverage is initiated by a star analyst after becoming a star. Results are presented in Table 4. Throughout, we include only stocks that are larger than the NYSE size median.¹³

(Insert Table 4 about here.)

The results presented in Model 1 show that the coefficient of *battleground* hardly changes and remains negative (-0.071) and highly significant in this portfolio. Hence, if the alternative selection argument is the main driving force behind our results, then star analysts have the ability to identify firms with better information environments even before they obtain star status.

We use this feature to distinguish between the two alternative explanations. The stock-selection explanation suggests that higher accuracy is characteristic of analysts that experience star status at some point in their careers, whereas our competition-driven explanation suggests that higher accuracy is more likely to occur when two (or more) analysts that are *concurrently* incumbent stars cover the same stock. We define analysts as *timeless stars* if they are chosen to be a star at some point during their careers. In our sample, more than half of the forecasts by *timeless-star* analysts are made before they become stars, roughly one third during their reign, and less than 10% after they are demoted from star status.¹⁴ Correspondingly, we define a stock as a *timeless-battleground* stock if it is followed by at least two *timeless-star* analysts. Timeless-battleground stocks pool together three types of stocks: stocks that are covered by two or more reigning star analysts (battleground stocks as originally defined), stocks that are covered by a single reigning star and stocks that are not covered by any reigning star analyst. Since our focus is on the accuracy of reigning star analysts, we exclude the latter, and compare the accuracy of reigning star analysts across the first two types. Putting it differently, our test compares the accuracy of reigning star analysts when they compete with other reigning star analyst(s) to their accuracy when they compete with analyst(s) that are chosen to be a star at some point but are not currently reigning. If the self-selection argument holds, there should be no

¹³ Dropping all stocks in the lowest-size quintile or including only stocks in the two highest-size quintiles leads to qualitatively similar results in all specifications.

¹⁴ The average star analyst spends as long as 7.5 years before becoming a star. In contrast, analysts tend to quickly disappear from the I/B/E/S database shortly after losing star status.

material difference between star analyst accuracy while competing with another reigning star and her accuracy while competing with an analyst that is currently not reigning but was or will be a star. In contrast, according to the competition argument, star analysts are likely to be more accurate in battleground stocks because they put more effort when other *reigning* star analyst(s) cover the same stock.

In Model 2, we limit the sample to stocks that are covered by at least two *timeless-star* analysts, and then estimate the same regression of the previous test for this subsample. Our results show that the coefficient of battleground is negative (-0.05) and significant at the 5% level. That is, when we focus on the competition between reigning stars and analysts that experience star status at some point in their career, the accuracy of reigning stars is higher when their competitors are currently reigning as well. As mentioned earlier in this section, more than half of the forecasts by timeless-star analysts are made before they become stars, while less than 10% after they are demoted from star status. This test therefore largely compares between the accuracy of a star analyst when competing with another star analyst(s) to her accuracy when competing with an analyst that will become a star later on in her career.¹⁵ Recall that Table 3, on the other hand, compared between the accuracy of a star analyst when competing with another star analyst(s) to her accuracy when competing with recently demoted star analyst(s). Taken together, our results indicate that a reigning star is more accurate when competing with another reigning star(s) than with former or future stars. The latter result cannot be explained by self-selection in star analyst coverage, even if stars are gifted with superior stock-picking ability.

In Model 3, we perform a more direct test, albeit at the cost of losing many observations. We limit the sample to include only stocks that changed from battleground to single-star stocks or vice versa at least once during our sample period. By holding the set of stocks constant, this test is meant to ensure that our results are not driven by any cross-sectional differences between single-star and battleground stocks. The results in Model 3 show that the coefficient of battleground stocks slightly increases (in absolute terms)

¹⁵ Arguably, star analysts can identify the aspiring analysts they are likely to compete with for star status in the future. This suggests that star analysts may put more effort into timeless-battleground stocks before the potential entrant becomes a star. However, such foresight ability would only bias against finding a difference between timeless-battleground stocks and stocks that are covered by at least two reigning star analysts (battleground stocks).

compared with the results in Table 2. Thus, even when we use a fixed set of stocks and compare periods in which they are battleground to periods in which they are single-star stocks, star analysts are more accurate during battleground periods. We note that we no longer control for firm fixed effects, since this subsample inherently holds the stock portfolios constant.¹⁶

In the next test, we take a different approach and focus on situations in which stock selection is expected to play a minor role, if any. According to the selection argument, star analysts are able to distinguish between good and bad information environments. As such, we examine portfolios that include stocks with minimal variation in their information environments, and test whether battleground stocks still display higher accuracy. While a firm's information environment is unobservable, we use the fact that volatility in the information environment reduces with size. We therefore focus our attention on firms in the highest size decile, with a market value of over \$10 billion. More than 99% of these stocks are followed by 10 analysts or more, and two thirds of them are followed by 20 or more analysts. Furthermore, there are hardly any firms in the highest-size decile that experience negative earnings. Hence, these stocks are likely to have limited volatility in their information environments. Our results show that the coefficient of battleground slightly increases in absolute value and remains significant at the 1% level. A potential concern in focusing on the largest firms is the scarcity of large single-star stocks in this subsample. Indeed, using our original definition of battleground stocks (covered by at least two analysts that are ranked in the first three places), more than 80% of the largest stocks are battleground stocks, which account for almost 95% of the forecasts in this subsample. The small number of single-star stocks in the highest-size decile is a concern, since our results may be influenced by a few large firms with bad information environments that star analysts do not generally cover. We therefore redefine stars as analysts who are ranked in the top two places in the I/I rankings. Accordingly, a battleground stock becomes a stock that is covered by at least two analysts who are ranked in the first or second (but not the third)

¹⁶ We note that according to the competition argument, star analyst accuracy is expected to be higher the longer the firm is a battleground stock. Therefore, using firm fixed-effects is likely to capture part of the relation which we are trying to unveil. Consistent with this observation, we find that when we include firm fixed-effects, the coefficient of battleground stocks decreases (in absolute terms) by one third and becomes statistically insignificant, although it is still more than one and a half standard errors from 0.

place in the I/I rankings. With this more restrictive definition, 35% of the stocks in the highest-size decile are defined as single-star stocks. The results in this subsample are presented in Model 4. The coefficient of *battleground* is negative (-0.04) and significant at the 1% level. Thus, even among the very large firms, it seems that coverage by more than one star analyst leads to higher accuracy. Since the largest firms seem to have similarly stable information environments, this result is inconsistent with the notion that the higher accuracy in battleground stocks is driven by their information environments.

Finally, we examine the relation between forecast error and the number of stars *within* battleground stocks. So far, we have established that the forecast error decreases when we compare single-star stocks with stocks covered by two or more stars. If star analysts were to select firms with better information environments, we would expect a general negative relation between forecast error and the number of stars *within* battleground stocks. Therefore, we examine whether the drop in forecast error in adding a second star to a single-star stock extends to the third star and so on. In Model 5, we limit the sample to include only battleground stocks, and we examine whether a larger number of star analysts is associated with a lower forecast error within these stocks. Our empirical findings do not support this relation, as the coefficient of the number of star analysts that cover a battleground stock is small and insignificant. We can report that when we replace the total number of star analysts with a binary variable, to which we assign a value of 1 if the number of star analysts is larger than two, and 0 otherwise, our results still hold. The irrelevance of the number of analysts within battleground stocks is consistent with Lindsey and Mola (2014), who show that earnings management decreases when two analysts cover a particular stock. When the number of analysts covering a firm goes above two, however, there are no material differences in earnings management.

Overall, our results favor the competition explanation over the alternative selection argument. First, we show that when a stock switches from battleground to single-star sort, the remaining star generates a large increase in forecast error. We do not observe a similar increase in stocks that experience a decrease in star analyst coverage but maintain their battleground status. Second, when we consider only stocks that switch from battleground to single-star stocks or vice versa during our sample period, the accuracy of star analysts remains higher in battleground stocks. Third, we find that the higher accuracy in battleground stocks persists even after we limit the sample to stocks that are covered by

star analysts prior to becoming stars. Hence, if the stock-picking argument is correct, then the ability of star analysts to select stocks with better information environments is not limited to the period during which they have obtained star status, but represents a talent they have always possessed. This observation facilitates our main test. We compared the accuracy of star analysts in stocks covered by another reigning star analyst to that in stocks covered by former or future stars. Consistent with our competition argument, we find that star analysts are more accurate when they deal with another reigning star.

4 Implicit incentives in the competition among star analysts

Our results so far highlight the importance of star analyst coverage to the information environment of the firm. Specifically, we find a large decrease in forecast errors when two or more star analysts cover the firm. While we argue that the competition between analysts induces them to devote more effort, there are alternative explanations that are likely to lead to similar empirical results. For example, it is plausible that brokerage houses allocate more resources and devote more attention to firms covered by star analysts in order to foster their reputation. Alternatively, Hong and Kacperczyk (2010) suggest that competition can improve the information environment as it is more difficult for the firm to influence analyst reports in its favor as more and more analysts cover the firm. A larger number of analysts increases the total cost the firm needs to spare in order to suppress unfavorable information. In addition, it becomes more likely that (at least) one of the analysts covering the firm cannot be bought as the number of analysts covering the firm increases. Both channels proposed by Hong and Kacperczyk (2010) are especially relevant to star analysts: star analysts are likely to be the most expensive to solicit, and their incentive to keep their star status is likely to hinder their bias. For example, it may be that a firm covered by a single star analyst can suppress unfavorable news by offering future deals for the brokerage house. However, most firms may find it difficult to manipulate more than one brokerage house.

In this section we try to identify the mechanism that induces star analysts to perform better in battleground stocks. Bringing forward a clear incentive to perform better in battleground stocks will further support our effort-driven argument, whether it tells the whole story or not. Previous literature has found that star status is associated with higher

pay to the analyst and higher deal flow to the brokerage house. In particular, Groysberg, Healy, and Maber (2011) find that analysts selected to the I/I All-American Team earn much higher salaries than other analysts. In addition, they show a large increase in analyst compensation—of roughly 25%—when they become stars. Clarke, Khorana, Patel, and Rau (2007) find that when the stars switching brokerage houses the deal flow for the new (old) brokerage houses increases (decreases). Arguably, the most important challenge that a star analyst faces is to maintain star status. While star status is sticky, roughly 25% of all stars fail to retain their star status in the consecutive year (e.g. Emery and Li (2009) and our own findings). Maintaining star status becomes even more difficult with age, as the I/I survey respondents seem to prefer younger blood (as evident from the negative relation between experience and star status).

Most of the literature compares between stars and non-stars while not focusing on the ranking itself. Arguably, the compensation for a star analysts and her ability to attract new deals are likely to improve with the rankings. Most importantly, a higher ranking substantially decreases the probability that the analyst will lose star status—i.e., will no longer be ranked in any of the top three places. 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 $t + 1$. Table 5 shows that during our sample period the probability of an analyst ranked in first place being 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, 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. Both Groysberg, Healy, and Maber (2011) and Clarke, Khorana, Patel, and Rau (2007) do not differentiate between specific rankings. Results of Table 5 demonstrate that current ranking is crucial in maintaining star status and the benefits that come with it.

(Insert Table 5 about here.)

Taking into account the importance of I/I rankings, we ask whether performing well in battleground stocks is rewarded with a better chance to remain stars. The I/I rankings are based on a questionnaire sent out to thousands of professionals in hundreds of institutions on an annual basis. Importantly, the survey respondents do not receive any type of

compensation, and so it seems reasonable to assume that they use “rules of thumb” that allow them to respond to the survey in a limited amount of time while providing adequate answers. We suggests that success in battleground stocks can serve as such “rules of thumb” as it allows the I/I respondents to directly compare between the performance of star analysts with the need to take into account the heterogeneity in information environment across firms. Since three-quarter of stars analysts retain their star status it seems that I/I rankings are mainly affected by this exclusive tournament between star analysts.

Several papers examine whether star analysts have better predictive ability, both before and after they become stars, and typically report a positive relation between accuracy and star status. For example, Stickel (1992) reports that star analysts are more accurate than non-star analysts. Leone and Wu (2007) find a positive relation between pre-selection accuracy and star status. Emery and Li (2009) use a logistic regression to examine which variables affect the probability of being a star. They report that accuracy plays a role in determining whether star analysts are likely to retain or improve their position in the subsequent year, but only among existing star analysts. Our tests are distinct from the previous literature in several important regards. First, we are only interested in the determinants of ranking improvements of *existing* star analysts. Since existing star analysts are already highly recognized, variables related to recognition are likely to play a minor role. Second, our sample period begins after regulation Fair Disclosure (FD) was introduced. Earlier papers using pre-FD regulation data document that analysts' accuracy is not only influenced by their intellectual ability but also by their relationship with the management of the firm. For example, Cohen, Frazzini, and Malloy (2010) find that prior to regulation FD analysts who have the same educational background as the CEO produce better stock recommendations. This relationship disappears after the introduction of regulation FD, which mandates that all publicly traded companies must disclose material information to all investors at the same time.

4.1 Success in Battleground Stocks and Ranking Improvements

Table 6 tests the relationship between the accuracy of star analysts in battleground stocks and their promotion in the I/I rankings. The dependent variable is binary, and we

assign it the value of 1 if the star analyst improves her ranking. A rank improvement takes place when an analyst ranked in the second or third place moves up, or when an analyst ranked in the highest position remains in the first place in the subsequent year.¹⁷ Our sample includes 1,184 analyst-years, of which 35% experience a ranking improvement in the subsequent year. Given the annual frequency of I/I rankings, we aggregate all forecasts made by each analyst in each year by using a simple mean.

(Insert Table 6 about here.)

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

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

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 relative to all analysts covering the same firm, and thus it inherently controls for firm-specific differences. Specifically, relative forecast accuracy controls for variations in the information environment across companies and time. The results of Model 1 show that the coefficient of mean relative accuracy is positive (0.89) and significant at the 5% level. The insignificant results for most of our control variables are to be expected due to the loss of information in aggregation. The only control variable that is significant is firm experience. The negative coefficient suggests that there is a tendency to promote relatively young analysts. This finding is consistent with Emery and Li (2009), who suggest that the assessment of older analysts is less likely to change. Surprisingly, there is a negative, albeit insignificant, relation between brokerage size and the probability of promotion. A possible explanation of this

¹⁷ 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.

finding is that star analysts are already recognized, making recognition variables such as the brokerage house less important. Model 2 adds to the regression the number of battleground stocks that the analyst covers during the year. The coefficient of this variable is positive (0.06) and significant at the 1% level. This suggests that the higher the number of battleground stocks an analyst covers, the more likely she is to be promoted in the I/I rankings. The coefficient of mean relative accuracy hardly changes and remains positive and significant.

The previous tests, based on the variable *relative accuracy*, demonstrate that relative performance affects the likelihood of ranking improvements. To further explore this result, we study whether being the most accurate star analyst in a battleground stock particularly affects the likelihood of ranking improvements. 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, her forecast error is the smallest among all star analysts covering the stock. Then, we count the total number of wins that an analyst has accumulated in a given year, which we refer to as *No. of wins*. Adding this variable to the regression significantly changes the results. The coefficient of *No. of wins* is positive (0.10) and highly significant. The coefficient of *No. battleground* is reduced by more than half (0.02) and becomes statistically insignificant. Similarly, the coefficient of mean relative accuracy is also reduced by roughly one half and becomes statistically insignificant. Therefore, our results suggest that wins in battleground stocks are pivotal in one’s chance to be promoted in the I/I rankings.

In Model 4, we examine the importance of the number of wins in comparison to that of relative accuracy. We do so by normalizing the value of *No. of wins* using a methodology similar to the one used with our control variables, so that

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

where *wins* is the number of wins of analyst *i* in year *t*, and *MAX (MIN) wins* is the maximum (minimum) number of wins of all star analysts in the same year. Since both *relative wins* and *mean relative accuracy* are normalized—as are all of the other variables—between 0 and 1, the magnitude of the coefficient indicates their relative importance. Our results show that

the coefficient of *relative wins* is almost four times larger than that of *mean relative accuracy* (0.15 and significant, compared with 0.04 and insignificant).

In Models 5 and 6, we explore the possibility that I/I respondents use more complex rules than simply ranking existing stars by their total number of wins in battleground stocks. In Model 5, we add to the regression an interaction variable that measures the relative accuracy in battleground stocks. Our results show that the coefficient of this interaction variable is small and statistically insignificant. In contrast, the coefficient of *No. of wins* is hardly affected. We next note that our binary variable *win* only compares accuracy across star analysts. However, it is possible that being the most accurate among all analysts, whether stars or non-stars, also has an effect on ranking improvement. Specifically, we try to determine whether wins that are accompanied by supreme overall accuracy relative to all analysts in the I/B/E/S database carry more weight than wins associated with relatively poor overall accuracy. To do so, we create a binary variable *Win plus ranked in the top 2*, to which we assign the value of 1 if, in at least one of the wins of the star analyst, the analyst's accuracy is also ranked in the top two places relative to the entire I/B/E/S universe.¹⁸ The results in Model 6 show that the coefficient of this interaction variable is slightly negative and very close to 0. This suggests that the performance of star analysts relative to non-star analysts in battleground stocks does not play a substantial role in the I/I magazine rankings.

4.2 *Success in Battleground vs. Non-Battleground Stocks*

We have shown that accuracy among star analysts in battleground stocks is highly correlated with an improvement in I/I rankings. However, we have yet to examine the importance of a win in battleground stocks compared to performing well in non-battleground stocks. 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 non-stars. Then we 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

¹⁸ We use the top two places rather than the first place alone in order to increase the power of our test. We can report that when we use first place alone relative to all analysts, the coefficient is negative (-0.08) and insignificant.

main goal is to compare the importance of performing well in battleground stocks (*No. of wins*) to that of performing well in non-battleground stocks (*No. of top1*).

(Insert Table 7 about here.)

Table 7 shows the relation between the accuracy of star analysts in both battleground and non-battleground stocks and their promotion in the I/I rankings. Same as in Table 6, the dependent variable indicates whether the star analyst improves ranking or remains in the highest position. In Model 1 we estimate the effect of the total number of I/B/E/S wins that an analyst has accumulated in a particular year on the probability of ranking improvement, and our results show that the coefficient of *No. of top1* is positive (0.25) and highly significant. In Model 2, we add back to the regression the variable *No. of wins* (the number of battleground stocks in which the analyst is the most accurate relative to other stars), and we find that the coefficient of *No. of top1* drops by almost half and is significant only at the 10% level. In comparison, the coefficient of *No. of wins* is significant at the 1% level. Interestingly, both coefficients seem to be of the same magnitude, however, while the unconditional probability of a star analyst being the most accurate in the entire I/B/E/S universe is less than 10%, the probability of a star analyst being the most accurate relative to other stars is 35%. This suggests that the weight of a win relative to other stars is much greater than the weight of an I/B/E/S win relative to all other analysts. In order to further examine the relative importance of both variables, we normalize the variable *No. of top1* to between 0 and 1 using the same method employed to compute *relative wins*. In Model 3, we include the two normalized variables in order to learn about their relative importance in I/I rankings. Consistent with our previous results, Model 3 shows that the coefficient of *relative wins* is roughly two and a half times larger than that of *Relative top1* (1.35 compared with 0.58, respectively).

The variable *No. of top1* pools together I/B/E/S wins in both battleground and non-battleground stocks, and thus its weakness may be driven by the insignificance of *ibes* wins in battleground stocks. Indeed, our previous findings (cf. Model 6 in Table 6) suggest that the performance of star analysts in battleground stocks relative to non-star analysts does not play a key role in the I/I magazine rankings. To better distinguish between the

importance of battleground and non-battleground stocks, we use an alternative definition of *No. of top1* that includes I/B/E/S wins only in non-battleground stocks. That is, we count the total number of *ibes wins* in single-star stocks in each year.

Models 4–6 re-estimate Models 1–3 while replacing the pooled *No. of top1* variable with the unblended one.¹⁹ Our results show that the coefficient of *No. of top1* increases materially from 0.25 in Model 1 to 0.34 in Model 4. Furthermore, when we estimate it together with *No. of wins*, the coefficient of *No. of top1* is almost twice as large in Model 5 as in Model 2, which confirms that being the most accurate overall is much more important in non-battleground stocks than in battleground stocks. The literature typically assumes that the success of star analysts is measured against the entire I/B/E/S universe. The results in Model 5 suggest this holds only in non-battleground stocks. Success in battleground stocks is predominantly measured against other star analysts. In Model 6, we again normalize the unblended variable *No. of top1* (I/B/E/S wins in non-battleground stocks) so that we can compare its magnitude to that of *relative win*. Consistent with our main argument, which is that star analysts are being evaluated primarily on the basis of their performance in battleground stocks, we find that the coefficient of *relative wins* is 1.8 times larger than the coefficient of the normalized variable *Relative top1*.

A potential concern with our findings is that the special weight given to performing well in battleground stocks is driven by the fact that battleground stocks represent larger firms. It may be that performing well in large stocks is the real underlying driver of ranking promotions. Indeed, our univariate analysis (cf. Table 1) shows that battleground stocks are larger than single-star stocks. In order to distinguish between the two explanations, we examine the effect of performing well in extremely large stocks. We count the number of wins in battleground stocks (*No. of wins*) and the number of I/B/E/S wins (*No. of top1*) in non-battleground stocks, but this time only in stocks that are in the highest NYSE size quintile. That is, we re-estimate the same three regressions as in Models 4–6 in Table 7 while only collecting wins in the largest firms. Our unreported results show that the coefficient of *No. of top1* remains insignificant, whereas the coefficient of *No. of wins* remains large and significant. Our findings confirm that, even among large firms, doing well

¹⁹ Using an interaction variable between *battleground* and *Top1* leads to similar results.

relative to other star analysts carries more weight in the I/I ranking than doing well relative to ordinary analysts.

In order to ensure the robustness of our results, we estimate multiple alternative specifications for *No. of wins* and *No. of top1*. We can report that using the NYSE median as the size threshold (that is, counting both the number of wins in battleground stocks and the number of I/B/E/S wins in non-battleground stocks in stocks larger than the NYSE median), barely changes our results. Our results also hold when we drop firms that are in the highest size decile, ensuring that the higher importance of battleground stocks is not driven by a few distinguished stocks. Finally, our results are not sensitive to whether we define good performance in non-battleground stocks (*No. of top1*) as the 20% most accurate analysts in the I/B/E/S universe, rather than the most accurate one alone. In all of these specifications, the magnitude of *relative wins* is at least 1.6 times higher than that of the number of I/B/E/S wins in non-battleground stocks. Hence, our findings suggest that I/I respondents focus on the performance of star analysts in battleground stocks.

5 Conclusions

A large body of literature examines the strategic behavior of analysts. One of the main reasons for why analysts may choose to bias their forecasts is related to career concerns. Strategic behavior driven by career concerns is typically associated with the behavior of ordinary, lower-tier, analysts. Ordinary analysts tend to “herd” in order to avoid negative consequences (turnaround) in case their private information turns out to be wrong, or instead they opt to overstate their private signals in order to stand out from the crowd. In this paper, we examine the career concerns of a group of analysts who are at the top of their profession—star analysts—who are already prominent and enjoy a high level of job security, and who are thus unlikely to face the same considerations as ordinary analysts. We suggest that star analysts have an incentive to retain star status and that this incentive influences the financial forecasts they release to the public.

The most influential rankings of analysts are provided by *Institutional Investor* magazine, which annually sends out thousands of questionnaires to money managers and, based on the responses, ranks the top three analysts in each sector. Since the respondents are not compensated for their participation in the survey, it is likely that they look for ways

to minimize their effort, while still providing reasonable answers. A simple rule of thumb would be to compare star analysts who cover the same stock. This one-on-one comparison allows the respondents to determine that the more accurate analyst is “better,” while avoiding the time consuming process of comparing across a larger set of stocks and taking into account factors such as earnings surprises, information environments, and earnings management.

The findings in this paper are supportive of the previous argument. We show that the performance of star analysts is not equally important across all of the stocks they cover. The performance of a star analyst in a stock that is covered by one or more other star analysts (i.e., a battleground stock) carries more weight than performance in stocks that are not covered by other star analysts. Specifically, being the most accurate star analyst in a battleground stock materially improves the probability of being re-selected as a star in the following year. Our findings also suggest that star analysts are more accurate in forecasting earnings in battleground stocks than in non-battleground stocks, and this finding is consistent with the notion that the competition among star analysts affects the information environment of the firms that they cover.

While this paper provides insight into the strategic considerations unique to star analysts, it also sheds more light on the criteria used in analyst rankings. We show that ordinal accuracy in battleground stocks, and in particular the highest accuracy, plays an important role in I/I rankings. Our results show that existing star analysts are rewarded for winning—i.e., being the most accurate among all star analysts that cover a particular stock. Our findings suggest that I/I respondents apply simple rules of thumb in order to rank existing star analysts. I/I survey respondents seem to count wins and rank analysts by the number of wins they have managed to accumulate during the past year.

By highlighting the importance of the competition among star analysts, this paper has two seminal contributions to the literature. First, this paper provides evidence for economic factors behind the selection process of analyst rankings. Stickel (1992) reports that star analysts are more accurate than non-star analysts. Leone and Wu (2007) find a positive relation between pre-selection accuracy and star status. Emery and Lee (2009) find that both the accuracy of earnings forecasts and the profitability of investment recommendations play a minor role in the selection of star analysts. They deem I/I rankings

to be nothing but a beauty contest. Taking into account the large effect that star analysts have on financial markets, their findings suggest that investors, managers and other analysts place their trust in a bunch of gifted salesmen. While understanding the methodology used in analyst rankings is outside the scope of this paper, our emphasis on the importance of the competition among existing star analysts can serve as a spring board to further research.

Second, this paper identifies a novel strategic consideration that may bias forecasts issued by financial analysts. A large body of literature argues that analysts bias the information they release in order to accommodate their brokerage house interests. The evidence whether this bias extends to star analysts is mixed. Star analysts have been shown to herd less, to be less optimistic during hot equity periods, and not to revise their recommendations when they switch brokerage houses (Fang and Yasuda (2009), Clarke, Khorana, Patel, and Rau (2007) and Hong, Kubik, and Solomon (2000)). These findings are consistent with the argument that reputational concerns prevent star analysts from engaging in such opportunistic behavior. In contrast, both Mola and Guidolin (2009) and Brown et al. (2013) show that stars bias their recommendations to accommodate the affiliated mutual funds and hedge funds. Our results also show that star analysts bias their recommendations as a response to their own incentive. However, unlike the first moment effects documented in the literature, the bias documented in this paper relates to the second moment—the forecast error. Specifically, we show that forecast error depends on whether a star analyst faces competition with other star analysts.

REFERENCES

- Bartov, Eli, Dan Givoly, and Carla Hayn, 2002, The rewards to meeting or beating earnings expectations, *Journal of Accounting and Economics* 33(2), 173–204.
- Bernhardt, Dan, and Edward Kutsoati, 2004, Analyst compensation and forecast bias, mimeo, University of Illinois.
- Brown, Nerissa C., Kelsey D. Wei, and Russ Wermers, 2013, Analyst recommendations, mutual fund herding, and overreaction in stock prices, *Management Science* 60(1), 1–20.
- Bushman, Robert, Joseph Piotroski, and Abbie Smith, 2004, What determines corporate transparency? *Journal of Accounting Research* 42, 207–252.
- Chang, Xin, Sudipto Dasgupta, and Gilles Hilary, 2006, Analyst coverage and financing decisions, *The Journal of Finance* 61(6), 3009–3048.
- Chen, Tao, Jarrad Harford, and Chen Lin, 2013, Do Analysts Matter for Governance? Evidence from Natural Experiments, Working paper.
- Clarke, Jonathan, Ajay Khorana, Ajay Patel, and P. Raghavendra Rau, 2007, The impact of all-star analyst job changes on their coverage choices and investment banking deal flow, *Journal of Financial Economics* 84 (3) 713–737.
- Clement, Michael B., and Senyo Y. Tse, 2005, Financial analyst characteristics and herding behavior in forecasting, *The Journal of finance* 60(1), 307–341
- Cohen, Lauren, Andrea Frazzini, and Christopher Malloy, 2010, Sell-side school ties, *The Journal of Finance* 65, 1409–1437.
- Derrien, François, and Ambrus Kecskés, 2013, The real effects of financial shocks: Evidence from exogenous changes in analyst coverage, *The Journal of Finance* 68(4), 1407–1440.
- Emery, Douglas R., and Xi Li, 2009, Are the Wall Street analyst rankings popularity contests? *Journal of Financial and Quantitative Analysis* 44(2), 411–437.
- Fang, Lily, and Ayako Yasuda, 2009, The effectiveness of reputation as a disciplinary mechanism in sell-side research, *Review of Financial Studies* 22, 3735–3777.
- Francis, Jennifer, Douglas Hanna, and Donna Philbrick, 1998, Management communications with securities analysts, *Journal of Accounting and Economics* 24, 363–394.
- Groysberg, Boris, Paul M. Healy, and David A. Maber, 2011, What drives sell-side analyst compensation at high-status investment banks?, *Journal of Accounting Research* 49(4), 969–1000.
- Hong, Harrison, and Jeffery D. Kubik, 2003, Analyzing the analysts: Career concerns and biased earnings forecasts, *The Journal of Finance* 58(1), 313–352.

- Hong, Harrison, Jeffery D. Kubik, and Amit Solomon, 2000, Security analysts' career concerns and herding of earnings forecasts, *RAND Journal of Economics* 31, 121–144.
- Irvine, Paul J, 2003, The incremental impact of analyst initiation of coverage, *Journal of Corporate Finance* 9(4), 431–451.
- Kelly, Bryan, and Alexander Ljungqvist, 2012, Testing asymmetric-information asset pricing models, *Review of Financial Studies* 25(5), 1366–1413.
- Lang, Mark H., and Russell J. Lundholm, 1996, Corporate disclosure policy and analyst behavior, *The Accounting Review* 71, 467–492.
- Leone, Andrew, and Joanna Wu, 2007, What does it take to become a superstar? Evidence from institutional investor rankings of financial analysts, Working Paper.
- Li Yinghua, P., Raghavendra Rau, and Jin Xu, 2009, The five stages of analyst careers: Coverage choice and changing influence, Working Paper.
- Lindsey Laura, and Simona Mola, 2014, Analyst competition and monitoring: Earnings management in neglected firms, Working Paper Series.
- Loh, Roger K., and René M. Stulz, 2011, When are analyst recommendation changes influential?, *Review of Financial Studies* 24(2), 593–627.
- McNichols, Maureen, and Patricia C. O'Brien, 1997, Self-selection and analyst coverage, *Journal of Accounting Research* 35, 167–199.
- Michaely, Roni, and Kent L. Womack, 1999, Conflict of interest and the credibility of underwriter analyst recommendations, *Review of Financial Studies* 12, 653–686.
- Mola, Simona, and Massimo Guidolin, 2009, Affiliated mutual funds and analyst optimism, *Journal of Financial Economics* 93(1), 108–137.
- Scharfstein, David S., and Jeremy C. Stein, 1990, Herd behavior and investment, *American Economic Review* 80, 465–479.
- Stickel, Scott E., 1992, Reputation and performance among security analysts, *The Journal of Finance* 47, 1811–1836.
- Wu, Joanna Shuang, and Amy Y. Zang, 2009, What determines financial analysts' career outcomes during mergers? *Journal of Accounting and Economics* 47, 59–86.
- Yu, Fang Frank, 2008, Analyst coverage and earnings management, *Journal of Financial Economics* 88(2), 245–271.

Table 1
Summary Statistics

We divide all sample stocks 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 (Battleground stocks). We use *Institutional Investor* (I/I) rankings in order to determine star status. All analysts ranked in the first three places in the previous year are considered to be stars. *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 in the top two NYSE size quintiles. *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 follow that firm in a given fiscal year. Δ *analysts* 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.

| | No Star Analyst | Single Star Analyst | Battleground Stocks |
|---|------------------------|----------------------------|----------------------------|
| 1 No. of firms | 12,831 | 3,690 | 3,639 |
| 2 Large firms | 1,008 | 1,187 | 2,569 |
| 3 Size | 12.92 | 14.09 | 15.48 |
| 4 Proportion small | 0.56 | 0.21 | 0.03 |
| 5 Average EPS | 0.34 | 0.65 | 0.84 |
| 6 Proportion negative EPS | 0.28 | 0.15 | 0.03 |
| 7 No. Analysts | 6.88 | 11.45 | 18.51 |
| 8 Δanalysts | 0.37 | 0.66 | 1.05 |
| 9 Absolute error | 0.55 | 0.41 | 0.31 |
| 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 withdrawals per year (stars) | --- | 0.27 | 0.32 |

Table 2

Forecast Error of Star Analysts

The table presents the accuracy of star analysts. We define a star analyst as an analyst ranked in the first three places in I/I rankings. We measure analyst forecast error in a stock as the absolute difference between the analyst's EPS forecast and the realized EPS scaled by the realized EPS. Throughout, we use only the first forecast each year for each stock. *Battleground* is a binary variable to which we assign the value of 1 if the firm is covered by two or more star analysts. The control variables are all scaled as in previous tests. *No. analyst* is the total number of analysts that cover the stock. *Days elapsed* is the number of days between the last and current forecasts of the analyst. *Forecast horizon* is the number of days until the end of the fiscal year. *Order* is the order 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 is in I/B/E/S files, whereas *Firm experience* is the number of years the analyst has been covering a specific firm. In Model 6, we include only the first announcement by any star analyst for each stock. We exclude from the analysis firms that are in the lowest size quintile. All standard errors are clustered by firm. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

Panel A – all firms

| | Model 1 | Model 2 | Model 3 | Model 4 | Model 5 | Model 6 |
|-----------------------------|------------------------|------------------------|-----------------------|------------------------|-----------------------|-----------------------|
| Battleground | -0.0550*** (0.0147) | -0.0629*** (0.0157) | -0.0431** (0.0202) | -0.0520*** (0.0152) | -0.0514** (0.0207) | -0.0500** (0.0269) |
| No. analyst | | -0.125** (0.0495) | 0.137 (0.101) | -0.285*** (0.0588) | 0.146 (0.0976) | 0.250* (0.138) |
| Days elapsed | | 0.0235 (0.0193) | 0.00274 (0.0176) | 0.00864 (0.0186) | -0.000938 (0.0178) | 0.00557 (0.0314) |
| Forecast horizon | | 0.371*** (0.0350) | 0.157*** (0.0324) | 0.271*** (0.0334) | 0.167*** (0.0338) | 0.172*** (0.0589) |
| Order | | 0.228*** (0.0370) | 0.0266 (0.0339) | 0.122*** (0.0341) | 0.0266 (0.0350) | 0.0210 (0.0664) |
| Broker size | | 0.0310* (0.0164) | -0.00308 (0.0156) | -0.0469 (0.0312) | -0.0495 (0.0313) | -0.0808 (0.0562) |
| General experience | | -0.0738*** (0.0244) | -0.0139 (0.0237) | -0.261 (0.283) | -0.178 (0.297) | -0.0143 (0.498) |
| Firm experience | | -0.0133 (0.0367) | 0.0309 (0.0317) | -0.0326 (0.0336) | 0.0179 (0.0345) | -0.0488 (0.0775) |
| Constant | 0.363*** (0.0233) | 0.0778 (0.0495) | 0.185*** (0.0563) | 0.285 (0.257) | 0.210 (0.313) | 0.0171 (0.623) |
| Year fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Ranking fixed effect | No | Yes | Yes | No | No | No |
| Firm fixed effect | No | No | Yes | No | Yes | Yes |
| Analyst fixed effect | No | No | No | Yes | Yes | Yes |
| N | 11691 | 10787 | 10787 | 10787 | 10787 | 5410 |
| Adj. R-sq | 0.013 | 0.035 | 0.318 | 0.117 | 0.330 | 0.289 |

Panel B – firms larger than the NYSE median

This panel replicates the previous table while dropping all firms smaller than the median NYSE size. All the variables are defined as in Panel A.

| | Model 1 | Model 2 | Model 3 | Model 4 | Model 5 | Model 6 |
|-----------------------------|-----------------------|------------------------|------------------------|------------------------|------------------------|-----------------------|
| Battleground | -0.0240** (0.0115) | -0.0449*** (0.0163) | -0.0653*** (0.0207) | -0.0372*** (0.0131) | -0.0725*** (0.0207) | -0.087*** (0.0269) |
| No. analyst | | 0.0112 (0.0502) | 0.211** (0.105) | -0.117*** (0.0397) | 0.233** (0.104) | 0.323** (0.152) |
| Days elapsed | | 0.0132 (0.0199) | -0.00332 (0.0177) | 0.00462 (0.0190) | -0.000621 (0.0184) | 0.0454 (0.0344) |
| Forecast horizon | | 0.329*** (0.0356) | 0.156*** (0.0334) | 0.247*** (0.0298) | 0.162*** (0.0357) | 0.232*** (0.0737) |
| Order | | 0.183*** (0.0370) | 0.0372 (0.0337) | 0.0995*** (0.0307) | 0.0321 (0.0348) | 0.0701 (0.0754) |
| Broker size | | 0.0201 (0.0161) | -0.00432 (0.0139) | -0.0585* (0.0330) | -0.0371 (0.0316) | -0.0920 (0.0605) |
| General experience | | -0.0593** (0.0246) | -0.0217 (0.0206) | -0.150 (0.266) | -0.130 (0.310) | -0.0476 (0.575) |
| Firm experience | | -0.00348 (0.0362) | 0.0482 (0.0295) | -0.0109 (0.0287) | 0.0717** (0.0316) | 0.114 (0.0757) |
| Constant | 0.276*** (0.0173) | 0.0120 (0.0490) | -0.131* (0.0672) | 0.142 (0.255) | 0.300 (0.293) | 0.221 (0.656) |
| Year fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Ranking fixed effect | No | Yes | Yes | No | No | No |
| Firm fixed effect | No | No | Yes | No | Yes | Yes |
| Analyst fixed effect | No | No | No | Yes | Yes | Yes |
| N | 9102 | 8505 | 8505 | 8505 | 8505 | 3841 |
| Adj. R-sq | 0.008 | 0.030 | 0.300 | 0.113 | 0.319 | 0.281 |

Table 3

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 all star analysts that cover a firm in both the year of portfolio formation and the prior year. Then, we divide all stocks that are 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 switch from battleground to single star and stocks that remain battleground stocks. Note that we include only stocks that are covered by at least one star analyst in the year of portfolio formation and in the previous year.

The first column presents the mean forecast error one year prior to portfolio formation. The second column presents the mean forecast error in the year of portfolio formation. The third column presents the difference in forecast error between the year of portfolio formation and the previous 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 sub-sample 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.

| | Error Year t-1 | Error year t | Diff | Diff in diff analysis | | |
|--|-------------------|-----------------|---------------------|-----------------------|---------------------|--------------------|
| | | | | All firms | Large firms | Ex-star remains |
| Stable star coverage (n=2174) | 0.292 | 0.293 | 0.000 (0.024) | | | |
| Increase in star analyst coverage (n=1106) | 0.264 | 0.270 | -0.006 (0.356) | -0.043* (1.836) | -0.064** (2.448) | -0.035 (1.592) |
| Decrease in star analyst coverage (all) (n=915) | 0.262 | 0.316 | 0.054** (2.535) | 0.066** (2.401) | 0.015 (0.626) | 0.552 (1.629) |
| Switch to single-star (n=455) | 0.307 | 0.423 | 0.116*** (3.138) | 0.139*** (2.993) | 0.079* (1.790) | 0.124** (2.117) |
| Remain battleground (n=460) | 0.220 | 0.227 | 0.007 (0.365) | -0.003 (0.098) | -0.028 (0.962) | -0.012 (0.346) |

Table 4
Reverse Causality

This table examines whether the smaller error in battleground stocks can be the result of analysts seeking to cover stocks with better information environment. Control variables include all controls in Table 2, normalized to be between 0 and 1, and also year, and firm fixed effects. We call timeless-star those analysts that at some point in their careers are selected as stars (top three places) in the I/I ranking. Model 1 drops all stocks that are chosen by the star analyst after becoming a star. In Model 2 we limit the sample to firms covered by at least two timeless-star analysts. Model 3 limits the sample to firms that switch from battleground to non-battleground stocks at least once. In Model 4 we limit the sample to firms in the highest size decile, and we redefine battleground stocks to be based only on analysts that are ranked in the first and second places in the I/I rankings. In Model 5, we limit the sample to battleground stocks and examine whether the number of star analysts who cover a battleground stock (*No. stars in battleground*) is associated with a lower forecast error. All standard errors are clustered by firm. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

| | Model 1 | Model 2 | Model 3 | Model 4 | Model 5 |
|----------------------------------|-----------------------|----------------------|---------------------|----------------------|----------------------|
| Battleground | -0.076*** (0.0198) | -0.052** (0.0215) | -0.075* (0.0446) | -0.096** (0.0486) | |
| No. analyst | 0.343*** (0.0817) | 0.197* (0.104) | -0.111 (0.175) | 0.300** (0.118) | 0.147 (0.114) |
| Days elapsed | 0.00681 (0.0235) | -0.00614 (0.0176) | -0.0306 (0.0601) | -0.0234 (0.0239) | -0.0226 (0.0164) |
| Forecast horizon | 0.171*** (0.0391) | 0.172*** (0.036) | 0.266** (0.122) | 0.164*** (0.0571) | 0.163*** (0.0374) |
| Order | 0.0637* (0.0378) | 0.0429 (0.0348) | 0.14 (0.131) | 0.0443 (0.0441) | 0.0483 (0.0368) |
| Broker size | -0.0732* (0.0426) | -0.0215 (0.0318) | -0.102 (0.124) | 0.0449 (0.0437) | -0.00228 (0.0124) |
| General experience | -0.143 (0.348) | -0.045 (0.313) | 0.912 (0.767) | -0.63 (0.405) | -0.011 (0.0198) |
| Firm experience | 0.034 (0.0576) | 0.0691** (0.0321) | 0.206** (0.0902) | 0.0258 (0.0421) | 0.0328 (0.0288) |
| No. stars in battleground | | | | | -0.0053 (0.00791) |
| Constant | -0.657 (0.779) | 0.06 (0.324) | -1.084 (0.824) | 0.636 (0.439) | 0.0372 (0.0463) |
| Year fixed effects | Yes | Yes | Yes | Yes | Yes |
| Firm fixed effect | Yes | Yes | No | Yes | Yes |
| Analyst fixed effect | Yes | Yes | Yes | Yes | Yes |
| N | 5600 | 8042 | 1021 | 2515 | 7064 |
| Adj. R-sq | 0.3 | 0.317 | 0.327 | 0.384 | 0.329 |

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 in the I/I All-American research team. Ranking 4 represents runner-ups, and Ranking 5 represents analysts that are not at all included in the I/I rankings.

| Ranking(t) | Ranking (t+1) | | | | | Total |
|--------------|------------------------------|------------------------------|------------------------------|------------------------------|------------------------------|------------------------------|
| | 1 | 2 | 3 | 4 | 5 | |
| 1 | 418 (68.75) | 86 (14.14) | 32 (5.26) | 20 (3.29) | 52 (8.55) | 608 (100) |
| 2 | 100 (17.15) | 236 (40.48) | 98 (16.81) | 59 (10.12) | 90 (15.44) | 583 (100) |
| 3 | 45 (7.88) | 106 (18.56) | 178 (31.17) | 145 (25.39) | 97 (16.99) | 571 (100) |
| 4 | 22 (2.03) | 99 (9.12) | 155 (14.29) | 418 (38.53) | 391 (36.04) | 1,085 (100) |
| Total | 585 (20.55) | 527 (18.51) | 463 (16.26) | 642 (22.55) | 630 (22.13) | 2847 (100) |

Table 6

Success in Battleground Stocks and Ranking Improvement

The table presents the relation between analyst accuracy in battleground stocks and the probability of promotion in the I/I rankings. The dependant variable is binary, and we assign it the value of 1 if the star analyst (ranked in the first three places) improves her 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. battleground stocks* counts the number of stocks covered by more than one star analyst. The variable *No. of wins* counts the number of wins in battleground stocks. A win is defined as a stock in which the star analyst is closer to the actual earnings than all other star analysts covering the stock. All other control variables are normalized to take a value between 0 and 1. There are 1,184 analyst-years in our sample, of which 35% are promoted. ***, **, * 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 | 0.895** (0.420) | 0.896** (0.434) | 0.552 (0.453) | 0.425 (0.440) | 0.440 (0.443) | 0.433 (0.448) |
| No. Battleground stocks | | 0.065*** (0.013) | 0.028 (0.020) | | | |
| No. of wins | | | 0.109*** (0.042) | | 0.153*** (0.039) | 0.154*** (0.042) |
| Relative wins | | | | 1.562*** (0.295) | | |
| Mean relative accuracy (BG) | | | | | -0.024 (0.095) | |
| Win plus ranked in the top 2 | | | | | | -0.028 (0.047) |
| Mean No. analyst | 0.137 (0.570) | 0.514 (0.585) | 0.592 (0.586) | 0.512 (0.589) | 0.571 (0.593) | 0.545 (0.584) |
| Mean days elapsed | -0.418 (0.522) | -0.487 (0.541) | -0.450 (0.542) | -0.442 (0.539) | -0.413 (0.540) | -0.421 (0.538) |
| Mean forecast horizon | 0.223 (0.728) | -0.137 (0.751) | -0.104 (0.754) | -0.024 (0.748) | -0.015 (0.746) | -0.017 (0.748) |
| Mean order | -0.707 (0.741) | -1.059 (0.765) | -1.091 (0.767) | -1.026 (0.761) | -1.028 (0.763) | -1.029 (0.761) |
| Mean brokerage size | -0.326 (0.261) | -0.398 (0.263) | -0.440* (0.264) | -0.434 (0.264) | -0.413 (0.264) | -0.413 (0.264) |
| Mean general experience | 0.505 (0.375) | 0.399 (0.381) | 0.388 (0.384) | 0.416 (0.393) | 0.404 (0.381) | 0.441 (0.381) |
| Mean firm experience | -2.348*** (0.788) | -2.507*** (0.815) | -2.500*** (0.819) | -2.499*** (0.814) | -2.464*** (0.817) | -2.464*** (0.814) |
| Contant | 0.142 | 0.215 | 0.023 | -0.065 | -0.177 | -0.494 |
| N | 1184 | 1184 | 1184 | 1184 | 1184 | 1184 |

Table 7

Success in Battleground and Non-Battleground Stocks and Ranking Improvement

The table presents the relation between analyst accuracy in battleground and non-battleground stocks and the probability of promotion in the I/I rankings. The dependant 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. battleground 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 battleground stocks and the number of I/B/E/S wins in non-battleground stocks, respectively. In Models 4–6, *No. of top1* counts only I/B/E/S wins in non-battleground stocks. All other control variables are normalized to take a value between 0 and 1. There are 1,184 analyst-years in our sample, of which 35% are promoted. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

| | Top 1: all stocks | | | Top 1: only non-BG stocks | | |
|--------------------------------|----------------------|----------------------|----------------------|---------------------------|----------------------|----------------------|
| | Model 1 | Model 2 | Model 3 | Model 4 | Model 5 | Model 6 |
| Mean relative accuracy | 0.567 (0.433) | 0.314 (0.446) | 0.307 (0.446) | 0.726* (0.426) | 0.297 (0.445) | 0.300 (0.445) |
| No. of top1 | 0.253*** (0.072) | 0.130* (0.078) | | 0.344*** (0.101) | 0.304*** (0.103) | |
| No. of wins | | 0.133*** (0.031) | | | 0.145** (0.029) | |
| Relative top1 | | | 0.580* (0.305) | | | 0.832** (0.302) |
| Relative wins | | | 1.353*** (0.315) | | 0.153*** (0.039) | 1.509*** (0.297) |
| Mean No. analyst | 0.642 (0.589) | 0.752 (0.597) | 0.743 (0.597) | 0.509 (0.582) | 0.851 (0.594) | 0.793 (0.594) |
| Mean days elapsed | -0.446 (0.529) | -0.438 (0.540) | -0.471 (0.542) | -0.426 (0.528) | -0.435 (0.543) | -0.454 (0.561) |
| Mean forecast horizon | 0.330 (0.736) | 0.072 (0.752) | 0.024 (0.752) | 0.299 (0.733) | 0.064 (0.754) | 0.036 (0.753) |
| Mean order | -0.712 (0.746) | -0.997 (0.763) | -1.075 (0.763) | -0.686 (0.745) | -0.998 (0.770) | -1.013 (0.765) |
| Mean brokerage size | -0.305 (0.260) | -0.435 (0.265) | -0.458 (0.265) | -0.411 (0.263) | -0.511* (0.267) | -0.499* (0.266) |
| Mean general experience | 0.477 (0.377) | 0.404 (0.383) | 0.403 (0.384) | 0.406 (0.373) | 0.307 (0.386) | 0.376 (0.384) |
| Mean firm experience | -2.407*** (0.797) | -2.482*** (0.816) | -2.516*** (0.818) | -2.341*** (0.796) | -2.449*** (0.820) | -2.476*** (0.820) |
| Constant | -0.846 | -0.572 | -0.521 | -0.065 | -0.177 | -0.494 |
| N | 1184 | 1184 | 1184 | 1184 | 1184 | 1184 |