Peer effects among financial analysts

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ABSTRACT

We investigate how the turnover of star analysts affects the performance of incumbent analysts. Using two measures of analysts' performance (forecast accuracy and the likelihood of becoming an Institutional Investor's All-star), we find consistent evidence that the arrival of star analysts benefits the incumbents. Our tests show that our results are not driven by the alternative explanation that star analysts' turnovers reflect changes in resources available to the incumbents. In addition, we show that the positive impact of the arrival of star analysts is more pronounced when the star analyst covers the same industry as the incumbents, when the star analyst is more established, when the incumbent analysts are less experienced, and when the brokerage house has fewer existing star analysts. Overall our paper offers strong evidence of peer effects among analysts.

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"A man only learns in two ways, one by reading, and the other by association with smarter people."

Will Rogers

1. Introduction

Sell-side financial analysts are the rainmakers on the capital market and their opinions have substantial valuation consequences (Bradshaw, 2004; Gleason and Lee, 2003; Jegadeesh et al., 2004; Stickel, 1992). Decades of research on analysts have generally focused on the effects of information environment and analysts' own individual characteristics on their performance (Brown, 1983; Brown and Rozeff, 1979; Byard et al., 2011; Clement, 1999; Hope, 2003; Jacob et al., 1999; Lang and Lundholm, 1996; Mikhail et al., 1997). The question whether analysts' performance is influenced by their colleagues has however received scant attention. We attempt to fill this void by examining how the turnover of star analysts affects the performance of incumbent analysts.

Star analysts are characterized by superior performance and high visibility. They are accurate forecasters (Stickel, 1992), they have superior stock-picking skills (Desai et al., 2000; Leone and Wu, 2007), and the stock price reacts strongly to their opinions (Gleason and Lee, 2003; Stickel, 1992). In addition, their names are published in the rankings of analysts and they receive disproportionate attention from the media. Naturally, their turnovers are economically important events and worthwhile academic topics.

We hypothesize that the arrival of stars improves the performance of incumbents while the departure has the opposite effect, because, as discussed in detail in Section 2, the incumbents can learn from star analysts through either knowledge transfer or social learning. For the sake of brevity, our discussion focuses on the arrival of stars, since the departure is simply the flip side.

Although our hypothesis is intuitive, it is not without tension. The arrival of star analysts can potentially hurt incumbent analysts' performance. Resources offered to analysts for their research are limited in brokerage houses. The newly arrived star analyst is likely to command a bigger slice of the pie, given her reputation and her high negotiation power with the new employer. Consequently, the resources available to the incumbent analysts are likely to drop, denting their productivity. Furthermore, power struggles may arise when the incoming star seeks greater influence at the brokerage house. The conflicts are likely to divert the incumbent analyst's attention from work to in-house politics, resulting in lower performance (Jehn and Mannix, 2001; Magee and Galinsky, 2008; Overbeck et al., 2005).

Using a sample of 275,119 analyst-firm-year observations for the period 1994-2011, we empirically test our main hypothesis. We use two measures of analysts' performance: earnings forecast accuracy and *Institutional Investor*'s (*II*) All-star recognition. These two are considered useful and important analysts' performance measures in the literature (Groysberg et al., 2011; Hong and Kubik, 2003; Mikhail et al., 1999; Wu and Zang, 2009). We find that, relative to analysts whose brokerage house experiences neither a departure nor an arrival of star analysts, analysts whose brokerage house sees the arrival of star analysts become more accurate forecasters and more likely to be recognized as an *II* All-star. The impact is economically significant. For example, the odds of becoming an *II* All-star increase by 30% after the arrival of star analysts. The opposite is true for star departures. Those analysts who experience a departure of stars exhibit lower forecast accuracy and diminished chances of *II* All-star recognition[1].

Although our results are consistent with incumbents learning from incoming stars, there exists an alternative explanation. The arrival of star analysts may be a signal of an

[1] In general, the impact of star departure is less significant than star arrival. This is consistent with the notion that the star arrival initiates learning, and, by the time the star departs, part of learning has taken place.

increase in resources made available to analysts. For example, when a brokerage house intends to beef up its research division, it may hire star analysts and simultaneously increase the research budget for all. To assess this resource-based alternative explanation, we conduct three empirical tests.

Our first approach is to directly control for variables measuring changes in resources available to the incumbents. We use three measures that are reflective of resources available to the incumbents: number of employed analysts, total assets, and total revenues of the brokerage house. If the brokerage house aims to beef up its research capabilities, increasing the number of analysts seems to be a reasonable outcome. The growth in headcount therefore reflects the brokerage house's intention to build up its research division and possible increases in resources[2]. Furthermore, when the brokerage house experiences changes in total assets and total revenues, the resources available to incumbent analysts may vary accordingly. If our results are driven by the alternative explanation, we expect that after we include variables representing changes in resources, the arrival of star analysts will become insignificant in explaining the changes in incumbent analysts' performance. This expectation receives no empirical support: star turnovers continue to explain incumbent analysts' performance.

In our second test, we use an instrumental variable approach, similar to that used in Agrawal et al. (2014). Our instrumental variable is the count of the number of star analysts at other brokerage houses who are at risk of moving to the focal brokerage house in the current year. The risk of moving is a function of the star's career age and her prior interactions with analysts from the focal brokerage house. The idea is that the star is more likely to move at a certain stage of her career (an analog is assistant professors who are more likely to move at the time of tenure promotion, typically six years after the start of their careers) and she is

[2] Zhang (2007) uses the growth in the number of employees to measure growth of the firm.

more likely to join the focal firm if she has prior interactions with the analysts from the firm. This instrument is correlated with the probability of the focal brokerage house hiring a star in year *t* but is not correlated with the resources available at the focal brokerage house. Our instrumental variable approach yields results consistent with our earlier findings.

Third, we conduct a falsification test by examining the star arrival/star departure in the twelve months *after* incumbent analysts issue their forecasts. If, as we conjecture, the star arrival/departure causally leads to changes in incumbent analysts' performance, we expect the later star turnover to have no impact on incumbents' performance. However, if the incumbents' performance is driven by contemporaneous changes in resources, we expect to observe a correlation between the two, because changes in resources are likely to precede the turnovers of star analysts. Empirically, the correlation is statistically insignificant, evidence inconsistent with the resource-based explanation.

We next develop other hypotheses. These hypotheses not only are interesting by themselves but also provide further support for our interpretation of the results. Specifically, we hypothesize that the positive impact of star analyst's arrival on the performance of incumbent analysts is more pronounced when the star analyst and the incumbent analysts cover the same industry, when the star analyst is more established, when the incumbent analysts are less experienced, and when the incumbent analysts work for brokerage houses with fewer existing star analysts. Our empirical results support these hypotheses. For example, the odds of the incumbent analyst becoming an *II* All-star are higher by 29% when the incoming star covers the same industry than when she covers other industries. Relative to the departure of a less established star (i.e., a star analyst who has been elected as an *II* All-star few times), the departure of a more established star analyst (i.e., a star analyst who has been elected as an *II* All-star many times) decreases the odds of the incumbents being selected as *II* All-star by an additional 37%. The star arrival increases the odds of becoming a star by 46% / 12% for inexperienced incumbents / experienced incumbents, and by 52% / 29% for incumbents working for brokerage houses with few / many existing stars. Overall, our results suggest that the impact of star arrival is greater when learning is more likely to occur.

Our study contributes to three streams of academic literature. First, this study contributes to the line of research on determinants of analysts' performance. Prior studies have suggested that the performance of analysts is affected by analyst characteristics, firm characteristics, brokerage house characteristics and the macro-economic environment (Brown et al., 2015; Brown and Mohammad, 2010; Clement, 1999; Jacob et al., 1999; Kumar, 2010; Ramnath et al., 2008). Our study extends this line of research and shows that analysts' performance is also influenced by their co-workers.

Second, this study adds to the literature on peer effects. There is a burgeoning economics literature on peer effects. Sacerdote (2001) documents that roommates positively affect college students' grade point average. Mas and Moretti (2009) find strong evidence of positive productivity spillovers from the introduction of highly productive personnel in the grocery market setting. Azoulay et al. (2010) show that sudden deaths of star researchers have a permanent negative effect on their co-authors' productivity. We extend this line of literature by documenting peer effects among financial analysts, who play an important role in the capital market. As discussed in Section 2, peer effects findings from prior studies do not readily apply to financial analysts, as a result of the competition among analysts.

Finally, our paper advances our understanding of the impact of star analysts' turnover. Clarke et al. (2007) show that the investment bank acquiring the star analyst significantly increases its market share in the industry covered by the analyst, relative to the investment bank losing the star. Groysberg et al. (2008) find that star analysts who switch employers experience an immediate decline in performance and the decline persists for at least five years. We extend this line of inquiry by examining the impact on incumbent analysts, a topic which has received scant attention.

In addition to contributing to the academic literature, our paper has practical implications. We find that the arrival of star analysts benefits incumbents to a greater extent when incumbent analysts are less experienced and when the incumbent's brokerage houses have fewer existing star analysts. These results are likely to be useful to the executives of brokerage houses in their hiring decisions. Our results also help to understand sky-high compensations offered to star analysts. For example, *The Wall Street Journal* reported that Goldman, Sachs & Co. offered a star analyst, Jack B. Grubman, a compensation package worth $25 million to attract him from Salomon Smith Barney Inc. (Raghavan and Mcgheehan, 1998). Our results suggest that the arrival of star analysts benefits the incumbents substantially. Therefore, the high compensation to the star may be appropriate.

The rest of the paper proceeds as follows. Section 2 develops hypotheses. Section 3 covers data and variable definitions. Section 4 discusses empirical results. Section 5 concludes.

2. Hypothesis development

The arrival of stars can benefit incumbents through the following two channels. The first channel is through explicit knowledge transfer from stars. Groysberg and Lee (2010) show that the performance of star analysts depends not only on their innate abilities but also on their collaboration with colleagues. Stars therefore have incentives to share their proprietary knowledge to improve their colleagues' performance. Doing so helps to build up rapport. In addition, more knowledgeable colleagues may be beneficial to the stars, since they become more reliable sources of information and insights. Anecdotally, there is evidence in support of explicit knowledge transfer. For example, Gary Black, a sixth-time all-star analyst in the tobacco industry, shared his "Eight Simple Rules to Success as an Analyst" with his colleagues (Groysberg and Healy, 2013).

The second channel is through social learning. The setting of financial analysts offers a unique setting for peer effects in that there exists strong competition among financial analysts while in other settings where peer effects are documented, competition is largely absent.[3] Financial analysts employed by the same brokerage house can be considered as tournament participants, vying for promotions and bonuses in the brokerage house (Yin and Zhang, 2014). The tournament theory (Main et al., 1993) predicts that tournament participants have incentives to undermine their competitors' productivity, in an attempt to win. From this perspective, the star analyst has little incentive to share her proprietary knowledge.

However, incumbent analysts can still improve their performance through social learning. The importance of learning through social interactions can be traced to classic writings by Marshall (1890) and Lucas (1988). Social learning theory (Bandura, 1977), an influential and well-established psychology theory, posits that human beings learn by observing models and they are more likely to adopt the model's behavior if the model holds admired status.[4] The arrival of star analysts offers incumbent analysts role models and gives them the opportunity to observe and learn, for example, the star's professional attitude and

[3] Sacerdote (2001), Mas and Moretti (2009) and Azoulay et al. (2010) document peer effects among college roommates, co-workers in the grocery market (who have to cooperate in their work), and coauthors of research papers. In these settings, there is a lack of competition among the peers.
[4] The social learning theory has been applied in various settings, including nurse education Bahn (2001), and several recent studies have attempted to understand social learning on the neural level (see Clark and Dumas (2015) for a review).

her way of interacting with clients and other members of the team. These tacit learnings are helpful to improve analysts' performance[5].

Since the incumbents can learn from the star analyst, we hypothesize the following:

H1: *The arrival of a star analyst improves the performance of incumbent analysts.*

We next develop other hypotheses. If indeed the effect we observe is through incumbent analysts' learning, we expect that the impact of star arrival is more pronounced for incumbent analysts covering the same industry as the incoming star. Obviously, these incumbent analysts are likely to have more interaction with the star, given the overlap in their work. They are more likely to be the recipients of knowledge transfer and have more opportunities for social learning. Therefore, if our learning based story is responsible for our empirical result, we would expect the effect to be more pronounced for analysts covering the same industry as the incoming star. Our H2 is therefore stated below.

H2: *The positive impact of star analyst's arrival on the performance of incumbent analysts is more pronounced when the star analyst and the incumbent analysts cover the same industry.*

We continue to hypothesize that the effect of the star arrival varies with the status of the incoming star. More established star analysts are likely regarded as better role models for social learning and they probably have more knowledge to share with incumbents. We therefore predict that the positive effect of star arrival is more pronounced when the star is more established. Our H3 is stated below.

H3: *The positive impact of the star analyst's arrival on the performance of incumbent analysts is more pronounced when the star analyst is more established.*

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[5] Altered incentives may explain our finding that incumbent analysts improve their performance after star arrivals. For example, the newly joined star analysts may be made the benchmark for promotion and bonus, and the higher standards incentivize analysts to work harder. This explanation however is inconsistent with the tournament theory. Financial analysts can be considered as tournament participants, vying for promotions and bonuses inside the brokerage house (Yin and Zhang, 2014). Knoeber and Thurman (1994) show that when a participant with higher ability (such as a star analyst) enters the tournament, existing tournament participants provide lower levels of efforts, because that they know that they are less likely to win.

We further hypothesize that less experienced incumbent analysts benefit more from the arrival of star analysts. Prior literature (e.g., Clement and Tse, 2005) shows that inexperienced analysts exhibit poorer performance. They probably have more to learn than more experienced incumbent analysts. Our H4 is described below.

H4: *The positive impact of the star analyst's arrival on the performance of incumbent analysts is more pronounced when the incumbent analysts are less experienced.*

Finally, we argue that the marginal benefit of star arrival decreases with the number of existing star analysts at the brokerage houses. For a brokerage house with many existing stars, the new knowledge or skill brought by an additional star is likely to be limited. This yields the following hypothesis.

H5: *The positive impact of the star analyst's arrival on the performance of incumbent analysts is more pronounced when the incumbent analysts work for brokerage houses with fewer existing star analysts.*

3. Data and variable definition

We obtain annual earnings forecasts from I/B/E/S detail file for the period 1994 – 2011. We start our sample in 1994 because forecasts were delivered to I/B/E/S in batches before 1994, rendering the dates assigned to forecasts inaccurate (Hilary and Hsu, 2013). We eliminate all observations for firms with only one analyst following, because most of our variables are based on a comparison among all analysts following the firm and such a comparison is unavailable for these firms. Following Clement and Tse (2005), we retain the last forecast an analyst issues within 30 – 360 days before the financial year end. We restrict our sample to forecasts issued by incumbent analysts, defined as analysts whose brokerage house is the same in both current year and the prior year. After requiring all variables to be non-missing for the forecast accuracy regression, we end up with a baseline sample of 275,119 analyst-firm-year observations.

We hand collect all-star information from *II* All-star list. Each year, the All-star ranking is published by *Institutional Investor* Magazine in October and any analyst who is named will be designated as a star analyst until the next ranking. For example, if an analyst is ranked in October 1996, she will be deemed a star analyst from October 1996 to September 1997. We merge the star analyst data with I/B/E/S data by matching on the name and the brokerage house, and identify moves of star analysts through the change in the brokerage house[6].

The main dependent variables are forecast accuracy ($accuracy_{kit}$) and the likelihood of being selected as *II* All-star ($star_{kt}$). Forecast accuracy is calculated using the following formula:

$$Accuracy_{\mathrm{kit}} = \frac{Max\ AFE_{it} - \ AFE_{kit}}{Max\ AFE_{it} - \ Min\ AFE_{it}}$$

Where AFE_{kit} is the absolute difference between the forecast by analyst k and the actual value of firm i's EPS in year t (i.e. absolute forecast error). $Min\ AFE_{it}$ / $Max\ AFE_{it}$ is the minimum / maximum absolute forecast error among all analysts issuing forecasts for firm i in year t. $Accuracy_{kit}$ ranges between 0 and 1. A higher value of $accuracy_{kit}$ indicates that the analyst is more accurate. Specifically, when $accuracy_{kit}$ equals 1, it suggests that the analyst is the most accurate among all the analysts following firm i in year t.

$Star_{kt}$ is the other dependent variable. It is an indicator variable, which equals 1 if the analyst k is selected as *II* All-star in year t, and 0 otherwise.

To test H1, the independent variables of interest are $star\_arrival_{kit}$ and $star\_departure_{kit}$. $Star\_arrival_{kit}$ / $Star\_departure_{kit}$ is a dummy variable which equals 1 if there is at least one star analyst arriving at / departing from the brokerage house of analyst k

[6] Erroneous matching biases against finding any statistically significant results.

within 12 months before the forecast is made in year t, and 0 otherwise. Figure 1 offers a timeline.

We control for the following variables in our analyses: *days_elapsed*, the number of days between the forecast and the most recent forecast issued by any analyst; *horizon*, the number of days between the forecast and the financial year end date; *frequency*, the number of forecasts the analyst issues for the firm in the year; *companies*, the number of firms the analyst follows in the year; *broker_size*, the number of analysts in the brokerage house; *industries*, the number of industries the analyst follows in the year; *experience*, the number of years the analyst has been issuing forecasts; and *bold*, the indicator of whether the forecast is bold. Prior research, such as Clement (1999); Clement and Tse (2003); Hong et al. (2000); Yin and Zhang (2014), has established that these characteristics have an impact on the analyst's performance. We also control for *lag_performance*, the lagged value of the dependent variable. This is because analyst performance may be sticky, i.e., an analyst who performs well in year t-1 is also expected to perform well in year t.

For easy comparison and interpretation of coefficient estimates, following Clement and Tse (2005), we scale all the control variables, except *bold,* to range from 0 to 1. The scaled control variables for analyst k following firm i in year t is

$$Characteristic_{kit} = \frac{Characteristic_{kit} - \ Min\ Characteristic_{it}}{Max\ Characteristic_{it} - \ Min\ Characteristic_{it}}$$

where $Max\ Characteristic_{it}$ / $Min\ Characteristic_{it}$ is the maximum / minimum value of a characteristic of all analysts following firm i in year t.

Bold$_{kit}$ is a dummy variable to indicate whether the forecast issued by analyst k for firm i in year t is bold. It equals 1 if the forecast is greater (smaller) than both analyst k's previous forecast and the prior consensus forecast, and 0 otherwise.[7]

Detailed variables definition can be found in the Appendix.

4. Results

4.1. Descriptive statistics

Table 1 presents descriptive statistics for the main variables used in the analysis. The mean value of *accuracy* is 0.686 and the median value is 0.618. The mean value of *star* indicates that about 13.5% of incumbent analysts are selected as *II* All-stars. The mean value of *star_arrival / star_departure* suggests that about 23.5% / 24.2% of incumbent analysts experience stars' arrivals / departures at their brokerage houses. The mean value of *day_elapsed* is 0.489, *horizon* averages about 0.490, and the mean value of *frequency* is 0.501. The mean value of *companies* is 0.435 and the mean value of *broker_size* is 0.558. *Industries* has a mean value of 0.369. The average value of *experience* is 0.628. Finally, the mean value of *bold* suggests that about 67.7% of forecasts are bold.

4.2. Test of H1

4.2.1. Main analyses

We use the following model to examine how the arrival / departure of star analyst affects the performance of incumbent analysts[8]:

[7] For brevity, we will drop all the subscripts (*k,i,t*) from now on unless we introduce new variables

[8] We obtain similar inferences when we try an alternative model to test H1, in which the main independent variables are two dummies indicating the net increase and decrease in the number of star analysts employed by

$$Performance_{kit} = \alpha + \beta_1 * Star\_arrival_{kit} + \beta_2 * Star\_departure_{kit} + Control\ variables + Analyst\ fixed\ effects + Year\ fixed\ effects + u_{kit} \quad (1)$$

Our dependent variables include *accuracy* and *star*. We use OLS regressions for *accuracy*, and our inferences are based on standard errors clustered at the brokerage house level. Given that *star* is a dummy variable, we use a logistic regression and we report both coefficient estimates and their odds ratios.

We control for analyst fixed effects and year fixed effects to take care of analyst- and year- specific impact on the performance. Since we include both *star_arrival* and *star_departure*, our benchmark is the incumbent analysts whose brokerage house experiences neither arrival nor departure of star analysts. We focus on β_1 and β_2, which indicate respectively how the arrival and departure of a star analyst at the brokerage house affects the performance of the incumbent analysts, compared to the benchmark. Control variables are discussed in the prior section. Our results are reported in Table 2.

We do not control for firm characteristics in our model due to the following three reasons. First, our dependent variable (*accuracy*) is ranked on the firm-basis. For example, a*ccuracy* equals 1 / 0 when the analyst is the most / least accurate among all analysts following the same firm. It is unlikely that any firm characteristics will affect with-in firm rankings. Clement and Tse (2005) investigate similar dependent variables and they do not include firm characteristics in their analyses. Second, we control for analyst fixed effects. To the extent that analyst coverage remains unchanged over time, the impact of firm characteristic is going to be absorbed by the fixed effects. Third, the independent variables of interest, *star_arrival* and *star_departure*, reflect the arrival / departure of star analysts in the

the brokerage house respectively. This model specification however does not allow the arrival and departure of star analysts to have differential impact on incumbent analysts.

analyst's brokerage house. These two variables are unlikely correlated with the characteristics of the firms being covered by incumbent.

In Columns 1 and 3 of Table 2, we report the results where we only control for lagged performance, analyst- and year-fixed effects. In the rest of the columns, we report the results where we include all control variables. Column 1 shows that analysts whose brokerage house experiences the arrival of star analysts become more accurate in their earnings forecasts. The coefficient on *star_arrival* is 0.008 and it is significant at the 5% level. The coefficient on *star_departure* is -0.007 and it is significant at the 10% level. Column 2 suggests that the finding on *star_arrival* is robust to inclusion of additional control variables. The coefficient on *star_arrival* is 0.006 and it is significant at the 1% level. The coefficient on *star_departure* remains negative but it is not significant at the 10% level. Consistent with Clement and Tse (2005), we observe that *day_elapsed*, *horizon* and *industries* are negatively correlated with forecast accuracy whereas *frequency, experience*, *lag_accuracy* and *bold* are positively correlated with forecast accuracy. Columns 3 and 4 show that star arrival substantially elevates the chances of incumbent analysts to become *II* All-star. The coefficient on *star_arrival* is 0.320 and significant at the 1% level in Column 3. It is 0.264 and significant at the 1% level in Column 4. The odds ratio statistics show that the odds of becoming *II* All-star are increased by 30% for those incumbent analysts experiencing star arrival. Consistent with Leone and Wu (2007), we observe that the likelihood of being ranked in the *II* magazine is positively correlated with *frequency, companies, broker_size, experience* and *lag_star.*

Overall, we find consistent evidence that the arrival of star analysts enhances the performance of incumbent analysts while their departure has a detrimental effect.

4.2.2. Control for resources

As we discussed in the Introduction, there exists an alternative explanation for our findings. The arrival of star analysts may be one measure that the brokerage house takes to strengthen its research division. Other unobservable measures, such as an increase in resources available to analysts, may explain our empirical results. To assess this alternative explanation, we conduct three empirical tests.

The first approach is to directly control for the changes in resources available to incumbent analysts in our regression. We use three different measures that are reflective of available resources: number of employed analysts, total assets, and total revenues of the brokerage house. Number of analysts employed by the broker in each year is calculated from I/B/E/S database. For total assets and total revenue, we Google each of the 742 brokers in our sample period to find their websites. For brokers that are listed, we collect information from Compustat using the GVKEY. For brokers that are not listed, we collect total revenues/total assets information from their websites. In cases that the broker is a subsidiary of another listed firm and we can't collect data from other sources, we supplement with the data for the parent company. Conceptually, when a brokerage house's parent firm grows, the resources available to the brokerage house increases as well. We note that, during the 2008 financial crisis, several brokerage houses were acquired by banks and other financial institutions. Care is taken so that revenues/assets information is for the brokerage house on a stand-alone basis before the acquisition.

$Growth\_analyst_{kit}$ is the change in the number of financial analysts employed by the brokerage house that employs analyst k who covers firm i in year t. Similar to other control variables, we scale this variable so that it takes the value of 1 / 0 if the brokerage house experiences the highest / lowest change in the headcount among all brokerage houses. We add this variable to Model 1 and report our results in Table 3. Column 1 shows that the coefficient on *star_arrival* is 0.005, significant at the 5% level, when *accuracy* is the dependent variable. In Column 2, when the dependent variable is *Star*, the coefficient on *star_arrival* is 0.256, significant at the 1% level. The related odds ratios suggest that the odds of becoming *II* All-star analysts are increased by 29% for analysts experiencing star arrival. Similarly, we also compute the change in total assets ($growth\_asset_{kit}$) and change in total revenues ($growth\_revenue_{kit}$) for the brokers and add them to the baseline regression. Since we are unable to obtain financial accounting information for every broker-year observation, our sample size is reduced. Columns 3 and 4 report the results when we add the change in the total assets. The coefficient on *star_arrival* is 0.004, significant at the 10% level when *accuracy* is the dependent variable (Column 3); and it is 0.269, significant at the 1% level, when *star* is the dependent variable (Column 4). The coefficient on *star_departure* is -0.0007 and not significant at the 10% level, when *accuracy* is the dependent variable (Column 3); and it is -0.139, significant at the 1% level, when *star* is the dependent variable (Column 4). The related odds ratios suggest that the odds of becoming *II* All-star analysts are increased by 31% for analysts experiencing star arrival and are reduced by 13% for analysts experiencing star departure. Columns 5 and 6 report the results when we control for the growth in total revenues in the regression. The coefficient on *star_arrival* is 0.004, significant at the 10% level, when *accuracy* is the dependent variable (Column 5); and it is 0.269, significant at the 1% level, when *star* is the dependent variable (Column 6). The coefficient on *star_departure* is -0.0008 and not significant at the 10% level, when *accuracy* is the dependent variable (Column 5); and it is -0.148, significant at the 1% level, when *star* is the dependent variable (Column 6). The related odds ratios suggest that the odds of becoming *II* All-star analysts are increased by 31% for analysts experiencing star arrival and are reduced by 14% for analysts experiencing star departure.[9]

Overall, our results remain robust after controlling for variables representing changes in resources, suggesting that our results are not driven by the resource-based alternative explanation.

4.2.3. Instrumental variable regression

In our regression analysis, the arrival of star is endogenous and might be correlated with changes in resources available to analysts. This suggests the need to use an instrument for the star arrival.

We employ an instrumental variable analysis based on the count of the number of star analysts at other brokerage houses who are at risk of moving to the focal brokerage house in the current year. The risk of moving is a function of the star's career age and her prior interactions with analysts from the focal brokerage house. The idea is that the star is more likely to move at a certain stage of her career (an analog is assistant professors who are more likely to move at the time of tenure promotion, which is typically six years after the start of their careers) and she is more likely to join the focal firm if she has prior interactions with the analysts from that firm. This instrument is correlated with the probability of the focal brokerage house hiring a star in year t but is not correlated with the resources available at the focal brokerage house. This approach is similar to the one employed by Agrawal et al. (2014).

[9] We do not control for all three measures of changes in resources in the same regression because of the concern of multi-collinearity. For example, the correlation coefficient between change in asset and change in revenue is 0.96 (p-value < 0.01).

To identify the analysts' prime moving window, we plot the move probability against the career age in Figure 2. We use the maximum sample period available from I/B/E/S (1970-2011) to plot this for greater accuracy. We identify each analyst's career age by first identifying the first year the analyst's forecast appears in the I/B/E/S database, and then subtract the first year of her forecast from the current year to obtain her career age. We include all analysts (both star and non-star analysts) in this analysis. Similar to our main test, we identify an analyst moving between brokerage houses when we observe a change in the ID of the broker the analyst is associated with. For each career age, we divide the number of analysts moving by the total number of analysts at that career age to compute the move probability. Figure 2 shows that the likelihood of analysts moving to another brokerage house (y-axis) peaks when the analyst's career age is between eight and ten years (x-axis).

To identify the star's prior interactions, we examine the work experience of each star analyst who is not employed by the focal broker at time *t*. If the star has worked in the same firm with analysts currently in the focal brokerage during the first five years of her career, we deem this star having a connection with the focal brokerage house. For example, if Star A worked in the same brokerage house with Analyst B during the first five years of Star A's career and Analyst B is currently working for brokerage house XYZ, Star A is deemed to have a connection with XYZ. This link is important because hiring on the Wall Street is often through personal connection and reference, and Analyst B is more likely to recommend Star A when XYZ is looking for star analysts. It is also less costly for Star A to move to XYZ because of the help and information she can get from Analyst B.

Our instrument variable, *N_Potential*, is the number of external star analysts having a connection with the focal broker and in their prime moving years (i.e., their career age is between eight and ten years).

In the first stage, we regress *star_arrival* on our instrumental variable (IV), while controlling for the number of analysts the broker employs. This control is important because the number of external star analysts having a connection is likely higher for brokerage houses employing more analysts. In the second stage, we regress measures of incumbents' performance on the instrumented *star_arrival*. Our results are reported in Table 4. Column 1 shows that *N_potential* is significantly correlated with *star_arrival,* which helps to validate our IV. Column 2 shows that incumbent analysts whose brokerage house experiences the arrival of star analysts become more accurate in their earnings forecasts. The coefficient on *star_arrival* (instrumented) is 0.070 and it is significant at the 1% level. Column 3 shows that analysts whose brokerage house experiences the arrival of star analysts have higher chances of becoming a star. The coefficient on *star_arrival* (instrumented) is 0.894 and it is significant at the 1% level. Interestingly, the results for the arrival of stars seem much stronger here than those reported in Table 2, indicating that the endogenous relationship between changes in resources and star analysts' turnover biases against us. Our additional empirical analyses show that the correlation coefficient between the hiring of stars and change in brokerage house's revenue is -0.004, significant at the 10% level, while the correlation coefficient between the hiring of stars and change in brokerage house's income is -0.05, significant at the 1% level. These statistics suggest that brokerage houses that experience a decline in their fortune actively seek to hire star analysts in an attempt to turn around their business (Bibeault, 1998). Therefore, relative to the instrumented *star_arrival,* the observed *star_arrival* is likely contaminated by a decline in resources available to incumbents, resulting in weaker results.

Overall, our instrumental variable regression results show that our main findings are not explained by the endogeneity associated with star analyst turnovers. In fact, the endogeneity seems to work against our conclusion.

4.2.4. Falsification test – Later star turnovers

This subsection reports the results of the falsification test.

Specifically, we construct two new variables, $later\_star\_arrival_{kit}$ *and* $later\_star\_departure_{kit}$, which equal 1 if the incumbent analyst k's brokerage house experiences an arrival / departure of star analysts 12 months *after* the forecast for firm i is made in year t, and 0 otherwise. We then estimate the following model:

$$Performance_{kit} = \alpha + \beta_1 * Later\_star\_arrival_{kit} + \beta_2 * Later\_star\_departure_{kit} + Control\ variables + Analyst\ fixed\ effects + Year\ fixed\ effects + u_{kit} \quad (2)$$

We focus on the coefficients of *later_star_arrival and later_star_departure*. If our results are driven entirely by changes in resources that predate the hiring/firing of star analysts, we expect the coefficients to be significant. However, if the star analyst turnover causally influences incumbents' performance, we expect these coefficients to be insignificant. Our results are reported in Table 5.

Columns 1 and 2 report results for the regressions where the dependent variable is *accuracy* while Columns 3 and 4 report for *star*. The coefficients on *later_star_arrival* and *later_star_departure* are never significant at the 10% level in all four columns.

In sum, we find that later arrivals and departures of star analysts have no impact on incumbents' performance, evidence consistent with the notion that star analysts' turnovers causally influence incumbents' performance.

4.2.5 Stock recommendation profitability as another measure of analysts' performance

Financial analysts issue stock recommendations and their stock recommendation profitability can be deemed another measure of their performance. We do not consider this performance measure in our main tests, because its computation takes a heavy toll on the sample size. Specifically, requiring this measure to be available reduces our sample size from 275,119 to 98,193, which is likely to reduce the power of the test. Having said this, we examine whether our conclusion applies to this measure in Table 6.

For this analysis, we obtain the analyst's last stock recommendation made within 30 – 360 days before the financial year end from I/B/E/S stock recommendation file. We follow the definition of stock recommendation profitability in Leone and Wu (2007) and compute the 30-day [0, +30] (day 0 is the recommendation issuance date) size-adjusted abnormal return for each recommendation (returns for hold and sell recommendations are multiplied by -1). $Profit_{kit}$ is computed according to the formula below:

$$\text{Profit}_{\text{kit}} = \frac{Return_{kit} - Min\ Return_{it}}{Max\ Return_{it} - Min\ Return_{it}}$$

where $return_{kit}$ is the 30-day size-adjusted return related to the recommendation issued by analyst k for firm i in year t. $Min\ Return_{it}$ / $Max\ Return_{it}$ is the minimum / maximum $return_{kit}$ among all analysts issuing stock recommendations for firm i in year t. Similar to *accuracy*, a higher value of *profit* indicates that the analyst's stock recommendation is more profitable.

We run our regression model as specified in Equation (1) with *profit* as the dependent variable. Our results are reported in Table 6. We find that incumbent analysts issue less profitable recommendations after the departure of star analysts from the brokerage house. In Column 1, the coefficient on *star_departure* is -0.009 and significant at the 10% level.

Column 2 shows that adding control variables does not alter our conclusion: the coefficient on *star_departure* is -0.009, significant at the 10% level.

Overall, our results show that our conclusion is robust to an alternative measure of analyst performance.

4.3. Test of H2

H2 predicts that the positive impact of star analyst's arrival on the performance of incumbent analysts is more pronounced when the star analyst and the incumbent analysts cover the same industry. We use the following model to examine H2:

$$Performance_{kit} = \alpha + \beta_1 * Indstar\_arrival_{kit} + \beta_2 * Indstar\_departure_{kit} + \beta_3 * Star\_arrival_{kit} + \beta_4 * Star\_departure_{kit} + Control\ Variables + Analyst\ fixed\ effects + Year\ fixed\ effects + u_{kit} \quad (3)$$

$Indstar\_arrival_{kit}$ and $Indstar\_departure_{kit}$ indicate respectively the arrival and departure of star analysts covering the same industry as the incumbent analysts. $Indstar\_arrival_{kit}$ / $Indstar\_departure_{kit}$ equals 1 if at least one star analyst covering the same industry as analyst k arrives at / departs from the brokerage house of analyst k within 12 months before the forecast is made in year t, and 0 otherwise. We focus on the coefficient on *indstar_arrival* / *indstar_departure*, which reflects the effect of the arrival / departure of star analysts covering the same industry, *incremental* to the arrival / departure of other star analysts.

Table 7 reports the results of estimating the above regression. Column 1 shows that the coefficient on *indstar_arrival* is 0.010, significant at the 10% level and the coefficient on *indstar_departure* is -0.011 (insignificant). This result indicates that the arrival of star analysts has a greater impact on incumbent analysts when the star covers the same industry as the incumbents but the departure of star analysts covering the same industry has no such impact. Column 2 shows that the arrival of star analysts covering the same industry elevates the chances of incumbent analysts to become *II* All-star and the departure of star analysts covering the same industry diminishes their chances. The coefficient on *indstar_arrival* is 0.253, significant at the 1% level, while the coefficient on *indstar_departure* is -0.362, significant at the 1% level. The odds ratios indicate that the odds of becoming *II* All-star are further increased / decreased by 29% / 30% when the incoming / departing star analysts cover the same industry as the incumbents. The coefficients on control variables are similar to those reported in Table 2.

Overall, across both measures of analysts' performance, we find consistent evidence that the benefit to the incumbent analyst is more pronounced when the incoming star analyst covers the same industry as the incumbents. This evidence is consistent with the notion that the improvement in incumbent analysts' performance is through either knowledge transfer or social learning.

4.4. Test of H3

We use the following model to examine whether more established star analysts affect the performance of incumbent analysts to a greater extent:

$$Performance_{kit} = \alpha + \beta_1 * Eststar\_arrival_{kit} + \beta_2 * Eststar\_departure_{kit} + \beta_3 * Star\_arrival_{kit} + \beta_4 * Star\_departure_{kit} + Control\ Variables + Analyst\ fixed\ effects + Year\ fixed\ effects + u_{kit} \quad (4)$$

Eststar_arrival$_{kit}$ / *Eststar_departure*$_{kit}$ is a dummy variable, which equals 1 if there is at least one established star analyst arriving at / departing from the brokerage house of analyst k within 12 months before the forecast for firm i is made in year t, and 0 otherwise. We infer the star's status via the number of times she has been selected as an *II* All-star. If the number is greater than the star analyst sample's median, the analyst is deemed an established analyst. The coefficient on *eststar_arrival* / *eststar_departure* reflects the effect of the arrival / departure of established star analyst, *incremental* to the arrival / departure of other star analysts.

Table 8 reports the results of estimating the above regression. In Column 1, the coefficient on *eststar_departure* is -0.006, significant at the 10% level, suggesting that the departure of established stars has a negative impact on analysts' forecast accuracy incremental to the effect of the turnover of less established star analysts. Column 2 shows that the departure of established star analysts diminishes the chances of incumbent analysts to become *II* All-star. The coefficient on *eststar_departure* is -0.468, significant at the 1% level. The related odds ratio suggests that the odds of becoming *II* All-star further decrease by 37% for those incumbent analysts experiencing the departure of established star analysts.

In sum, we document that the arrival of established star analysts has a greater impact on the incumbents.

4.5. Test of H4

H4 predicts that the positive impact of the star analyst's arrival on the performance of incumbent analysts is more pronounced when the incumbent analysts are less experienced. To test H4, we sort our sample observations into two subsamples based on the experience of the incumbents. The less / more experienced subsample consists of those whose experience is below / above the median. We then rerun the regression as specified in Model (1). Table 9 presents the results.

Columns 1 and 2 report the results for less experienced incumbents and more experienced incumbents respectively, when *accuracy* is the dependent variable. The coefficient on *star_arrival* is 0.007, significant at the 1% level, in Column 1, while it is 0.004, not significant at the 10% level, in Column 2. The difference between the two coefficients is significant at the 10% level. This result is consistent with the notion that the impact of the star arrival on forecast accuracy is more pronounced for inexperienced incumbents. Our results in Columns 3 and 4 offer similar inferences. The coefficient on *star_arrival* in Column 3 is 0.376 while it is only 0.112 in Column 4; the difference between the two coefficients is significant at the 10% level, suggesting that the impact of star arrival on the likelihood of becoming a star is greater for inexperienced incumbents.

Overall, using both measures of analysts' performance, we document that the impact of star arrival is more pronounced for inexperienced incumbents.

4.6. Test of H5

H5 predicts that the positive impact of the star analyst's arrival on the performance of incumbent analysts is more pronounced when the incumbent analysts work for brokerage houses with fewer existing star analysts. To test H5, each year, we conduct a median-split based on the number of stars each brokerage house employs. We then repeat our regression as specified in Model (1) for each subsample and report our results in Table 10.

Columns 1 / 2 reports the results for incumbents working at brokers with fewer / more existing stars, when *accuracy* is the dependent variable. The coefficient on *star_arrival* in Column 1 is 0.008, significant at the 1% level, while it is less than 0.001 in Column 2; the difference between the two is significant at the 10% level. Columns 3 and 4 report the results when *star* is the dependent variable. The coefficient on *star_arrival* is 0.417 in Column 3 while it is only 0.251 in Column 4; the difference between the two coefficients is again significant at the 10% level.

Overall, using both measures of analysts' performance, we document that the impact of the star arrival is greater for incumbent analysts working for brokers with fewer existing star analysts.

5. Conclusion

Financial analysts play an important role in the capital market. In this paper, we seek to understand whether they learn from their peers. Specifically, we focus on the impact of star analysts' turnover on incumbent analysts' performance, which is measured by forecast accuracy and the odds of becoming an *II* All-star. We find strong and consistent evidence that the arrival of star analysts is beneficial to the incumbents. For example, the odds of becoming *II* All-star increase by 30% when the incumbents experience the arrival of star analysts.

We conduct three tests to address the alternative explanation that the turnover of star analysts is related to the change in resources available to the incumbents. We find that our conclusion continues to hold when we add variables representing changes in resources. In addition, we use an instrumental variable approach and conduct a falsification test, and our results do not lend support to the alternative explanation.

Our further analyses show that the effect of the star arrival is greater when the star analyst covers the same industry as the incumbents, when the star analyst is more established, when the incumbent analysts are less experienced, and when the incumbents' brokerage houses have fewer existing star analysts. These findings not only are interesting by themselves but also buttress our argument that the effect we document is through learning.

Overall, our results suggest that star analysts elevate the performance of incumbent analysts through either knowledge transfer or social learning. While prior literature has focused on the effect of information environment and individual characteristics on analyst performance, our findings indicate that the peer influence is an overlooked determinant of analyst performance.

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Figure 1

This timeline depicts the time when we measure incumbent analyst's performance and the arrival / departure of star analysts. We identify an analyst in a brokerage house to experience a star arrival (departure) in a year if there is at least one star analyst coming to (leaving) the brokerage house within 12 months before the date of the forecast.

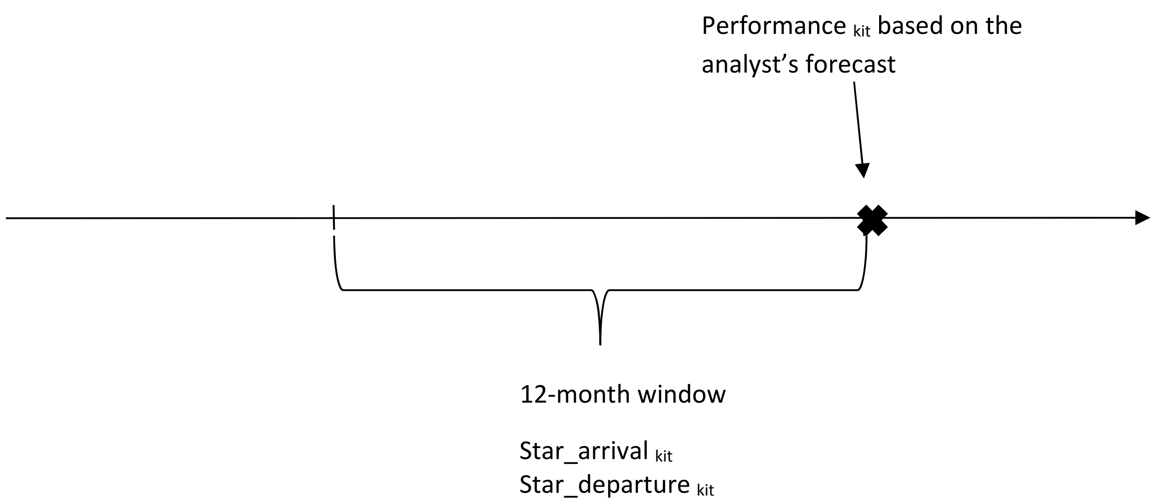

Figure 2

This graph displays the probability of analyst making a move to another brokerage house conditioning on the career age of the analyst.

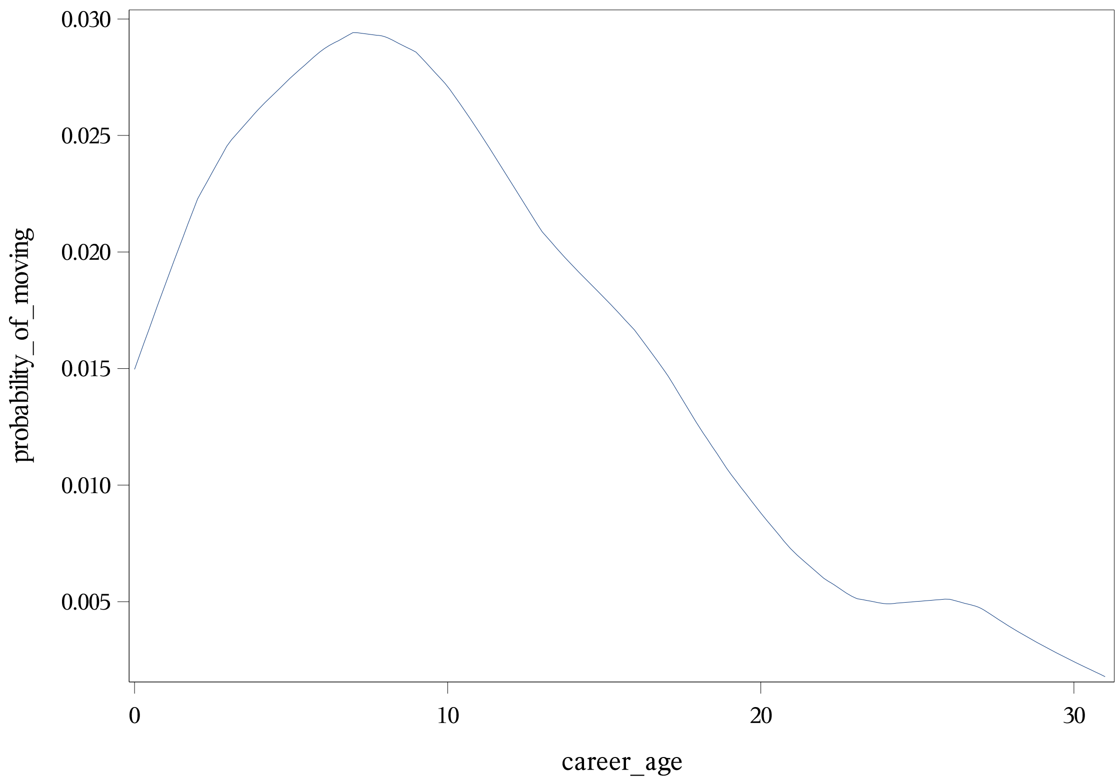

Table 1 - Descriptive Statistics

This table reports the descriptive statistics for the main variables in the analyses. The definition of each variable can be found in the appendix.

VARIABLES	N	mean	s.d	Q1	median	Q3
accuracy	275,119	0.686	0.331	0.300	0.618	0.757
star	275,119	0.135	0.342	0	0	0
star_arrival	275,119	0.235	0.424	0	0	0
star_departure	275,119	0.242	0.429	0	0	0
day_elapsed	275,119	0.489	0.366	0.200	0.295	0.686
horizon	275,119	0.490	0.341	0.232	0.322	0.659
frequency	275,119	0.501	0.330	0.250	0.500	0.750
companies	275,119	0.435	0.307	0.188	0.382	0.645
broker_size	275,119	0.558	0.318	0.287	0.467	0.746
industries	275,119	0.369	0.327	0.100	0.286	0.571
experience	275,119	0.628	0.348	0.333	0.667	1
bold	275,119	0.677	0.468	0	1	1

Table 2

Effects of Star Arrival / Departure on Incumbent Analysts' Performance

This table reports the results of estimating the following equation:

$$Performance_{kit} = \alpha + \beta_1 * Star\_arrival_{kit} + \beta_2 * Star\_departure_{kit} + Control\ variables + Analyst\ fixed\ effects + Year\ fixed\ effects + u_{kit}$$

The dependent variable is forecast accuracy for Columns 1-2 and likelihood of becoming stars for Columns 3-4. *Star_arrival* equals one if there is at least a star analyst arriving at the brokerage house of analyst k within 12 months before the forecast is made at time t, and 0 otherwise. *Star_departure* equals one if there is at least a star analyst leaving the brokerage house of analyst k within 12 months before the forecast is made at time t, and 0 otherwise. Control variables include *day_elapsed, horizon, frequency, companies, broker_size, industries, experience, bold* and *lag_performance*. All variables are defined in Appendix. Coefficients on the analyst and year dummies are not tabulated for parsimony. The robust standard errors (in parentheses) are adjusted for brokerage house clustering. ***, **, and * denote significance at the 1%, 5%, and 10% levels. OLS regression is used for forecast accuracy analysis whereas logit regression is used for likelihood of becoming star analysis.

	(1) *Accuracy*	(2) *Accuracy*	(3) *Star*		(4) *Star*	
	Coefficient	*Coefficient*	*Coefficient*	*Odds ratio*	*Coefficient*	*Odds ratio*
star_arrival	0.008**	0.006***	0.320***	1.377	0.264***	1.302
	(0.004)	(0.002)	(0.028)		(0.028)	
star_departure	-0.007*	-0.0001	0.021	1.021	-0.038	0.963
	(0.004)	(0.002)	(0.026)		(0.026)	
day_elapsed		-0.023***			-0.028	0.972
		(0.002)			(0.029)	
horizon		-0.319***			-0.465***	0.628
		(0.004)			(0.039)	
frequency		0.047***			0.258***	1.294
		(0.003)			(0.039)	
companies		-0.004			0.613***	1.846
		(0.004)			(0.053)	
broker_size		-0.053***			0.853***	2.347
		(0.004)			(0.052)	
industries		-0.015***			-0.065	0.937
		(0.003)			(0.051)	
experience		0.014**			0.855***	2.351
		(0.006)			(0.098)	
bold		0.046***			0.025	1.025
		(0.002)			(0.022)	
lag_performance	0.042***	0.032***	1.584***	4.874	1.503***	4.495
	(0.003)	(0.003)	(0.024)		(0.024)	
Constant	0.715***	0.755***				
	(0.007)	(0.006)				
Observations	275,119	275,119	66,391		66,391	
Adjusted R-squared	0.005	0.135	0.125		0.138	
Year fixed effects	YES	YES	YES		YES	
Analyst fixed effects	YES	YES	YES		YES	

Table 3

Effects of Star Arrival / Departure on Incumbent Analysts' Performance, Controlling for the Growth in Brokers' Resources

This table reports the results of estimating the following equation:

$$Performance_{kit} = \alpha + \beta_1 * Star\_arrival_{kit} + \beta_2 * Star\_departure_{kit} + Control\ variables + Analyst\ fixed\ effects + Year\ fixed\ effects + u_{kit}$$

The dependent variable is forecast accuracy for columns 1, 3 & 5 and likelihood of becoming stars for Columns 2, 4 & 6. *Star_arrival* equals one if there is at least a star analyst arriving at the brokerage house of analyst k within 12 months before the forecast is made at time t, and 0 otherwise. *Star_departure* equals one if there is at least a star analyst leaving the brokerage house of analyst k within 12 months before the forecast is made at time t, and 0 otherwise. Control variables include *day_elapsed, horizon, frequency, companies, broker_size, industries, experience, bold, growth_analyst, growth_asset, growth_revenue* and *lag_performance*. All variables are defined in Appendix. Coefficients on the analyst and year dummies are not tabulated for parsimony. The robust standard errors (in parentheses) are adjusted for brokerage house clustering. ***, **, and * denote significance at the 1%, 5%, and 10% levels. OLS regression is used for forecast accuracy analysis whereas logit regression is used for likelihood of becoming star analysis.

	(1)	**(2)**		**(3)**	**(4)**		**(5)**	**(6)**	
	Accuracy	***Star***		***Accuracy***	***Star***		***Accuracy***	***Star***	
	Coefficient	*Coefficient*	*Odds ratio*	*Coefficient*	*Coefficient*	*Odds ratio*	*Coefficient*	*Coefficient*	*Odds ratio*
star_arrival	0.005**	0.256***	1.292	0.004*	0.269***	1.309	0.004*	0.269***	1.309
	(0.002)	(0.028)		(0.002)	(0.032)		(0.002)	(0.032)	
star_departure	0.0006	-0.032	0.969	-0.0007	-0.139***	0.870	-0.0008	-0.148***	0.862
	(0.002)	(0.026)		(0.002)	(0.029)		(0.002)	(0.029)	
day_elapsed	-0.023***	-0.027	0.973	-0.025***	-0.009	0.991	-0.025***	-0.006	0.994
	(0.002)	(0.029)		(0.002)	(0.032)		(0.002)	(0.032)	
horizon	-0.319***	-0.464***	0.629	-0.315***	-0.473***	0.623	-0.315***	-0.475***	0.622
	(0.004)	(0.039)		(0.005)	(0.043)		(0.005)	(0.043)	
frequency	0.047***	0.259***	1.296	0.047***	0.262***	1.300	0.047***	0.265***	1.303
	(0.003)	(0.039)		(0.004)	(0.044)		(0.004)	(0.044)	
companies	-0.004	0.615***	1.850	-0.006	0.652***	1.919	-0.006	0.655***	1.925
	(0.004)	(0.053)		(0.004)	(0.059)		(0.004)	(0.059)	
broker_size	-0.055***	0.823***	2.277	-0.052***	0.689***	1.992	-0.052***	0.723***	2.061
	(0.004)	(0.053)		(0.005)	(0.060)		(0.005)	(0.060)	
industries	-0.015***	-0.067	0.935	-0.015***	-0.199***	0.820	-0.015***	-0.195***	0.823
	(0.003)	(0.051)		(0.004)	(0.057)		(0.004)	(0.057)	
experience	0.014**	0.856***	2.354	0.011	0.980***	2.664	0.011	0.986***	2.680
	(0.006)	(0.098)		(0.007)	(0.113)		(0.007)	(0.113)	
bold	0.046***	0.024	1.024	0.046***	0.015	1.015	0.046***	0.016	1.016
	(0.002)	(0.022)		(0.002)	(0.025)		(0.002)	(0.025)	

growth_analyst	0.008***	0.105***	1.111						
	(0.002)	(0.033)							
growth_asset				-0.002	0.313***	1.368			
				(0.003)	(0.038)				
growth_revenue							0.001	-0.041	0.960
							(0.003)	(0.036)	
lag_performance	0.032***	1.506***	4.509	0.034***	1.368***	3.927	0.033***	1.369***	3.931
	(0.003)	(0.024)		(0.004)	(0.027)		(0.004)	(0.027)	
Constant	0.752***			0.770***			0.769***		
	(0.006)			(0.007)			(0.007)		
Observations	275,119	66,391		174,730	53,194		174,506	53,183	
Adjusted R-squared	0.135	0.138		0.132	0.128		0.132	0.127	
Year fixed effects	YES	YES		YES	YES		YES	YES	
Analyst fixed effects	YES	YES		YES	YES		YES	YES	

Table 4

Instrumental Variable Regression on Effects of Star Arrival on Incumbent Analysts' Performance

This table reports the results of estimating the following equations:

(Stage 1) $Star\_arrival_{kit} = \gamma + \lambda_1 * N\_potential_{kit} + \lambda_2 * No\_analyst_{kit} + e_{kit}$

(Stage 2) $Performance_{kit} = \alpha + \beta_1 * Star\_arrival_{kit} + Control\ variables + Year\ fixed\ effects + u_{kit}$

The dependent variable is forecast accuracy for column 2 and likelihood of becoming stars for Column 3. $N\_potential_{kit}$ is the number of star analysts who are in the prime moving years (8-10 of career age) that the broker employing analyst k covering firm i in year t has connection to. $No\_analyst_{kit}$ is the total number of analysts employed by the broker employing analyst k covering firm i in year t. *Star_arrival* equals one if there is at least a star analyst arriving at the brokerage house of analyst k within 12 months before the forecast is made at time t, and 0 otherwise. *Star_departure* equals one if there is at least a star analyst leaving the brokerage house of analyst k within 12 months before the forecast is made at time t, and 0 otherwise. *Control variables include day_elapsed, horizon, frequency, companies, broker_size, industries, experience, bold* and *lag_performance*. All variables are defined in Appendix. Coefficients on the year dummies are not tabulated for parsimony. The robust standard errors (in parentheses) are adjusted for brokerage house clustering. ***, **, and * denote significance at the 1%, 5%, and 10% levels. OLS regression is used for forecast accuracy analysis whereas logit regression is used for likelihood of becoming star analysis.

	(1)	**(2)**	**(3)**	
	Star_arrival	***Accuracy***	***Star***	
	Coefficient	*Coefficient*	*Coefficient*	*Odds ratio*
N_potential	0.054***			
	(0.006)			
no_analyst	0.006***			
	(0.001)			
star_arrival		0.070***	0.894***	2.445
		(0.010)	(0.134)	
day_elapsed		-0.027***	-0.050**	0.951
		(0.002)	(0.024)	
horizon		-0.342***	-0.333***	0.717
		(0.004)	(0.026)	
frequency		0.041***	0.031	1.031
		(0.003)	(0.032)	
companies		-0.002	0.251***	1.285
		(0.003)	(0.077)	
broker_size		-0.041***	0.534***	1.706
		(0.006)	(0.081)	
industries		-0.020***	-0.188***	0.829
		(0.003)	(0.045)	
experience		0.016***	0.134**	1.143
		(0.003)	(0.060)	
bold		0.050***	0.025**	1.025
		(0.002)	(0.010)	
lag_performance		0.064***	2.205***	9.070
		(0.003)	(0.106)	
Constant	-1.940***	0.687***	-2.701***	0.067
	(0.110)	(0.007)	(0.157)	
Observations	275,119	275,119	275,119	
Year fixed effects	YES	YES	YES	

Table 5

Falsification Test: Effects of Later Star Arrival / Departure on Incumbent Analysts' Performance

This table reports the results of estimating the following equation:

$Performance_{kit} = \alpha + \beta_1 * Later\_star\_arrival_{kit} + \beta_2 * Later\_star\_departure_{kit} + Control\ variables + Analyst\ fixed\ effects + Year\ fixed\ effects + u_{kit}$

The dependent variable is forecast accuracy for columns 1-2 and likelihood of becoming stars for Columns 3-4. *Later_star_arrival* equals one if there is at least a star analyst arriving at the brokerage house of analyst k within 12 months after the forecast is made at time t, and 0 otherwise. *Later_star_departure* equals one if there is at least a star analyst leaving the brokerage house of analyst k within 12 months after the forecast is made at time t, and 0 otherwise. Control variables include *day_elapsed, horizon, frequency, companies, broker_size, industries, experience, bold* and *lag_performance*. All variables are defined in Appendix. Coefficients on the analyst and year dummies are not tabulated for parsimony. The robust standard errors (in parentheses) are adjusted for brokerage house clustering. ***, **, and * denote significance at the 1%, 5%, and 10% levels. OLS regression is used for forecast accuracy analysis whereas logit regression is used for likelihood of becoming star analysis.

	(1) **Accuracy**	(2) **Accuracy**	(3) **Star**		(4) **Star**	
	Coefficient	*Coefficient*	*Coefficient*	*Odds ratio*	*Coefficient*	*Odds ratio*
later_star_arrival	0.008	0.003	0.111	1.117	0.100	1.105
	(0.006)	(0.003)	(0.363)		(0.344)	
later_star_departure	0.007	-0.0004	-0.392	0.676	-0.321	0.725
	(0.006)	(0.004)	(0.431)		(0.415)	
day_elapsed		-0.023***			-0.030	0.971
		(0.003)			(0.061)	
horizon		-0.319***			-0.465***	0.628
		(0.014)			(0.149)	
frequency		0.047***			0.253	1.288
		(0.003)			(0.216)	
companies		-0.005			0.614***	1.848
		(0.005)			(0.149)	
broker_size		-0.053***			0.802***	2.230
		(0.005)			(0.257)	
industries		-0.015***			-0.066	0.937
		(0.005)			(0.116)	
experience		0.014			0.862	2.368
		(0.009)			(1.876)	
bold		0.046***			0.024	1.024
		(0.002)			(0.078)	
lag_performance	0.042***	0.032***	1.563***	4.773	1.483***	4.406
	(0.006)	(0.005)	(0.116)		(0.109)	
Constant	0.708***	0.757***				
	(0.008)	(0.007)				
Observations	275,119	275,119	66,391		66,391	
Adjusted R-squared	0.004	0.135	0.125		0.138	
Year fixed effects	YES	YES	YES		YES	
Analyst fixed effects	YES	YES	YES		YES	

Table 6

Effects of Star Arrival / Departure on Incumbent Analysts' Performance (Stock Picking Ability)

This table reports the results of estimating the following equation:

$$Performance_{kit} = \alpha + \beta_1 * Star\_arrival_{kit} + \beta_2 * Star\_departure_{kit} + Control\ variables + Analyst\ fixed\ effects + Year\ fixed\ effects + u_{kit}$$

The dependent variable is recommendation profitability for Columns 1-2. *Star_arrival* equals one if there is at least a star analyst arriving at the brokerage house of analyst k within 12 months before the recommendation is made at time t, and 0 otherwise. *Star_departure* equals one if there is at least a star analyst leaving the brokerage house of analyst k within 12 months before the recommendation is made at time t, and 0 otherwise. *Control variables include day_elapsed, horizon, frequency, companies, broker_size, industries, experience, bold* and *lag_performance*. All variables are defined in Appendix. Coefficients on the analyst and year dummies are not tabulated for parsimony. The robust standard errors (in parentheses) are adjusted for brokerage house clustering. ***, **, and * denote significance at the 1%, 5%, and 10% levels. OLS regression is used for recommendation profitability analysis.

	(1) ***Stock Picking***	**(2)** ***Stock Picking***
	Coefficient	*Coefficient*
star_arrival	-0.002	-0.002
	(0.006)	(0.006)
star_departure	-0.009*	-0.009*
	(0.005)	(0.005)
day_elapsed		0.0005
		(0.003)
horizon		0.002
		(0.005)
frequency		0.009**
		(0.005)
companies		0.002
		(0.006)
broker_size		0.004
		(0.006)
industries		-0.008
		(0.006)
experience		0.015*
		(0.008)
bold		-0.001
		(0.003)
lag_performance	0.0176***	0.018***
	(0.00293)	(0.003)
Constant	0.302	0.293
	(0.228)	(0.227)
Observations	98,193	98,193
Adjusted R-squared	0.001	0.001
Year fixed effects	YES	YES
Analyst fixed effects	YES	YES

Table 7

Effects of Expertise Similarity of Incoming / Departing Stars on Incumbent Analysts' Performance

This table reports the results of estimating the following equation:

$$Performance_{kit} = \alpha + \beta_1 * Indstar\_arrival_{kit} + \beta_2 * Indstar\_departure_{kit} + \beta_3 * Star\_arrival_{kit} + \beta_4 * Star\_departure_{kit} + Control\ variables + Analyst\ fixed\ effects + Year\ fixed\ effects + u_{kit}$$

The dependent variable is forecast accuracy for Column 1 and likelihood of becoming stars for Column 2. *Indstar_arrival* equals one if there is at least a star analyst arriving at the brokerage house of analyst k within 12 months before the forecast is made at time t, and both share the same industry expertise as defined by I/B/E/S, and 0 otherwise. *Indstar_departure* equals one if there is at least a star analyst leaving the brokerage house of analyst k within 12 months before the forecast is made at time t, and both share the same industry expertise as defined by I/B/E/S, and 0 otherwise. Control variables include *day_elapsed, horizon, frequency, companies, broker_size, industries, experience, bold* and *lag_performance*. All variables are defined in Appendix. Coefficients on the analyst and year dummies are not tabulated for parsimony. The robust standard errors (in parentheses) are adjusted for brokerage house clustering. ***, **, and * denote significance at the 1%, 5%, and 10% levels. OLS regression is used for forecast accuracy whereas logit regression is used for likelihood of becoming star analysis.

	(1)	**(2)**	
	Accuracy	***Star***	
	Coefficient	*Coefficient*	*Odds ratio*
indstar_arrival	0.010*	0.253***	1.288
	(0.006)	(0.074)	
indstar_departure	-0.011	-0.362***	0.696
	(0.008)	(0.071)	
star_arrival	0.005**	0.255***	1.290
	(0.002)	(0.028)	
star_departure	0.0003	-0.022	0.978
	(0.002)	(0.026)	
day_elapsed	-0.023***	-0.025	0.975
	(0.002)	(0.029)	
horizon	-0.319***	-0.463***	0.629
	(0.004)	(0.039)	
frequency	0.047***	0.258***	1.294
	(0.003)	(0.039)	
companies	-0.004	0.614***	1.848
	(0.004)	(0.053)	
broker_size	-0.053***	0.857***	2.356
	(0.004)	(0.052)	
industries	-0.015***	-0.062	0.940
	(0.003)	(0.051)	
experience	0.014**	0.852***	2.344
	(0.006)	(0.098)	
bold	0.046***	0.024	1.024
	(0.002)	(0.022)	
lag_performance	0.032***	1.504***	4.500
	(0.003)	(0.024)	
Constant	0.755***		
	(0.006)		
Observations	275,119	66,391	
Adjusted R-squared	0.135	0.139	
Year fixed effects	YES	YES	
Analyst fixed effects	YES	YES	

Table 8

Effects of Established Star Status of Incoming/ Departing Stars on Incumbent Analysts' Performance

This table reports the results of estimating the following equation:

$$Performance_{kit} = \alpha + \beta_1 * Eststar\_arrival_{kit} + \beta_2 * Eststar\_departure_{kit} + \beta_3 * Star\_arrival_{kit} + \beta_4 * Star\_departure_{kit} + Control\ variables + Analyst\ fixed\ effects + Year\ fixed\ effects + u_{kit}$$

The dependent variable is forecast accuracy for column 1 and likelihood of becoming stars for Column 2. *Eststar_arrival* equals one if there is at least one established star analyst arriving at the brokerage house of analyst k within 12 months before the forecast is made at time t, and 0 otherwise. *Eststar_departure* equals one if there is at least one established star analyst leaving the brokerage house of analyst k within 12 months before the forecast is made at time t, and 0 otherwise. Established star analysts are star analysts who have been selected as II All-stars more times than the star analyst sample median. Control variables include *day_elapsed, horizon, frequency, companies, broker_size, industries, experience, bold* and *lag_performance*. All variables are defined in Appendix. Coefficients on the analyst and year dummies are not tabulated for parsimony. The robust standard errors (in parentheses) are adjusted for brokerage house clustering. ***, **, and * denote significance at the 1%, 5%, and 10% levels. OLS regression is used for forecast accuracy whereas logit regression is used for likelihood of becoming star analysis.

	(1) *Accuracy*	**(2)** *Star*	
	Coefficient	*Coefficient*	*Odds ratio*
eststar_arrival	0.005	-0.041	0.960
	(0.004)	(0.039)	
eststar_departure	-0.006*	-0.468***	0.626
	(0.003)	(0.037)	
star_arrival	0.004	0.293***	1.340
	(0.003)	(0.033)	
star_departure	0.003	-0.294***	0.745
	(0.003)	(0.033)	
day_elapsed	-0.023***	-0.029	0.971
	(0.002)	(0.029)	
horizon	-0.319***	-0.474***	0.623
	(0.004)	(0.039)	
frequency	0.047***	0.253***	1.288
	(0.003)	(0.034)	
companies	-0.004	0.612***	1.844
	(0.004)	(0.053)	
broker_size	-0.053***	0.858***	2.358
	(0.004)	(0.052)	
industries	-0.015***	-0.073	0.930
	(0.003)	(0.051)	
experience	0.014**	0.909***	2.482
	(0.006)	(0.098)	
bold	0.046***	0.024	1.024
	(0.002)	(0.022)	
lag_performance	0.032***	1.499***	4.477
	(0.003)	(0.024)	
Constant	0.755***		
	(0.006)		
Observations	275,119	66,391	
Adjusted R-squared	0.135	0.141	
Year fixed effects	YES	YES	
Analyst fixed effects	YES	YES	

Table 9

Effects of Star Arrival / Departure on Incumbent Analysts' Performance, Conditioning on Experience Level of Incumbents

This table reports the results of estimating the following equation:

$Performance_{kit} = \alpha + \beta_1 * Star\_arrival_{kit} + \beta_2 * Star\_departure_{kit} + Control\ variables + Analyst\ fixed\ effects + Year\ fixed\ effects + u_{kit}$

The dependent variable is forecast accuracy for columns 1-2 and likelihood of becoming stars for Columns 3-4. *Star_arrival* equals one if there is at least a star analyst arriving at the brokerage house of analyst k within 12 months before the forecast is made at time t, and 0 otherwise. *Star_departure* equals one if there is at least a star analyst leaving the brokerage house of analyst k within 12 months before the forecast is made at time t, and 0 otherwise. Control variables include *day_elapsed, horizon, frequency, companies, broker_size, industries, experience, bold* and *lag_performance*. All variables are defined in Appendix. Coefficients on the analyst and year dummies are not tabulated for parsimony. The robust standard errors (in parentheses) are adjusted for brokerage house clustering. ***, **, and * denote significance at the 1%, 5%, and 10% levels. OLS regression is used for forecast accuracy analysis whereas logit regression is used for likelihood of becoming star analysis.

	(1) ***Accuracy (Less Experience)***	(2) ***Accuracy (More Experience)***	(3) ***Star (Less Experience)***		(4) ***Star (More Experience)***	
	Coefficient	*Coefficient*	*Coefficient*	*Odds ratio*	*Coefficient*	*Odds ratio*
star_arrival	0.007***	0.004	0.376***	1.456	0.112***	1.119
	(0.003)	(0.004)	(0.042)		(0.039)	
star_departure	-0.0006	-0.0002	-0.078**	0.925	-0.002	0.998
	(0.003)	(0.003)	(0.040)		(0.037)	
day_elapsed	-0.022***	-0.022***	-0.062	0.940	-0.008	0.992
	(0.003)	(0.003)	(0.043)		(0.040)	
horizon	-0.312***	-0.321***	-0.250***	0.779	-0.707***	0.493
	(0.005)	(0.005)	(0.056)		(0.056)	
frequency	0.048***	0.046***	0.259***	1.296	0.287***	1.332
	(0.004)	(0.004)	(0.057)		(0.057)	
companies	-0.005	-0.002	0.533***	1.704	0.659***	1.933
	(0.005)	(0.005)	(0.077)		(0.076)	
broker_size	-0.062***	-0.041***	0.949***	2.583	0.738***	2.092
	(0.006)	(0.005)	(0.078)		(0.075)	
industries	-0.015***	-0.014***	-0.132*	0.876	0.017	1.017
	(0.004)	(0.004)	(0.073)		(0.074)	
experience	0.078***	-0.105***	-3.577*	0.028	0.443***	1.557
	(0.009)	(0.025)	(2.030)		(0.146)	
bold	0.046***	0.046***	0.016	1.016	0.025	1.025
	(0.002)	(0.002)	(0.034)		(0.031)	
lag_performance	0.028***	0.031***	1.920***	6.821	1.007***	2.737
	(0.003)	(0.003)	(0.036)		(0.034)	
Constant	0.807***	0.861***				
	(0.017)	(0.024)				
P-value of test of equal coefficients	Between (1) and (2)		Between (3) and (4)			
star_arrival	p < 0.10		p < 0.10			
star_departure	p > 0.10		p > 0.10			
Observations	142,194	132,925	31,225		34,004	
Adjusted R-squared	0.130	0.137	0.166		0.125	
Year fixed effects	YES	YES	YES		YES	
Analyst fixed effects	YES	YES	YES		YES	

Table 10

Effects of Star Arrival / Departure on Incumbent Analysts' Performance, Conditioning on Number of Existing Stars

This table reports the results of estimating the following equation:

$$Performance_{kit} = \alpha + \beta_1 * Star\_arrival_{kit} + \beta_2 * Star\_departure_{kit} + Control\ variables + Analyst\ fixed\ effects + Year\ fixed\ effects + u_{kit}$$

The dependent variable is forecast accuracy for columns 1-2 and likelihood of becoming stars for Columns 3-4. *Star_arrival* equals one if there is at least a star analyst arriving at the brokerage house of analyst k within 12 months before the forecast is made at time t, and 0 otherwise. *Star_departure* equals one if there is at least a star analyst leaving the brokerage house of analyst k within 12 months before the forecast is made at time t, and 0 otherwise. Control variables include *day_elapsed, horizon, frequency, companies, broker_size, industries, experience, bold* and *lag_performance*. All variables are defined in Appendix. Coefficients on the analyst and year dummies are not tabulated for parsimony. The robust standard errors (in parentheses) are adjusted for brokerage house clustering. ***, **, and * denote significance at the 1%, 5%, and 10% levels. OLS regression is used for forecast accuracy analysis whereas logit regression is used for likelihood of becoming star analysis.

	(1) *Accuracy (Fewer Existing Stars)*	**(2) *Accuracy (More Existing Stars)***	**(3) *Star (Fewer Existing Stars)***		**(4) *Star (More Existing Stars)***	
	Coefficient	*Coefficient*	*Coefficient*	*Odds ratio*	*Coefficient*	*Odds ratio*
star_arrival	0.008***	0.0009	0.417***	1.517	0.251***	1.285
	(0.004)	(0.003)	(0.050)		(0.042)	
star_departure	-0.005	0.0008	-0.209***	0.811	-0.172***	0.842
	(0.006)	(0.002)	(0.051)		(0.038)	
day_elapsed	-0.028***	-0.016***	0.024	1.024	-0.030	0.970
	(0.003)	(0.003)	(0.050)		(0.038)	
horizon	-0.325***	-0.306***	-0.496***	0.609	-0.366***	0.694
	(0.005)	(0.006)	(0.070)		(0.051)	
frequency	0.044***	0.052***	0.238***	1.269	0.224***	1.251
	(0.004)	(0.004)	(0.070)		(0.052)	
companies	-0.002	-0.002	0.659***	1.933	0.519***	1.680
	(0.005)	(0.006)	(0.098)		(0.070)	
broker_size	-0.049***	-0.045***	0.894***	2.445	-0.019	0.981
	(0.007)	(0.006)	(0.108)		(0.078)	
industries	-0.017***	-0.018***	0.002	1.002	-0.131*	0.877
	(0.004)	(0.004)	(0.093)		(0.068)	
experience	0.007	0.017*	0.983***	2.672	1.177***	3.245
	(0.007)	(0.009)	(0.178)		(0.137)	
bold	0.043***	0.049***	-0.033	0.968	0.070**	1.073
	(0.002)	(0.002)	(0.039)		(0.030)	
lag_performance	0.024***	0.032***	1.267***	3.550	1.130***	3.096
	(0.003)	(0.006)	(0.043)		(0.034)	
Constant	0.760***	0.756***				
	(0.007)	(0.009)				
P-value of test of equal coefficients	Between (1) and (2)		Between (3) and (4)			
star_arrival	p < 0.10		p < 0.10			
star_departure	p > 0.10		p > 0.10			
Observations	154,590	120,529	21,976		37,622	
Adjusted R-squared	0.134	0.128	0.113		0.117	
Year fixed effects	YES	YES	YES		YES	
Analyst fixed effects	YES	YES	YES		YES	

Appendix - Variable definition

Name	Definition
$Star\_arrival_{kit}$	a dummy variable to indicate whether there has been at least a star analyst arriving at the brokerage house of analyst k within 12 months before the forecast is made at time t, where a star analyst is an analyst that has been ranked in the most recent issue of Institutional Investors before the date of the arrival
$Star\_departure_{kit}$	a dummy variable to indicate whether there has been at least a star analyst leaving the brokerage house of analyst k within 12 months before the forecast is made at time t, where a star analyst is an analyst that has been ranked in the most recent issue of Institutional Investors before the date of the departure
$Indstar\_arrival_{kit}$	a dummy variable to indicate whether there has been at least a star analyst arriving at the brokerage house of analyst k within 12 months before the forecast is made at time t, and the star analyst's industry expertise (as defined by I/B/E/S) is the same as the industry expertise of analyst k
$Indstar\_departure_{kit}$	a dummy variable to indicate whether there has been at least a star analyst leaving the brokerage house of analyst k within 12 months before the forecast is made at time t, and the star analyst's industry expertise (as defined by I/B/E/S) is the same as the industry expertise of analyst k
$Eststar\_arrival_{kit}$	a dummy variable to indicate whether there has been at least one established star analyst arriving at the brokerage house of analyst k within 12 months before the forecast is made at time t. Established star analysts are star analysts who have been selected as *II* All-stars more times than the star analyst sample's median
$Eststar\_departure_{kit}$	a dummy variable to indicate whether there has been at least one stablished analyst leaving the brokerage house of analyst k within 12 months before the forecast is made at time t. Established star analysts are star analysts who have been selected as *II* All-stars more times than the star analyst sample's median
$Accuracy_{kit}$	a measure of analyst k's forecast accuracy for firm i in year t (calculated as the maximum absolute forecast error for analysts who follow firm i in year t minus the absolute forecast error of analyst k following firm i in year t, with this difference scaled by the range of absolute forecast errors for analysts following firm i in year t)
$Star_{kit}$	a dummy variable to indicate whether analyst k is a star analyst in year t, where a star analyst is an analyst that has been ranked in the most recent issue of Institutional Investors before the date of the forecast
$Profit_{kit}$	profitability of analyst k's recommendation at year t for firm i. It is calculated as the difference between the 30-day, size-adjusted returns on the recommendation by analyst k in year t for firm i and the minimum profitability of a recommendation by another analyst in year t for firm i, with this difference scaled by the range of profitability of all recommendations by all analysts in year t for firm i
$Day\_elapsed_{kit}$	a measure of the days elapsed since the forecast by any analyst following firm in in year t (calculated as the days between analyst k's forecast for firm i and the most recent preceding forecast for firm i by any analyst, minus the minimum number of days between two adjacent forecasts for firm i by any two analysts in year t, with this difference scaled by the range of days between 2 adjacent forecasts)
$Horizon_{kit}$	a measure of the time from the forecast date to the end of the fiscal period (calculated as the forecast horizon (days from the forecast date to the fiscal year-end) for analyst k following firm i in year t minus the minimum forecast horizon for analysts who follow firm i in year t, with this difference scaled by the range of forecast horizons for analysts following firm i in year t)
$Frequency_{kit}$	a measure of the analyst k's frequency of forecasts for firm i in year t (calculated as the number of forecasts made by analyst k for firm i in year t, minus the minimum forecast frequency of all analysts who follow firm i in year t, with this difference scaled by the range of forecast frequency for analysts following firm i in year t)
$Companies_{kit}$	a measure of the number of firms analyst k follows in year t (calculated as the number of firms followed by analyst k following firm i in year t minus the minimum number of firms followed by analysts who follow firm i in year t, with this difference scaled by the range in the number of firms followed by analysts following firm i in year t)
$Broker\_size_{kit}$	a measure of analyst k's brokerage house size (calculated as the number of analysts employed by the brokerage employing analyst k following firm i in year t minus the minimum number of analysts employed by other brokerage houses for analysts following

	firm i in year t, with this difference scaled by the range of brokerage house size for analysts following firm i in year t)
$Industries_{kit}$	a measure of the number of industries analyst k follows in year t (calculated as the number of I/B/E/S industries followed by analyst k following firm i in year t minus the minimum number of I/B/E/S industries followed by analysts who follow firm i in year t, with this difference scaled by the range of the number of I/B/E/S industries followed by analysts following firm i in year t)
$Experience_{kit}$	a measure of analyst k's general experience (calculated as the number of years of general experience for analyst k following firm i in year t minus the minimum number of years of general experience for analysts following firm I in year t, with this difference scaled by the range of years of general experience for analysts following firm i in year t)
$Bold_{kit}$	a dummy variable to indicate whether the forecast issued by analyst k for firm i in year t is bold, i.e. the forecast is greater (smaller) than both analyst k's previous forecast for firm i in year t and the consensus forecast made by other analysts for firm i in year t prior to this forecast
$Growth\_analyst_{kit}$	a measure of analyst k's brokerage house size change (calculated as the change in number of analysts employed by the brokerage employing analyst k following firm i in year t minus the minimum change of analysts employed by other brokerage houses for analysts following firm i in year t, with this difference scaled by the range of brokerage house size changes for analysts following firm i in year t)
$Growth\_asset_{kit}$	a measure of analyst k's brokerage house asset change (calculated as the change in asset of the broker or parent company of the broker employing analyst k following firm i in year t minus the minimum change in asset of the brokers or parent companies of the brokers employing other analysts following firm i in year t, with this difference scaled by the range of brokerage house asset changes for analysts following firm i in year t)
$Growth\_revenue_{kit}$	a measure of analyst k's brokerage house revenue change (calculated as the change in revenue of the broker or parent company of the broker employing analyst k following firm i in year t minus the minimum change in revenue of the brokers or parent companies of the brokers employing other analysts following firm i in year t, with this difference scaled by the range of brokerage house revenue changes for analysts following firm i in year t)
$N\_potential_{kit}$	a measure of number of star analysts that are in the prime moving years (8-10 years of career age) that the brokerage house employing analyst k following firm i in year t has connections to. A connection is identified when the analysts in the brokerage house have worked at the same place with the stars in the first 5 years of the stars' career
$No\_analyst_{kit}$	a measure of the total number of analysts employed by the broker employing analyst k covering firm i in year t
$Later\_star\_arrival_{kit}$	a dummy variable to indicate whether there has been at least a star analyst arriving at the brokerage house of analyst k within 12 months after the forecast is made at time t, where a star analyst is an analyst that has been ranked in the most recent issue of Institutional Investors before the date of the arrival
$Later\_star\_departure_{kit}$	a dummy variable to indicate whether there has been at least a star analyst leaving the brokerage house of analyst k within 12 months after the forecast is made at time t, where a star analyst is an analyst that has been ranked in the most recent issue of Institutional Investors before the date of the departure