Peer Effects Among Financial Analysts

Truc (Peter) Thuc Do

Huai Zhang*

ABSTRACT

We hypothesize that the arrival of star analysts improves the performance of incumbent financial analysts while the departure of star analysts has the opposite effect. Our results consistent with this hypothesis are concentrated primarily in the tests related to star arrivals. Our findings are robust to an instrumental variable approach and a falsification test. In addition, we hypothesize that the impact of the arrival/departure of star analysts is more pronounced when the star analyst covers the same industry as the incumbents (especially for industries with high uncertainty), 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 evidence of peer effects among financial analysts, mainly through the arrival of star analysts.

Keyword(s): Financial analyst; Star analyst; Peer effect; Knowledge spillover

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*Do is at the University of Queensland, Australia, and Zhang is at Nanyang Technological University, Singapore. The email addresses are t.do@business.uq.edu.au and huaizhang@ntu.edu.sg (corresponding author) respectively. Zhang's postal address is Nanyang Business School, Nanyang Avenue, Nanyang Technological University, Singapore 639798. We would like to thank two anonymous referees, Arup Ganguly (the discussant), Haozhi Huang (the discussant), Bin Ke, Hai Lu (the editor), Stan Markov (the discussant), Rui Shen, Laurence van Lent, Yachang Zeng, and seminar participants at Nanyang Technological University and National University of Singapore, and participants at the 2017 CAPANA research conference, 2017 Vietnam International Conference in Finance, and 2017 Vietnam Symposium in Banking & Finance for their helpful comments. Zhang acknowledges the financial support from Singapore Ministry of Education for providing research funding (RG75/16 and RG163/17). Do acknowledges the financial support from UQ Business School (BEL new staff start-up funds). Both authors have no conflicts of interests to disclose. All errors are our own.

1. Introduction

Sell-side financial analysts are the rainmakers of capital markets, and their opinions have substantial valuation consequences (Bradshaw, 2004; Gleason & Lee, 2003; Jegadeesh, Kim, Krische, & Lee, 2004; Stickel, 1992). Previous research on financial analyst performance has typically focused on the effects of individual analyst characteristics and information environments (Brown, 1983; Brown & Rozeff, 1979; Byard, Li, & Yu, 2011; Clement, 1999; Hope, 2003; Jacob, Lys, & Neale, 1999; Lang & Lundholm, 1996; Mikhail, Walther, & Willis, 1997). However, the question of whether analyst performance is influenced by colleagues has received scant attention. We attempt to fill this gap by examining how the arrival/departure of star analysts affects the performance of incumbent analysts.

The star analyst is characterized by superior performance and higher visibility than the average analyst. Star analysts are more accurate forecasters (Stickel, 1992), have stronger stock-picking skills (Desai, Liang, & Singh, 2000; Leone & Wu, 2007), and exert greater influence on stock prices, than non-stars (Gleason & Lee, 2003; Stickel, 1992). In addition, star analysts' names are published in analyst rankings, and they receive disproportionate attention from the media (Groysberg & Healy, 2013; Rees, Sharp, & Twedt, 2015). Naturally, their arrivals/departures are economically important events and worthwhile academic topics.

We hypothesize that the arrival of star analysts to a brokerage house improves the performance of incumbents while their departure has the opposite effect because, as discussed in Section 2, the incumbents can learn from star analysts when stars join their brokerage house and the process of learning is likely attenuated when stars leave.

We empirically test our main hypothesis using a sample of 279,899 analyst-firm-year observations for the period 1994–2017. We use two measures of analyst performance:

earnings forecast accuracy, and *Institutional Investor*'s (*II*) All-star recognition. These two measures are considered useful and important in the extant literature. Hong and Kubik (2003), Mikhail, Walther, and Willis (1999), and Wu and Zang (2009) show that forecast accuracy is used by brokerage houses to judge analysts' performance in promotion and hiring/firing decisions, while Groysberg, Healy, and Maber (2011) show that star analysts enjoy substantially higher compensation than non-star analysts. Our model controls for changes in the number of employed analysts and changes in the total assets of the brokerage house, two variables reflecting changes in the resources available to the incumbents. 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 are more likely to be recognized as *II* All-stars. The impact is economically significant. Incumbent analysts' forecast accuracy, measured by the absolute forecast error, increases by 5.6%, while their odds of becoming an *II* All-star go up by 33% after the arrival of star analysts. However, our results are largely insignificant for star departure. The weaker results for star departure may be due to the fact that the knowledge acquired by incumbents persists, at least to some extent, after the departure of star analysts.

Conceptually, the arrival / departure of a star analyst is endogenous, and possibly, there exist unobservable omitted correlated variables, e.g., the culture of the brokerage house. Following high profile cases in which financial analysts died prematurely from over-work (Gysin & Ellicott, 2013), some brokerage houses took measures that promoted better work-life balance: Credit Suisse introduced the "Protecting Friday Night" initiative which encouraged employees to leave early on Friday (Berry, 2016), while Goldman Sachs published new guidelines to ensure that bankers stayed away from the office between midnight and 7 a.m. during weekdays (Baer & Huang, 2015). A culture that helps to maintain work-life balance may attract star analysts and simultaneously improve the efficiency of incumbent analysts.

To deal with this endogeneity concern, we use an instrumental variable (IV) approach, similar to that used in Agrawal, McHale, and Oettl (2014). Our instrumental variable for the arrival of stars is the number of star analysts at other brokerage houses who are in their prime moving age and who, in their early career, were colleagues of analysts currently at the focal brokerage house. Stars are more likely to move at a certain stage of their career, (an analogy 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 they are more likely to join a firm if they have prior interactions with analysts from that firm. Popular press and data analyses demonstrate that personal connections are important for employment opportunities. For example, the survey results in Adler (2016) indicate that about 85% of jobs are filled via personal networking, while Rigano (2015) shows that financial industries, such as venture capital and private equity, are among those that hire the most from their employee networks. Prior working relationships therefore play an important role in analysts' decisions to move to another employer. Conceptually, this instrument is correlated with the probability of the focal brokerage house hiring a star in year *t* but is not correlated with the performance of incumbent analysts. Likewise, our instrumental variable for the departure of stars is the number of star analysts at the focal brokerage house who are in their prime moving age and who, in their early career, were colleagues of analysts currently at other brokerage houses. To alleviate the concern that our instrumental variable is related to the size of the brokerage house, we deflate it by the brokerage house's total number of analysts. We take comfort in the fact that our conclusion is robust to the instrumental variable approach.

Furthermore, we conduct a falsification test by examining the star arrival/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 star's later arrival/departure to have no impact on incumbents' earlier performance. However, if the incumbents' performance is driven by omitted correlated variables, such as a change in corporate culture, we expect to observe a correlation between the two, because this change may result in immediate improvement in incumbents' performance, and the subsequent arrival of star analysts (since the negotiation with stars may take time). Empirically, the correlation between incumbents' performance and the later arrival/departure of star analysts is statistically insignificant, so the evidence is inconsistent with the endogeneity-based explanation.

We next develop cross-sectional hypotheses based on the premise that, if our main results are in fact due to incumbents learning from incoming stars, the impact of a star's arrival/departure will be more pronounced when learning is more likely to occur. Conceptually, incumbents have more opportunities to learn from stars when they cover the same industry (especially when the industry has high uncertainty), incumbents are more incentivized to learn from established stars, inexperienced analysts have greater motivation to learn from stars, and incumbents are more likely to learn from stars when their alternative sources of learning (i.e., the number of existing star analysts) are limited. Therefore, we hypothesize that the impact of a star analyst's arrival/departure 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.

Depending on which performance measure we use and whether we examine the arrival or departure of star analysts, there exists some evidence consistent with our hypotheses. For example, the odds of the incumbent analyst becoming an *II* All-star are 32%

lower when the departing star covers the same industry than when she covers other industries. The same-industry effect is greater for industries with high uncertainty, where guidance from star analysts is especially important. 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 an *II* All-star by an additional 37%. The star arrival increases the odds of becoming a star by 50% (23%) for inexperienced (experienced) incumbents and by 110% (-1%) for incumbents working for brokerage houses with few (many) existing stars.

Our study contributes to three streams of the academic literature. First, this study adds to the burgeoning literature on peer effects, especially the recent literature that documents how analysts' performance is affected by the broker's internal resources (including in-house human capital). For example, Chen and Martin (2011) show that analysts' forecast accuracy improves when the firms they cover start borrowing from banks that are affiliated with the analysts' brokers. Hugon, Kumar, and Lin (2016) document that in-house macro-economists help financial analysts better understand the impact of macro-economic news on corporate earnings. Hugon, Lin, and Markov (2018) find that high quality debt research at the brokerage house benefits analysts who cover financially distressed firms. Gao, Ji, and Rozenbaum (2018) demonstrate that analysts' forecast quality is influenced by the quality of the associates who work under the analysts' supervision. We add to this line of literature by showing that the arrival/departure of star analysts influences incumbents' performance.

Second, 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, Call, Clement, & Sharp, 2015; Brown & Mohammad, 2010;

Clement, 1999; Jacob et al., 1999; Kumar, 2010; Ramnath, Rock, & Shane, 2008). Our study expands on this line of research and shows that analysts' performance is also influenced by their co-workers. Brown and Hugon (2009) find that earnings forecasts issued by a team of analysts are less accurate, timelier, and more influential on stock prices than earnings forecasts made by individual analysts. Their analysis, however, is silent on the peer effects among financial analysts.

Finally, our paper advances our understanding of the impact of star analysts' arrival/departure. Clarke, Khorana, Patel, and Rau (2007) show that investment banks acquiring star analysts significantly increase their market share in the industry covered by the analyst, relative to investment banks losing star analysts. Groysberg, Lee, and Nanda (2008) find that star analysts who switch employers experience an immediate decline in performance, and the decline persists for at least five years. However, this finding offers no implications for how star analyst arrivals affect incumbents' performance. Groysberg and Lee (2010) find that analysts working with higher quality colleagues are less likely to switch firms. We extend this line of inquiry by examining how the arrival/departure of star analysts affects the performance of incumbent analysts, a topic which has not been addressed in prior literature.

In addition to contributing to the academic literature, our paper has practical implications. We find that the impact of star arrival/departure on incumbents is more pronounced when incumbent analysts are less experienced and when incumbents' brokerage houses have fewer existing star analysts. These results are likely to be useful to brokerage house executives in their hiring decisions. Our results also help to explain sky-high compensation 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 pull him away from Salomon Smith Barney Inc. (Raghavan &

Mcgheehan, 1998). Our results suggest that the arrival of star analysts benefits the incumbents substantially. Therefore, high compensation for star analysts may be appropriate.

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

2. Hypotheses development

The presence of star analysts can benefit incumbent analysts through at least the following two channels, between which we do not attempt to distinguish. The first is through the explicit knowledge transfer from stars to incumbents. Groysberg and Lee (2010) suggest that the performance of star analysts depends not only on their own abilities but also on their collaboration with colleagues. Stars therefore have incentive to share their proprietary knowledge to improve their colleagues' performance. In addition, more knowledgeable colleagues may be beneficial to the incoming star analysts, because they become more reliable sources of information and insight.

Anecdotally, plenty of evidence supports this explicit knowledge transfer. For example, Gary Black, a six-time All-star analyst in the tobacco industry, shared his "Eight Simple Rules to Success as an Analyst" with his colleagues (Groysberg & Healy, 2013). At Merrill Lynch, training seminars known as Research Excellence are held several times a month during which senior analysts share lessons from their experience. Topics of seminars include "Tips for becoming *II*-ranked," "How to build your franchise," "Effective uses of the morning call," and "Successful writing styles and stock picking" (Groysberg & Vargas, 2007). Lehman Brothers had an accelerated marketing training program to groom analysts. In this program, “A 40-year-old analyst who has been ranked for eight years might be sitting next to a 29-year-old who launched just a year ago. They help each other; they learn from each other” (Groysberg & Nanda, 2007). Star analysts are also explicitly tasked to provide guidance to incumbents. For example, a ranked star analyst, Helane Becker, was hired by Jack Rivkin, the head of Shearson Lehman’s global equity research department. Becker remembered, “…Jack recruited me to Shearson with the mandate to mentor the young, enthusiastic people and show them how to become good analysts. Jack specifically wanted me to teach analysts how to use trading, write good research reports, and make 150 phone calls a month” (page 11, Nanda, Groysberg, & Prusiner, 2008).

The second channel through which star analysts benefit incumbents is social learning. The importance of learning through social interactions can be traced all the way back to 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 are more likely to adopt the model’s behavior if the model holds an admired status. Star analysts offer incumbent analysts role models and give them the opportunity to observe and learn (e.g., the star analyst’s work ethic and way of interacting with clients and other members of the team). These tacit lessons are helpful in improving incumbents’ overall performance.

Conversely, we expect that the departure of star analysts has a negative effect on incumbents’ performance. Both knowledge transfer and social learning can be continuous. The dynamic and ever-changing business world gives star analysts the opportunity to generate new insights and knowledge continuously, and they may share their knowledge on an ongoing basis. In terms of social learning, star analysts are considered role models, and their daily activities serve as constant reminders of admirable practices in the industry. When star analysts leave, both knowledge transfer and social learning cease, negatively affecting incumbent analysts' performance.

Since incumbents can learn from a star analyst, we hypothesize from both the perspective of star arrival and the perspective of star departure. Our H1 therefore consists of two parts:

H1a: *The performance of incumbent analysts is improved by the arrival of a star analyst.*

H1b: *The performance of incumbent analysts is reduced by the departure of a star analyst.*

We develop our next hypotheses based on the premise that, if indeed our main results are due to incumbents learning from star analysts, the impact of star arrival/departure will be greater when learning is more likely to occur. If incumbent analysts cover the same industry as the star, they are likely to have more interaction with the star, to be on the receiving end of knowledge transfer, and to have more opportunities for social learning. Therefore, if our learning-based theory is responsible for our empirical results, we would expect the effect of a star's arrival/departure to be more pronounced for incumbent analysts covering the same industry as the star. Our H2a is as follows.

H2a: *The impact of a star analyst's arrival/departure on the performance of incumbent analysts is more pronounced when the star analyst and the incumbent analysts cover the same industry.*

In addition, the impact of same-industry star analysts is likely to be more pronounced for industries in which there is greater uncertainty. For these industries, industry mentors are likely more important. One analogy is that, when a student feels certain about the right approach to solve a problem, help from a teacher is often unnecessary; however, when a student is uncertain about which approach to take, the advice from a mentor becomes very helpful. This is similar to the findings in Chen and Martin (2011) who document that analysts have more pronounced improvement in their forecast accuracy (after their covered firms start borrowing from affiliated banks) when the firms have greater information asymmetry. Our discussions yield the following hypothesis:

H2b: *The impact of a same-industry star's arrival/departure on the performance of incumbent analysts is more pronounced for industries with greater uncertainty.*

We continue to hypothesize that the effect of the star's arrival/departure varies with the status of the 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. Social learning theory (Bandura, 1977) posits that human beings learn by observing models and they are more attentive to the model's actions, if the model holds high status. Bruning (1965) demonstrates, via an experiment, that learners are more likely to adopt a model's actions when they observe the model being highly rewarded. We thus predict that the effect of a star's arrival/departure is more pronounced when the star is more established. Our H3 is stated below:

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

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 and probably have greater motivation to learn than more experienced incumbent analysts. Less experienced analysts are also more likely to be "imprinted" by the star analysts with whom they work (Law, 2013). Azoulay, Liu, and Stuart (2017) show that inexperienced biomedical scientists are more easily influenced by their advisers. Our H4, stated below, is based on these studies.

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

Finally, we argue that the marginal benefit of a star decreases with the number of existing star analysts at a brokerage house. For a brokerage house with many existing stars, the new knowledge or skill brought by an additional star is likely to be limited, and incumbents have lower incentives to learn from her. The idea of diminishing returns on hiring stars has also been demonstrated in prior research in the setting of financial analysts (Groysberg, Polzer, & Elfenbein, 2011) and sports teams (Swaab, Schaerer, Anicich, Ronay, & Galinsky, 2014). This yields the following hypothesis:

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

3. Data and variable definition

We obtain annual earnings forecasts from the I/B/E/S detail file for the period 1994–2017. 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 & Hsu, 2013). We eliminate all observations for firms with only one analyst following them, because most of our variables are based on a comparison among all analysts following a firm. As per Clement and Tse (2005), we retain the last forecast each analyst issues within 30 to 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 the 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 279,899 analyst-firm-year observations.

We hand-collect all-star information from the *II* All-star list. Each October, *Institutional Investor* publishes the All-star ranking, and any analyst who is named is designated as a star analyst until the next ranking. For example, if an analyst is ranked in October 1996, he or 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 the name to the brokerage house and identify every time a star analyst switches brokerage house.[1]

The main dependent variables are incumbents' forecast accuracy (*$accuracy_{kit}$*) and their likelihood of being selected as an *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. The variable $accuracy_{kit}$ ranges from 0 to 1, where a higher value indicates that the analyst is more accurate. Specifically, when $accuracy_{kit}$ equals 1, the analyst is the most accurate among all analysts following firm i in year t.

$Star_{kt}$ is the other dependent variable. It is an indicator variable, which equals 1 if the incumbent analyst k is selected as an *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 at least one star analyst arrives at / departs from the brokerage house of analyst k within 12 months before the forecast is made in year t, and 0 otherwise.

Conceptually, it is unclear how quickly the peer effect manifests. On average, the forecasts are made 180 days after the star arrival/departure, suggesting that incumbents have

[1] I/B/E/S provides a translation file that contains the last name and the first name initial for each unique analyst code, as well as the name of each broker code. Based on this file, we match the star status (from *II* magazine) with the analysts in I/B/E/S. For names for which we cannot find a match, we refer to the names contained in I/B/E/S Recommendation file. Erroneous matching biases against finding any statistically significant results.

time to learn from stars. While we can choose a longer window to identify star analysts' arrival/departure, the use of a short window sharpens our test, because results based on longer windows may be attributed to factors unrelated to stars' arrival/departure. Nevertheless, we conduct a robustness check by using a 24-month window. Our un-tabulated results show that our conclusions are robust to this alternative research choice.

We control for the following variables in our analyses: *day_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 fiscal 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, Kubik, and Solomon (2000), Yin and Zhang (2014), has established that these characteristics have an impact on analysts' performance. We control for *lag_performance*, the lagged value of the dependent variable, 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*). We also control for *growth_analyst*, the annual change in the number of analysts at the broker, and *growth_asset*, the annual change in total assets of the broker.[2] The number of analysts employed by the broker in each year is calculated using the I/B/E/S database. For brokers that are listed, we collect information about their total assets from Compustat using their GVKEYs. For unlisted brokers, we Google them to collect total asset information from their websites. In cases where the broker is a subsidiary of another listed firm and we cannot collect data from other

[2] Our results are similar if *growth_analyst* and *growth_asset* indicate percentage changes instead of absolute changes or if we control for *growth_revenue*, the change in revenue of the brokerage house, instead of *growth_asset*.

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 increase as well. We note that, during the 2008 financial crisis, several brokerage houses were acquired by banks and other financial institutions. Care is taken to ensure that total asset information is for the brokerage house on a standalone basis before the acquisition.

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* are as follows:

$$Characteristic_{kit} = \frac{Characteristic_{kit} - Min\ Characteristic_{it}}{Max\ Characteristic_{it} - Min\ Characteristic_{it}} \qquad (1)$$

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.[3]

Detailed definitions of each variable can be found in the appendix.

4. Results

4.1. Descriptive statistics

Panel A of Table 1 presents descriptive statistics for the scaled variables used in the analysis. The mean value of *accuracy* is 0.589, and the median value is 0.621. The mean value of *star* indicates that about 12.3% of incumbent analysts are selected as *II* All-stars.

[3] For brevity, we drop all the subscripts (*k*,*i*,*t*) henceforth unless we introduce new variables.

The mean value of *star_arrival / star_departure* suggests that about 20.6% / 21.5% of incumbent analysts experience stars' arrivals / departures at their brokerage houses. The mean value of *day_elapsed* is 0.486, *horizon* averages about 0.467, and the mean value of *frequency* is 0.512. The mean value of *companies* is 0.448, and the mean value of *broker_size* is 0.527. *Industries* has a mean value of 0.390. The average value of *experience* is 0.570. The mean value of *bold* suggests that about 68.5% of forecasts are bold, which is comparable to the value reported in Clement and Tse (2005) (73%). Finally, the mean value of *growth_analyst* is 0.482, and the mean value of *growth_asset* is 0.417.

Panel B reports the raw values for the variables. The mean value of *absolute forecast error* is 0.190, indicating that, on average, analysts' forecasts deviate from the actual earnings by 19 cents per share. The mean values of *day_elapsed* and *horizon* suggest that, on average, a forecast is made 10 days after the preceding forecast and 99 days before the fiscal year end. In our sample, a typical analyst makes about 4 forecasts for the firm-year combination (*frequency*), covers 18 companies from 5 different industries, and has about 10 years of experience, while a typical brokerage house hires 61 analysts, increases the headcount by one analyst, and grows its assets by about $26 million each year. These statistics are largely comparable to the descriptive statistics reported by Clement and Tse (2005). For example, Clement and Tse (2005) report that, in their sample, on average, a forecast is made 13.6 days after the preceding forecast and 97.9 days before the fiscal year end, while an analyst makes about 3.8 forecasts for the firm-year combination.

4.2. Test of H1

4.2.1. Main analyses

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

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

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 report both coefficient estimates and their odds ratios.

We control for analyst fixed effects and year fixed effects to take care of the analyst- and year- specific impact on performance. Since we include both *star_arrival* and *star_departure*, our benchmark is the incumbent analysts whose brokerage house experiences neither the arrival nor the 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, as compared to the benchmark. Our H1a predicts that β_1 is positive, and H1b predicts that β_2 is negative. 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 because 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 within-firm rankings. Clement and Tse (2005) investigate similar dependent variables and do not include firm characteristics in their analyses.

In Columns 1 and 3 of Table 2, we report the results controlling only for lagged performance and analyst- and year-fixed effects. In the remaining columns, we report the results including 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 0.004 and is significant at the 10% level. The coefficient on *star_departure* is -0.005 and is also significant at the 10% level. Column 2 suggests that the finding on *star_arrival* is robust to the inclusion of additional control variables. The coefficient on *star_arrival* is 0.006 and is significant at the 1% level. The coefficient on *star_departure* is -0.003, which is not significant at the 10% level. To assess the economic significance of forecast accuracy improvement after star arrival, we run the same regression model as that in Column 2 and replace our dependent variable with *AFE* (absolute forecast error), defined as the absolute difference between the analyst's forecast of the EPS and the actual EPS of the firm. Our un-tabulated results show that after the arrival of star analysts, the incumbents reduce their absolute forecast errors by 1.06 cents. Given that incumbents' average absolute forecast error in our sample is 19 cents, this represents a 5.6% improvement in forecast accuracy. Consistent with Clement and Tse (2005), we observe that *horizon, companies,* and *industries* are negatively correlated with forecast accuracy, whereas *frequency*, *experience*, *bold,* and *lag_performance* are positively correlated with forecast accuracy.

Columns 3 and 4 of Table 2 show that star arrival substantially elevates the chances of incumbent analysts becoming *II* All-star analysts. The coefficient on *star_arrival* is 0.316 and significant at the 5% level in Column 3. In Column 4, it is 0.288 and significant at the 5% level. The odds ratio statistics show that the odds of becoming an *II* All-star increase by 33% among those incumbent analysts experiencing star arrival. The coefficient on *star_departure* is not significant at the 10% level in Column 3 or 4. [4] Consistent with Leone and Wu (2007), we observe that the likelihood of being ranked in *II* magazine is positively correlated with *frequency, companies, broker_size, experience,* and *lag_performance.*

Overall, we find that the arrival of star analysts enhances the performance of incumbent analysts, which is consistent with our H1a. Our findings related to star departure are largely insignificant (except the finding in Column 1 of Table 2), which prevents us from drawing inferences about H1b.

4.2.2. Instrumental variable regression

This subsection discusses our instrumental variable analysis. Our instrumental variable for star arrival, *Adj_arrival*, is the number of star analysts at other brokerage houses who are in their prime moving age and who, in their early career (i.e., their first five years), worked in the same brokerage house as analysts currently at the focal brokerage house, deflated by the total number of analysts of the focal brokerage house. Likewise, our instrumental variable for star departure, *Adj_departure*, is the number of star analysts at the focal brokerage house who are in their prime moving age and who, in their early career, were colleagues of analysts currently working at other brokerage houses, deflated by the total number of analysts of the focal brokerage house. Using the deflator alleviates the concern that the unscaled number reflects the size of the brokerage house (our results are similar if we do not deflate our instrumental variable).

To identify the analysts' prime moving age, we plot the move probability against the career age. We use the maximum sample period available from I/B/E/S (1970-2017) to plot this for greater accuracy. We identify each analyst's career age by first identifying the first

[4] In un-tabulated tests, we show that our baseline conclusion holds for another performance measure of analysts: stock-picking ability. Following Leone and Wu (2007), this measure is computed as the 30-day size-adjusted stock returns after the analyst makes a recommendation for a stock. The returns after "Sell" and "Strong Sell" recommendations are multiplied by -1.

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 with which the analyst is associated. For career age, we divide the number of analysts moving by the total number of analysts at that career age to compute the move probability. We observe that analysts are in their prime moving age when their career age is between eight and ten years (the likelihood of analysts moving to another brokerage house peaks when the analyst's career age is between eight and ten years).

Our results are reported in Table 3. Panel A reports the results when we examine the accuracy of analysts' forecasts. In the first stage, we regress *star_arrival* and *star_departure* on our IV. We also include all the control variables in the first stage to be in line with standard practice. Our results are reported in Columns 1 and 2. We find that *Adj_arrival* / *Adj_departure* is positively correlated with *star_arrival / star_departure*, and the coefficients on the IVs are both significant at the 1% level.

In the second stage, we regress measures of incumbents' performance on the instrumented *star_arrival* and *star_departure* and report our results in Column 3. Column 3 shows that incumbent analysts whose brokerage house experiences the arrival of star analysts become more accurate in their earnings forecasts; the departure of star analysts, however, does not have a significant association with the forecast accuracy of incumbent analysts. The coefficient on *star_arrival* (instrumented) is 0.07 and is significant at the 1% level, while the coefficient on *star_departure* (instrumented) is -0.047 and is not significant at the 10% level.

To assess the validity of the instruments, we conduct several statistical tests. We first compute partial R^2 between the IV and the variable to be instrumented. It is 0.049 for *star_* *arrival* and 0.069 for *star_departure*, suggesting weak associations. The related partial F-statistics show that the partial correlation between the IV and the variable to be instrumented is statistically significant. We then perform Hausman tests to evaluate the difference between the OLS and 2SLS results and find that the 2SLS results are significantly different from the OLS results ($p < 0.01$). We next conduct the weak instrument test based on Kleibergen and Paap (2006). The Kleibergen-Paap Wald *F*-statistic is 26, exceeding the Stock and Yogo (2005) 10% maximal IV size critical value of 13.43.

In un-tabulated tests, we assess how severe the endogeneity problem must be to overturn our OLS results. Our tests are similar to those conducted by Fu, Kraft, and Zhang (2012). The results suggest that for any unobserved confounding variable to overturn our OLS results, it must be more highly correlated with the dependent variable and *star_arrival* / *star_departure* than any of our existing control variables. Under the assumption that we have properly identified control variables, the likelihood is low that such a variable exists.

Panel B of Table 3 reports the results when we examine the likelihood of becoming stars. Columns 1 and 2 show that the correlation between the IV and the variable to be instrumented is highly significant. Column 3 shows that incumbent analysts whose brokerage house experiences the arrival of star analysts have higher chances of becoming a star; the odds of their becoming a star are, however, unrelated to the departure of stars. Specifically, the coefficient on *star_arrival* (instrumented) is 0.319, significant at the 5% level, while the coefficient on *star_departure* (instrumented) is -0.463, not significant at the 10% level.

The value of the partial R^2 indicates that, for 2SLS results to outperform OLS results, the squared correlation between the instruments and the structural error term must be less than 6.3%/ 5.2% of the comparable squared correlation between *star_arrival*/*star_departure* and the structural error. The partial F-statistics are significant at the 1% level, indicating that the partial correlation between the IV and the variable to be instrumented is highly significant. Our un-tabulated results suggest that conclusions based on our OLS results are likely robust to the influence of omitted confounding variables.

Overall, our results from Table 3 suggest that our findings are robust to the concern of endogeneity. In addition, comparison of the results in Table 2 and those in Table 3 indicates that our inferences are similar whether we use the IV approach or not.

4.2.3. Falsification test – Later star arrival/departure

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 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:

$$Performance_{kit} = \alpha + \beta_1 * Later\_star\_arrival_{kit} + \beta_2 * Later\_star\_departure_{kit} + Control\ variables + Analyst\ fixed\ effects + Year\ fixed\ effects + u_{kit} \quad (3)$$

We focus on the coefficients of *later_star_arrival and later_star_departure*. If our results are driven by omitted correlated variables that predate the arrival/departure of star analysts, such as a change in corporate culture, we expect the coefficients to be significant. However, if the arrival/departure of star analysts causally influences incumbents' performance, we expect β_1 *and* β_2 to be insignificant. Our results are reported in Table 4.

Columns 1 and 2 report the results for the regressions in which 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' arrival/departure causally influences incumbents' performance.

4.3 Test of H2

4.3.1 Test of H2a

H2a predicts that the impact of a star analyst's arrival/departure on the performance of incumbent analysts is more pronounced when the star analyst and the incumbent analysts cover the same industry than when they cover different industries. We use the following model to examine H2a:

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

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. Our H2a predicts that β_1 is positive and β_2 is negative.

Table 5 reports the results of estimating the above regression. Column 1 shows that the coefficient on *indstar_arrival* is 0.019, significant at the 10% level, while the coefficient on *indstar_departure* is -0.006, not significant at the 10% level. These results indicate that the incremental impact of the arrival of same-industry star analysts on incumbents' forecast accuracy is statistically detectable, while the incremental impact of the departure of these analysts is not. Column 2 shows that the coefficient on *indstar_arrival* is -0.061, not significant at the 10% level; the coefficient on *indstar_departure* is -0.384, significant at the 1% level, and the odds ratio indicates that the odds of becoming an *II* All-star are 32% lower when the same-industry star analysts depart than when other analysts depart. These results suggest that the departure of same-industry star analysts has an incrementally negative impact on incumbents' odds of being voted as stars, while their arrival does not exhibit an incremental impact.

In sum, we find that, incremental to arrival/departure of other star analysts, the arrival of same-industry stars improves incumbents' forecast accuracy and does not affect incumbents' likelihood of becoming stars; the departure of same-industry stars does not affect incumbents' forecast accuracy but it does hurt their chances of becoming stars.

4.3.2 Test of H2b

H2b predicts that the impact of a same-industry star's arrival/departure on the performance of incumbent analysts is more pronounced for industries with high uncertainty. We use analysts' forecast dispersion to measure uncertainty. High forecast dispersion indicates high disagreement among financial analysts, suggesting high uncertainty.[5] For each firm-year, we calculate the standard deviation of analysts' absolute forecast errors to capture forecast dispersion at the firm level. We then aggregate to the industry level by taking the average of all firms in the same industry-year combination. We sort our observations into two subsamples based on industry-level forecast dispersion. The low / high uncertainty subsample consists of those industries whose forecast dispersion is below / above the median. We rerun

[5] In un-tabulated tests, we use the standard deviation of quarterly earnings and monthly stock returns to measure uncertainty, and find qualitatively similar results.

the regression as specified in Model (4) and base our inferences on the comparison of the coefficients from the two subsamples.

Table 6 presents the results. Columns 1 and 2 report the results for industries with low forecast dispersion and high forecast dispersion, respectively, when *accuracy* is the dependent variable. The coefficient on *indstar_arrival* is 0.001, not significant at the 10% level, in Column 1, while in Column 2, it is 0.022, significant at the 5% level. The difference between the two coefficients is significant at the 10% level. This result is consistent with the notion that the arrival of same-industry stars is especially important in improving incumbents' performance for industries with high uncertainty. The coefficient on *indstar_departure* is 0.00007 and -0.009, respectively, in Columns 1 and 2, not significant at the 10% level, and the difference between the two coefficients is not significant.

Columns 3 and 4 of Table 6 report the results for industries with low forecast dispersion and high forecast dispersion, respectively, when the dependent variable is the likelihood of becoming a star. The coefficient on *indstar_arrival* in Column 3 is -0.206, while it is -0.0007 in Column 4; the difference between the two coefficients is not significant at the 10% level. The coefficient on *indstar_departure* is -0.002 and -0.716, respectively, in Columns 3 and 4, and the difference between the two coefficients is significant at the 5% level, suggesting that the departure of same-industry stars has a more pronounced effect on incumbents' likelihood of becoming stars in industries with high uncertainty.

4.4. Test of H3

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

$$Performance_{kit} = \alpha + \beta_1 * Eststar\_arrival_{kit} + \beta_2 * Eststar\_departure_{kit} + \beta_3 * Star\_arrival_{kit} + \beta_4 * Star\_departure_{kit} + Control\ variables + Analyst\ fixed\ effects + Year\ fixed\ effects + u_{kit} \quad (5)$$

$Eststar\_arrival_{kit}$ / $Eststar\_departure_{kit}$ 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. [6] The coefficient on *eststar_arrival* / *eststar_departure* reflects the effect of the arrival / departure of the established star analyst, *incremental* to the arrival / departure of other star analysts. Our H3 predicts that β_1 is positive and β_2 is negative.

Table 7 reports the results of estimating the above regression. In Column 1, the coefficient on *eststar_arrival* is 0.008, significant at the 10% level, suggesting that the arrival of established stars has a positive impact on analysts' forecast accuracy incremental to the effect of the arrival and departure of less established star analysts. The coefficient on *eststar_departure* is -0.007, not significant at the 10% level. These results suggest that the incremental impact of established stars on forecast accuracy is statistically significant for their arrivals but not so for their departures. Column 2 shows that the coefficient on *eststar_arrival* is -0.044, not significant at the 10% level. The coefficient on *eststar_departure* is -0.466, significant at the 1% level. The related odds ratio suggests that the incumbents' odds of becoming *II* All-stars are 37% lower when established star analysts depart than when non-established stars depart. These findings indicate that the incremental

[6] In our sample, we observe that star analysts are more accurate than non-star analysts and that more established star analysts are more accurate than less established star analysts. Using *accuracy* / *AFE* (absolute forecast error), we observe that star analysts are 5.93% / 9.5% more accurate than non-star analysts, while more established star analysts are 1.3% / 8.7% more accurate than less established star analysts.

impact of established stars on the likelihood of incumbents becoming star analysts is statistically significant for their departures but not so for their arrivals.

In sum, we show that, incremental to the arrival / departure of less established stars, the arrival of established stars improves incumbents' forecast accuracy but does not affect their chances of becoming a star, while the departure of established stars does not affect incumbents' forecast accuracy and hurts their likelihood of becoming stars.

4.5. Test of H4

H4 predicts that the positive impact of a 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 (2) and base our inferences on a comparison of the coefficients from the two subsamples.

Table 8 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 0.008, significant at the 5% level, in Column 1, while it is 0.001 in Column 2, not significant at the 10% level. 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. The coefficient on *star_departure* is -0.002 and -0.0005, respectively, in Columns 1 and 2, not significant at the 10% level, and the difference between the two coefficients is not significant.

Columns 3 and 4 of Table 8 report results for less experienced incumbents and more experienced incumbents respectively, when the dependent variable is the likelihood of becoming a star. The coefficient on *star_arrival* in Column 3 is 0.404, while it is only 0.209 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 an incumbent becoming a star is greater for inexperienced incumbents. The coefficient on *star_departure* is 0.080 and 0.066, respectively, in Columns 3 and 4, and the difference between the two coefficients is not significant at the 10% level.

Overall, we find that the impact of star arrival on incumbents' forecast accuracy and incumbents' likelihood of becoming a star is more pronounced for inexperienced incumbents than for experienced incumbents. However, we fail to find significant results for star departure.

4.6. Test of H5

H5 predicts that the impact of the star analyst's arrival/departure 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, we sort observations into two subsamples by conducting a median-split based on the number of stars each brokerage house employs each year. We then repeat our regression as specified in Model (2) for each subsample and report our results in Table 9. Our inferences are based on cross-subsample comparisons of the coefficients.

Columns 1 / 2 reports the results for incumbents working at brokerage houses with fewer / more existing stars, when *accuracy* is the dependent variable. The coefficient on *star_arrival* in Column 1 is 0.021, significant at the 5% level, while it is -0.003 in Column 2; the difference between the two is significant at the 10% level. This result is consistent with the notion that the impact of a star's arrival on forecast accuracy is more pronounced for brokerage houses with fewer star analysts. The coefficient on *star_departure* is -0.019 in Column 1 and 0.001 in Column 2, and the difference between the two is not statistically significant.

Columns 3 and 4 of Table 9 report the results when *star* is the dependent variable. The coefficient on *star_arrival* is 0.741 in Column 3, while it is -0.007 in Column 4; the difference between the two coefficients is significant at the 5% level. The coefficient on *star_departure* is, however, not statistically significantly different between the two subsamples.

In sum, we find that the impact of star arrival on incumbents' forecast accuracy and their likelihood of becoming stars is more pronounced for brokerage houses with few existing star analysts than for brokers with many existing star analysts. However, we fail to find significant results for star departure.

4.7. Alternative definition of stars

We employ an alternative definition of star analysts as a robustness test. For each year, we compute an analyst's overall forecast accuracy by taking the mean value of *accuracy* of all firms covered by the analyst. We then rank analysts based on their overall forecast accuracy, and analysts in the top decile (the decile with the highest forecast accuracy) are defined as "stars." We use two variables to indicate stars' arrival/departure based on the alternative definition of stars: *alt_star_arrival* / *alt_star_departure* is equal to 1 at least one star analyst has arrived at / departed from the brokerage house in the prior 12 months, and 0 otherwise. We run the regression as specified in Model (2) after replacing *star_arrival/star_departure* with *alt_star_arrival* / *alt_star_departure*. We report our results in Table 10.

Column 1 reports the results in which the dependent variable is forecast accuracy. In Column 1, the coefficient on *alt_star_arrival* is 0.021, significant at the 10% level, suggesting that incumbents experience an improvement in forecast accuracy when top forecasters arrive at their brokerage houses. The coefficient on *alt_star_departure* is 0.002, not significant at the 10% level. Column 2 reports the results when the dependent variable is the likelihood of becoming a star. The coefficient on *alt_star_arrival* is 0.411, significant at the 1% level, indicating that incumbents have a higher likelihood of becoming *II* All-stars when stars join their brokerage houses. The coefficient on *alt_star_departure* is 0.270, not significant at the 10% level.

Since stars in Table 10 are highly accurate forecasters, one might expect their influence on the incumbent's forecast accuracy to be more pronounced than that of *II* All-stars. This expectation is supported by comparing the results reported in Table 10 and those reported in Table 2. In the forecast accuracy regression, the coefficient on *alt_star_arrival* is 0.021 (reported in Table 10), while the coefficient on *star_arrival* is 0.006 (reported in Table 2), both significant at the 10% level; the coefficient on *alt_star_departure* is 0.002 (reported in Table 10), while the coefficient on *star_arrival* is -0.003 (reported in Table 2); neither is significant at the 10% level. Our results are consistent with the expectation that the impact of star arrival on incumbents' forecast accuracy is more pronounced if we use forecast accuracy to define stars.

In sum, our results suggest that the arrival of stars selected based on forecast accuracy has a beneficial impact on incumbents' forecast accuracy and their likelihood of becoming *II* All-stars, while the departure of these stars does not influence incumbent analysts' performance. This finding is broadly supportive of our general conclusion that peer effects exist among financial analysts, mainly through the arrival of 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' arrival/departure on incumbent analysts' performance, which is measured by forecast accuracy and the odds of becoming an *II* All-star. We find evidence that the arrival of star analysts to a brokerage house is beneficial to incumbents, while their departure is detrimental. For example, the odds of becoming an *II* All-star increase by 33% when incumbents experience the arrival of star analysts.

We use an instrumental variable approach and conduct a falsification test to address the alternative explanation that our results are due to the endogenous nature of the arrival/departure of star analysts. Such endogeneity may arise from unobservable omitted correlated variable that drives both arrival/departure of star analysts and performance of the incumbent analysts, such as the culture of the broker. Our results do not lend support to this alternative explanation.

If indeed incumbents learn from star analysts, we expect the impact of star arrival to be greater when learning is more likely to occur. We hypothesize that the effect of star arrival/departure is greater when the star analyst covers the same industry as the incumbents (especially for industries with high uncertainty), 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. Depending on which performance measure we use and whether we examine the arrival or departure of star analysts, there exists some evidence consistent with our hypotheses.

Overall, our results suggest that star analysts elevate the performance of incumbent analysts. While prior literature has focused on information environments and individual analyst characteristics as drivers of analyst performance, our findings indicate that peer influence is an overlooked determinant of analyst performance.

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Table 1 - Descriptive Statistics

VARIABLES	N	mean	s.d	Q1	median	Q3
Panel A: Scaled values						
accuracy	279,899	0.589	0.331	0.300	0.621	0.863
star	279,899	0.123	0.329	0	0	0
star_arrival	279,899	0.206	0.404	0	0	0
star_departure	279,899	0.215	0.411	0	0	0
day_elapsed	279,899	0.486	0.370	0	0.285	0.680
horizon	279,899	0.467	0.338	0.022	0.302	0.603
frequency	279,899	0.512	0.323	0.250	0.500	0.750
companies	279,899	0.448	0.305	0.208	0.405	0.667
broker_size	279,899	0.527	0.304	0.179	0.431	0.687
industries	279,899	0.390	0.327	0.125	0.333	0.600
experience	279,899	0.570	0.347	0.267	0.556	1
bold	279,899	0.685	0.464	0	1	1
growth_analyst	279,899	0.482	0.307	0.232	0.522	0.778
growth_asset	279,899	0.417	0.340	0.2	0.5	0.680
Panel B: Raw values						
absolute forecast error	279,899	0.190	0.261	0.023	0.070	0.330
day_elapsed	279,899	10.44	19.40	1	2	10
horizon	279,899	99.33	69.98	59	68	116
frequency	279,899	4.198	2.272	3	4	5
companies	279,899	17.51	9.206	12	16	21
broker_size	279,899	60.95	51.64	22	44	90
industries	279,899	4.570	2.846	3	4	6
experience	279,899	9.905	5.676	5	9	13
growth_analyst	279,899	0.997	8.362	-3	1	5
growth_asset ($m)	279,899	25.577	46.115	-6.313	3.158	38.694

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

Table 2
Effects of Star Arrival / Departure on Incumbent Analysts' Performance

		(1) *Accuracy*	(2) *Accuracy*	(3) *Star*		(4) *Star*	
	Pred. sign	*Coefficient*	*Coefficient*	*Coefficient*	*Odds ratio*	*Coefficient*	*Odds ratio*
star_arrival	+	0.004*	0.006***	0.316**	1.372	0.288**	1.334
		(0.002)	(0.002)	(0.128)		(0.128)	
star_departure	-	-0.005*	-0.003	0.032	1.032	0.016	1.016
		(0.003)	(0.003)	(0.113)		(0.112)	
day_elapsed	-		-0.021***			-0.024	0.976
			(0.002)			(0.039)	
horizon	-		-0.276***			-0.611***	0.543
			(0.003)			(0.070)	
frequency	+		0.029***			0.255***	1.290
			(0.003)			(0.064)	
companies	-		-0.007**			0.355***	1.426
			(0.003)			(0.138)	
broker_size	+		-0.053***			0.524***	1.689
			(0.004)			(0.147)	
industries	-		-0.008***			-0.096	0.908
			(0.003)			(0.138)	
experience	+		0.006**			0.720***	2.055
			(0.002)			(0.277)	
bold	+		0.038***			-0.0003	1.000
			(0.001)			(0.028)	
growth_analyst	+		0.015***			0.275***	1.316
			(0.002)			(0.105)	
growth_asset	+		0.003			0.194*	1.214
			(0.003)			(0.108)	
lag_performance	+	0.089***	0.078***	2.272***	9.700	2.182***	8.860
		(0.002)	(0.002)	(0.109)		(0.109)	
Observations		279,899	279,899	59,640		59,640	
Adjusted R-squared		0.050	0.107	0.179		0.190	
Year fixed effects		YES	YES	YES		YES	
Analyst fixed effects		YES	YES	YES		YES	

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 and 2 and the likelihood of becoming stars for Columns 3 and 4. *Star_arrival* equals 1 if at least one star analyst arrives at the brokerage house of analyst k within 12 months before the forecast is made at time t and 0 otherwise. *Star_departure* equals 1 if at least one star analyst leaves 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,* and *lag_performance*. All variables are defined in the appendix. Coefficients on the constant, 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 (two-tailed). OLS regression is used for forecast accuracy analysis, whereas logit regression is used for the likelihood of incumbents becoming star analysts.

Table 3
Instrumental Variable Regression on the Effects of Star Arrival on Incumbent Analysts' Performance

Panel A		**(1)** ***Star_arrival***	**(2)** ***Star_departure***	**(3)** ***Accuracy***
	Pred. sign	*Coefficient*	*Coefficient*	*Coefficient*
Adj_arrival / Adj_departure	+	0.080***	0.096***	
		(0.017)	(0.001)	
$\widehat{star\_arrival}$	+			0.070**
				(0.033)
$\widehat{star\_departure}$	-			-0.047
				(0.034)
day_elapsed	-	-0.118***	-0.192***	-0.005***
		(0.014)	(0.0143)	(0.0005)
horizon	-	-0.063***	-0.123***	-0.065***
		(0.017)	(0.0177)	(0.0007)
frequency	+	-0.210***	-0.220***	0.008***
		(0.018)	(0.0186)	(0.0007)
companies	-	-0.170***	-0.206***	-0.001
		(0.020)	(0.0205)	(0.0009)
broker_size	+	2.624***	2.920***	-0.014***
		(0.017)	(0.0172)	(0.001)
industries	-	-0.703***	-0.643***	-0.001*
		(0.019)	(0.0194)	(0.0008)
experience	+	1.103***	0.948***	-0.001
		(0.015)	(0.0159)	(0.002)
bold	+	-0.048***	-0.0456***	0.009***
		(0.011)	(0.0114)	(0.0004)
growth_analyst	+	-0.260***	-0.391***	0.003***
		(0.017)	(0.0179)	(0.0006)
growth_asset	+	0.411***	0.139***	-0.00003
		(0.014)	(0.0146)	(0.0008)
lag_performance	+	0.025	0.0665***	0.014***
		(0.016)	(0.0161)	(0.0005)
Observations		279,899	279,899	279,899
Adjusted R^2		0.142	0.167	0.139
Partial R^2		0.049	0.069	
Partial F-statistic		15.41***	19.23***	
Hausman test				F = 15.19***
Kleibergen-Paap rk Wald F statistic				26.208*
Year fixed effects		YES	YES	YES
Analyst fixed effects		YES	YES	YES

Panel B		**(1)** ***Star_arrival***	**(2)** ***Star_departure***	**(3)** ***Star***	
	Pred. sign	*Coefficient*	*Coefficient*	*Coefficient*	*Odds ratio*
Adj_arrival / Adj_departure	+	0.081***	0.101***		
		(0.017)	(0.002)		
$\widehat{star\_arrival}$	+			0.319**	1.376
				(0.127)	
$\widehat{star\_departure}$	-			-0.463	0.629
				(0.367)	
day_elapsed	-	-0.067***	-0.131***	-0.001	0.999
		(0.014)	(0.015)	(0.001)	
horizon	-	0.043**	0.011	-0.016***	0.984
		(0.017)	(0.018)	(0.001)	
frequency	+	-0.200***	-0.208***	0.008***	1.008
		(0.018)	(0.019)	(0.002)	
companies	-	-0.322***	-0.407***	0.004*	1.004
		(0.020)	(0.021)	(0.003)	
broker_size	+	2.334***	2.598***	0.033***	1.034
		(0.017)	(0.018)	(0.007)	

industries	-	-0.618***	-0.536***	-0.006***	0.994
		(0.019)	(0.020)	(0.002)	
experience	+	0.930***	0.716***	0.025***	1.025
		(0.016)	(0.016)	(0.004)	
bold	+	-0.054***	-0.053***	0.00001	1.000
		(0.011)	(0.012)	(0.001)	
growth_analyst	+	-0.207***	-0.327***	0.005***	1.005
		(0.018)	(0.018)	(0.002)	
growth_asset	+	0.406***	0.123***	0.009***	1.009
		(0.015)	(0.015)	(0.003)	
lag_performance	+	1.071***	1.356***	0.392***	1.481
		(0.013)	(0.014)	(0.005)	
Observations		59,640	59,640	59,640	
Adjusted R^2		0.164	0.203	0.189	
Partial R^2		0.063	0.052		
Partial F-statistic		13.79***	16.66***		
Hausman test				F = 14.12***	
Kleibergen-Paap rk Wald F statistic				13.772*	
Year fixed effects		YES	YES	YES	
Analyst fixed effects		YES	YES	YES	

This table reports the results of estimating the following equations:

(Stage 1) $$Star\_arrival_{kit} = \lambda_0 + \lambda_1 * Adj\_arrival_{kit} + \lambda_2 * No\_analyst_{kit} + \text{Analyst fixed effects} + \text{Control variables} + \text{Year fixed effects} + e_{kit}$$

$$Star\_departure_{kit} = \gamma_0 + \gamma_1 * Adj\_departure_{kit} + \gamma_2 * No\_analyst_{kit} + \text{Analyst fixed effects} + \text{Control variables} + \text{Year fixed effects} + e_{kit}$$

(Stage 2) $$Performance_{kit} = \alpha + \beta_1 * \widehat{Star\_arrival}_{kit} + \beta_2 * \widehat{Star\_departure}_{kit} + \text{Control variables} + \text{Analyst fixed effects} + \text{Year fixed effects} + u_{kit}$$

The dependent variable is forecast accuracy for Panel A and the likelihood of becoming stars for Panel B. $Adj\_arrival_{kit}$ is the number of star analysts who are in their prime moving years (8-10 of career age) that the broker employing analyst k covering firm i in year t has connection to, deflated by the number of analysts the broker employs. $Adj\_departure_{kit}$ is the number of star analysts who are in their prime moving years (8-10 of career age) that the broker employing analyst k covering firm i in year t is currently employing and these star analysts have connections to other brokers, deflated by the number of analysts the broker employs. *Star_arrival / Star_departure* equals 1 if at least one star analyst arrives at / departs from the brokerage house of analyst k within 12 months before the forecast is made at time t and 0 otherwise. $\widehat{Star\_arrival}$ *and* $\widehat{Star\_departure}$ denote the fitted values of *Star_arrival* and *Star_departure* from Stage 1. Control variables include *day_elapsed, horizon, frequency, companies, broker_size, industries, experience, bold, growth_analyst, growth_asset* and *lag_performance.* All variables are defined in the appendix. Coefficients on the constant, 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 (two-tailed). OLS regression is used for the forecast accuracy analysis, whereas logit regression is used for the likelihood of becoming star analysts.

Table 4

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

		(1) *Accuracy*	(2) *Accuracy*	(3) *Star*		(4) *Star*	
	Pred. sign	*Coefficient*	*Coefficient*	*Coefficient*	*Odds ratio*	*Coefficient*	*Odds ratio*
later_star_arrival	0	0.001	0.001	0.092	1.097	0.070	1.073
		(0.004)	(0.003)	(0.175)		(0.175)	
later_star_departure	0	0.005	-0.005	-0.046	0.955	-0.051	0.951
		(0.005)	(0.004)	(0.170)		(0.170)	
day_elapsed	-		-0.020***			-0.027	0.973
			(0.002)			(0.039)	
horizon	-		-0.263***			-0.612***	0.542
			(0.003)			(0.070)	
frequency	+		0.032***			0.255***	1.290
			(0.003)			(0.064)	
companies	-		-0.008**			0.346**	1.413
			(0.003)			(0.137)	
broker_size	+		-0.045***			0.571***	1.769
			(0.004)			(0.147)	
industries	-		-0.007**			-0.095	0.910
			(0.003)			(0.138)	
experience	+		-0.002			0.761***	2.140
			(0.006)			(0.275)	
bold	+		0.037***			-0.0007	0.999
			(0.002)			(0.028)	
growth_analyst	+		-0.014***			0.268**	1.308
			(0.002)			(0.105)	
growth_asset	+		0.003			0.187*	1.205
			(0.003)			(0.108)	
lag_performance	+	0.059***	0.054***	2.279***	9.765	2.184***	8.885
		(0.003)	(0.003)	(0.109)		(0.109)	
Observations		279,899	279,899	59,640		59,640	
Adjusted R-squared		0.004	0.087	0.178		0.189	
Year fixed effects		YES	YES	YES		YES	
Analyst fixed effects		YES	YES	YES		YES	

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 and 2 and the likelihood of becoming stars for Columns 3 and 4. *Later_star_arrival* equals 1 if at least one star analyst arrives 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 1 if at least one star analyst leaves 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, growth_analyst, growth_asset,* and *lag_performance.* All variables are defined in the appendix. Coefficients on the constant, 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 (two-tailed). OLS regression is used for the forecast accuracy analysis, whereas logit regression is used for the likelihood of incumbents becoming star analysts.

Table 5
Effects of Expertise Similarity of Incoming / Departing Stars on Incumbent Analysts' Performance

		(1) *Accuracy*	**(2)** *Star*	
	Pred. sign	*Coefficient*	*Coefficient*	*Odds ratio*
indstar_arrival	+	0.019*	-0.061	0.941
		(0.011)	(0.084)	
indstar_departure	-	-0.006	-0.384***	0.681
		(0.007)	(0.087)	
star_arrival	+	0.002	0.289***	1.335
		(0.002)	(0.034)	
star_departure	-	0.002	0.035	1.036
		(0.003)	(0.035)	
day_elapsed	-	-0.020***	-0.022	0.978
		(0.002)	(0.033)	
horizon	-	-0.263***	-0.610***	0.544
		(0.003)	(0.044)	
frequency	+	0.032***	0.254***	1.289
		(0.003)	(0.045)	
companies	-	-0.008**	0.351***	1.420
		(0.003)	(0.061)	
broker_size	+	-0.044***	0.524***	1.689
		(0.004)	(0.055)	
industries	-	-0.007**	-0.095*	0.909
		(0.003)	(0.057)	
experience	+	-0.002	0.729***	2.074
		(0.006)	(0.109)	
bold	+	0.037***	-0.0007	0.999
		(0.002)	(0.025)	
growth_analyst	+	0.014***	0.274***	1.315
		(0.002)	(0.046)	
growth_asset	+	0.004	0.191***	1.210
		(0.003)	(0.042)	
lag_performance	+	0.054***	2.186***	8.903
		(0.003)	(0.028)	
Observations		279,899	59,640	
Adjusted R-squared		0.097	0.191	
Year fixed effects		YES	YES	
Analyst fixed effects		YES	YES	

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 the likelihood of becoming stars for Column 2. *Indstar_arrival* equals 1 if at least one star analyst arrives 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 and captures the *incremental* impact of the arrival of stars in the same industry. *Indstar_departure* equals 1 if at least one star analyst leaves 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 and captures the *incremental* impact of departure of stars in the same industry. Control variables include *day_elapsed, horizon, frequency, companies, broker_size, industries, experience, bold, growth_analyst, growth_asset,* and *lag_performance.* All variables are defined in the appendix. Coefficients on the constant, 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 (two-tailed). OLS regression is used for forecast accuracy, whereas logit regression is used for the likelihood of incumbents becoming star analysts.

Table 6

Effects of Expertise Similarity of Incoming / Departing Stars on Incumbent Analysts' Performance, Conditioning on Industry Uncertainty

		(1) *Accuracy (Low Dispersion)*	(2) *Accuracy (High Dispersion)*	(3) *Star (Low Dispersion)*		(4) *Star (High Dispersion)*	
	Pred. sign	*Coefficient*	*Coefficient*	*Coefficient*	*Odds ratio*	*Coefficient*	*Odds ratio*
indstar_arrival	+	0.001	0.022**	-0.206	0.814	-0.0007	0.999
		(0.011)	(0.010)	(0.131)		(0.113)	
indstar_departure	-	0.00007	-0.009	-0.002	0.998	-0.716***	0.489
		(0.011)	(0.009)	(0.136)		(0.120)	
star_arrival	+	0.004	0.0006	0.265***	1.325	0.281***	1.303
		(0.003)	(0.003)	(0.047)		(0.052)	
star_departure	-	-0.001	0.005	-0.109**	0.896	-0.150***	0.861
		(0.004)	(0.003)	(0.051)		(0.048)	
day_elapsed	-	-0.017***	-0.021***	-0.084*	0.920	0.016	1.016
		(0.003)	(0.003)	(0.048)		(0.045)	
horizon	-	-0.255***	-0.258***	-0.496***	0.609	-0.696***	0.498
		(0.005)	(0.005)	(0.064)		(0.062)	
frequency	+	0.035***	0.026***	0.368***	1.445	0.202***	1.224
		(0.004)	(0.003)	(0.066)		(0.063)	
companies	-	-0.009*	-0.006	0.295***	1.344	0.457***	1.579
		(0.005)	(0.005)	(0.091)		(0.084)	
broker_size	+	-0.043***	-0.045***	0.466***	1.593	0.615***	1.850
		(0.005)	(0.005)	(0.082)		(0.079)	
industries	-	-0.010**	-0.006	0.293***	1.340	-0.309***	0.734
		(0.005)	(0.005)	(0.089)		(0.078)	
experience	+	-0.005	-0.004	0.688***	1.990	0.879***	2.408
		(0.009)	(0.008)	(0.163)		(0.153)	
bold	+	0.041***	0.030***	-0.018	0.982	0.007	1.007
		(0.002)	(0.002)	(0.038)		(0.034)	
growth_analyst	+	0.018***	0.008***	0.265***	1.303	0.255***	1.291
		(0.003)	(0.003)	(0.068)		(0.064)	
growth_asset	+	0.004	0.002	0.130**	1.139	0.247***	1.281
		(0.004)	(0.004)	(0.062)		(0.058)	
lag_performance	+	0.043***	0.049***	2.211***	9.126	2.078***	7.987
		(0.003)	(0.004)	(0.041)		(0.038)	
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 < 0.05			
Observations		132,682	147,217	27,767		31,873	
Adjusted R-squared		0.093	0.105	0.180		0.186	
Year fixed effects		YES	YES	YES		YES	
Analyst fixed effects		YES	YES	YES		YES	

This table reports the results of estimating the following equation:

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

The dependent variable is forecast accuracy for Columns 1 and 2 and likelihood of becoming stars for Column 3 and 4. *Indstar_arrival* equals 1 if at least one star analyst arrives at the brokerage house of analyst k within 12 months before the forecast is made at time t, and both the star(s) and analyst k share the same industry expertise as defined by I/B/E/S, and 0 otherwise. *Indstar_departure* equals 1 if at least one star analyst leaves the brokerage house of analyst k within 12 months before the forecast is made at time t, and both the star(s) and analyst k share the same industry expertise as defined by I/B/E/S, and 0 otherwise. We divide the sample into 2 subsamples based on industry uncertainty, which is measured by forecast dispersion. For each firm-year, we calculate the standard deviation of analysts' absolute forecast errors to capture forecast dispersion at the firm level. We then aggregate to the industry level by taking the average of all firms in the same industry-year combination. The low / high uncertainty subsample consists of those industries whose forecast dispersion is below / above the median. Control variables include *day_elapsed*, *horizon*, *frequency*, *companies*, *broker_size*, *industries*, *experience*, *bold*, *growth_analyst*, *growth_asset*, and *lag_performance*. All variables are defined in the appendix. Coefficients on the constant, 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 (two-tailed). OLS regression is used for forecast accuracy, whereas logit regression is used for the likelihood of incumbents becoming star analysts.

Table 7

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

		(1) *Accuracy*	(2) *Star*	
	Pred. sign	*Coefficient*	*Coefficient*	*Odds ratio*
eststar_arrival	+	0.008*	-0.044	0.957
		(0.004)	(0.157)	
eststar_departure	-	-0.007	-0.466***	0.627
		(0.005)	(0.160)	
star_arrival	+	-0.002	0.278	1.321
		(0.003)	(0.170)	
star_departure	-	0.005	-0.251	0.778
		(0.003)	(0.162)	
day_elapsed	-	-0.019***	-0.042	0.959
		(0.002)	(0.040)	
horizon	-	-0.259***	-0.699***	0.497
		(0.004)	(0.080)	
frequency	+	0.031***	0.332***	1.394
		(0.003)	(0.067)	
companies	-	-0.009**	0.974***	2.647
		(0.003)	(0.155)	
broker_size	+	-0.043***	1.132***	3.101
		(0.004)	(0.166)	
industries	-	-0.007**	-0.205	0.815
		(0.003)	(0.146)	
experience	+	-0.0009	1.251***	3.493
		(0.006)	(0.324)	
bold	+	0.035***	0.037	1.037
		(0.002)	(0.028)	
growth_analyst	+	0.013***	-0.056	0.946
		(0.002)	(0.118)	
growth_asset	+	0.003	0.497***	1.644
		(0.003)	(0.120)	
lag_performance	+	0.054***	1.933***	6.908
		(0.003)	(0.098)	
Observations		279,899	59,640	
Adjusted R-squared		0.098	0.214	
Year fixed effects		YES	YES	
Analyst fixed effects		YES	YES	

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 in Column 1 and the likelihood of becoming stars in Column 2. *Eststar_arrival* equals 1 if at least one established star analyst arrives at the brokerage house of analyst k within 12 months before the forecast is made at time t and 0 otherwise. *Eststar_departure* equals 1 if at least one established star analyst leaves the brokerage house of analyst k within 12 months before the forecast is made at time 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. Control variables include *day_elapsed, horizon, frequency, companies, broker_size, industries, experience, bold, growth_analyst, growth_asset,* and *lag_performance.* All variables are defined in the appendix. Coefficients on the constant, 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 (two-tailed). OLS regression is used for forecast accuracy, whereas logit regression is used for the likelihood of incumbents becoming star analysts.

Table 8
Effects of Star Arrival / Departure on Incumbent Analysts' Performance, Conditioning on Experience Level of Incumbents

		(1) *Accuracy* *(Less Experience)*	(2) *Accuracy* *(More Experience)*	(3) *Star* *(Less Experience)*		(4) *Star* *(More Experience)*	
	Pred. sign	*Coefficient*	*Coefficient*	*Coefficient*	*Odds ratio*	*Coefficient*	*Odds ratio*
star_arrival	+	0.008**	0.001	0.404***	1.498	0.209	1.233
		(0.003)	(0.003)	(0.135)		(0.145)	
star_departure	-	-0.002	-0.0005	0.080	1.084	0.066	1.068
		(0.003)	(0.004)	(0.126)		(0.133)	
day_elapsed	-	-0.024***	-0.017***	-0.062	0.940	0.060	1.062
		(0.003)	(0.003)	(0.049)		(0.059)	
horizon	-	-0.279***	-0.261***	-0.330***	0.719	-0.692***	0.500
		(0.004)	(0.004)	(0.079)		(0.111)	
frequency	+	0.032***	0.031***	0.241***	1.273	0.232**	1.261
		(0.004)	(0.003)	(0.073)		(0.101)	
companies	-	-0.004	-0.008*	0.177	1.193	0.366**	1.442
		(0.004)	(0.004)	(0.153)		(0.184)	
broker_size	+	-0.055***	-0.041***	0.516***	1.675	0.347	1.415
		(0.006)	(0.005)	(0.144)		(0.217)	
industries	-	-0.011**	-0.002	-0.147	0.864	-0.135	0.874
		(0.004)	(0.004)	(0.146)		(0.187)	
experience	+	0.002	-0.003	-0.240	0.786	1.117***	3.055
		(0.003)	(0.008)	(0.282)		(0.381)	
bold	+	0.037***	0.037***	0.002	1.002	0.013	1.013
		(0.002)	(0.002)	(0.038)		(0.041)	
growth_analyst	+	-0.013***	-0.015***	0.347***	1.415	0.296**	1.345
		(0.004)	(0.003)	(0.116)		(0.146)	
growth_asset	+	0.003	0.005	-0.024	0.976	0.257*	1.293
		(0.004)	(0.003)	(0.119)		(0.146)	
lag_performance	+	0.091***	0.041***	2.221***	9.220	1.858***	6.411
		(0.004)	(0.004)	(0.113)		(0.128)	
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		132,617	147,282	34,869		24,771	
Adjusted R-squared		0.112	0.085	0.177		0.165	
Year fixed effects		YES	YES	YES		YES	
Analyst fixed effects		YES	YES	YES		YES	

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 and 2 and the likelihood of becoming stars for Columns 3 and 4. *Star_arrival* equals 1 if at least one star analyst arrives at the brokerage house of analyst k within 12 months before the forecast is made at time t and 0 otherwise. *Star_departure* equals 1 if at least one star analyst leaves the brokerage house of analyst k within 12 months before the forecast is made at time t and 0 otherwise. We divide the sample into two subsamples based on the *experience* of the incumbents. The less / more experience subsample consists of those whose *experience* is below / above the sample median. Control variables include *day_elapsed, horizon, frequency, companies, broker_size, industries, experience, bold, growth_analyst*, *growth_asset*, and *lag_performance.* All variables are defined in the appendix. Coefficients on the constant, 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 (two-tailed). OLS regression is used for the forecast accuracy analysis, whereas logit regression is used for the likelihood of incumbents becoming star analysts.

Table 9
Effects of Star Arrival / Departure on Incumbent Analysts' Performance, Conditioning on Number of Existing Stars

		(1) *Accuracy (Fewer Stars)*	(2) *Accuracy (More Stars)*	(3) *Star (Fewer Stars)*		(4) *Star (More Stars)*	
	Pred. sign	*Coefficient*	*Coefficient*	*Coefficient*	*Odds ratio*	*Coefficient*	*Odds ratio*
star_arrival	+	0.021**	-0.003	0.741***	2.098	-0.007	0.993
		(0.008)	(0.002)	(0.217)		(0.154)	
star_departure	-	-0.019**	0.001	-0.197	0.821	-0.062	0.940
		(0.009)	(0.003)	(0.204)		(0.151)	
day_elapsed	-	-0.017***	-0.023***	0.010	1.010	-0.018	0.982
		(0.003)	(0.003)	(0.070)		(0.048)	
horizon	-	-0.266***	-0.253***	-0.498***	0.608	-0.646***	0.524
		(0.004)	(0.006)	(0.104)		(0.095)	
frequency	+	0.031***	0.034***	0.148	1.159	0.315***	1.370
		(0.004)	(0.003)	(0.107)		(0.083)	
companies	-	-0.005	-0.012**	0.054	1.055	0.473***	1.605
		(0.005)	(0.005)	(0.220)		(0.175)	
broker_size	+	-0.057***	-0.039***	0.725***	2.065	-0.294	0.745
		(0.006)	(0.006)	(0.261)		(0.186)	
industries	-	-0.002	-0.015***	-0.111	0.895	-0.006	0.994
		(0.004)	(0.005)	(0.232)		(0.175)	
experience	+	-0.005	0.002	1.309***	3.702	0.742*	2.100
		(0.007)	(0.011)	(0.377)		(0.413)	
bold	+	0.038***	0.034***	0.043	1.044	-0.022	0.978
		(0.002)	(0.002)	(0.046)		(0.040)	
growth_analyst	+	0.010***	0.022***	0.490***	1.632	0.227	1.254
		(0.003)	(0.003)	(0.164)		(0.148)	
growth_asset	+	0.003	0.001	0.218	1.243	0.134	1.143
		(0.004)	(0.004)	(0.202)		(0.141)	
lag_performance	+	0.048***	0.060***	1.973***	7.192	1.843***	6.313
		(0.003)	(0.005)	(0.169)		(0.160)	
P-value of test of equal coefficients		Between (1) and (2)		Between (3) and (4)			
star_arrival		$p < 0.10$		$p < 0.05$			
star_departure		$p > 0.10$		$p > 0.10$			
Observations		167,766	112,133	29,421		30,219	
Adjusted R-squared		0.090	0.078	0.189		0.156	
Year fixed effects		YES	YES	YES		YES	
Analyst fixed effects		YES	YES	YES		YES	

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 and 2 and the likelihood of becoming stars for Columns 3 and 4. *Star_arrival* equals 1 if at least one star analyst arrives at the brokerage house of analyst k within 12 months before the forecast is made at time t and 0 otherwise. *Star_departure* equals 1 if at least one star analyst leaves the brokerage house of analyst k within 12 months before the forecast is made at time t and 0 otherwise. We divide the sample into two subsamples based on the number of star analysts the broker employs. The fewer / more stars subsample consists of brokers that have less / more than the median number of stars each year. Control variables include *day_elapsed, horizon, frequency, companies, broker_size, industries, experience, bold, growth_analyst, growth_asset,* and *lag_performance.* All variables are defined in the appendix. Coefficients on the constant, 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 (two-tailed test). OLS regression is used for the forecast accuracy analysis, whereas logit regression is used for the likelihood of incumbents becoming star analysts.

Table 10
Effects of Star Arrival / Departure on Incumbent Analysts' Performance, where Stars Are Defined According to Forecast Accuracy

		(1) *Accuracy*	(2) *Star*	
	Pred. sign	*Coefficient*	*Coefficient*	*Odds ratio*
alt_star_arrival	+	0.021*	0.411***	1.508
		(0.011)	(0.118)	
alt_star_departure	-	0.002	0.270	1.310
		(0.002)	(0.216)	
day_elapsed	-	-0.019***	-0.044	0.957
		(0.002)	(0.040)	
horizon	-	-0.259***	-0.589***	0.555
		(0.002)	(0.069)	
frequency	+	0.031***	0.310***	1.363
		(0.002)	(0.066)	
companies	-	-0.008***	0.936***	2.550
		(0.003)	(0.155)	
broker_size	+	-0.044***	1.069***	2.913
		(0.003)	(0.158)	
industries	-	-0.007**	-0.219	0.804
		(0.003)	(0.149)	
experience	+	-0.0008	1.241***	3.461
		(0.005)	(0.328)	
bold	+	0.035***	0.010	1.010
		(0.001)	(0.028)	
growth_analyst	+	0.013***	-0.067	0.935
		(0.002)	(0.120)	
growth_asset	+	0.003	0.435***	1.544
		(0.002)	(0.121)	
lag_performance	+	0.054***	1.962***	7.112
		(0.002)	(0.100)	
Observations		279,899	59,640	
Adjusted R-squared		0.088	0.218	
Year fixed effects		YES	YES	
Analyst fixed effects		YES	YES	

This table reports the results of estimating the following equation:

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

The dependent variable is forecast accuracy for Columns 1 and 2 and the likelihood of becoming stars for Columns 3 and 4. *Alt_star_arrival* equals 1 if at least one analyst in the highest decile of forecast accuracy arrives at the brokerage house of analyst k within 12 months before the forecast is made at time t and 0 otherwise. *Alt_star_departure* equals 1 if at least one analyst in the highest decile of forecast accuracy leaves 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*, and *lag_performance*. All variables are defined in the appendix. Coefficients on the constant, 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 (two-tailed test). OLS regression is used for the forecast accuracy analysis, whereas logit regression is used for the likelihood of incumbents becoming star analysts.

Appendix - Variable Definition (in Alphabetical Order)

Name	Definition
$Accuracy_{kit}$	Incumbent analyst k's scaled forecast accuracy for firm i in year t (computed as the highest absolute forecast error for all analysts who cover firm i in year t minus the absolute forecast error of analyst k covering firm i in year t, divided by the min-max range of absolute forecast errors for all analysts covering firm i in year t).
$Adj\_arrival_{kit}$	A measure of the number of star analysts in their 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, deflated by the total number of analysts the broker employs. 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
$Adj\_departure_{kit}$	A measure of the number of star analysts in their prime moving years (8-10 years of career age) that the brokerage house employing analyst k following firm i in year t currently employs, and these star analysts have connections to other brokerage houses, deflated by the total number of analysts the broker employs. A connection is identified when the star analysts in the brokerage house have worked at the same place with the other analysts in other brokers in the first 5 years of the stars' careers.
$Alt\_star\_arrival_{kit}$	A dummy variable to indicate whether at least one star analyst has arrived at the brokerage house of analyst k within 12 months before the forecast is made at time t, where a star analyst is defined as an analyst whose mean value of *accuracy* of all firms covered is in the top decile.
$Alt\_star\_departure_{kit}$	A dummy variable to indicate whether at least one star analyst has left the brokerage house of analyst k within 12 months before the forecast is made at time t, where a star analyst is defined as an analyst whose mean value of *accuracy* of all firms covered is in the top decile.
$Bold_{kit}$	A dummy variable to indicate whether the forecast issued by analyst k for firm i in year t is considered bold (i.e., the forecast is greater or smaller than both analyst k's previous forecast for firm i in year t and the consensus forecast made by all other analysts covering firm i in year t prior to this forecast).
$Broker\_size_{kit}$	Analyst k's scaled brokerage house size (computed as the number of analysts working for the brokerage house employing analyst k following firm i in year t minus the minimum number of analysts working in other brokerage houses for all analysts covering firm i in year t, divided by the min-max range of brokerage house size for all analysts covering firm i in year t).
$Companies_{kit}$	The scaled number of firms analyst k covers in year t (computed as the number of firms covered by analyst k covering firm i in year t minus the lowest number of firms covered by all analysts who cover firm i in year t, divided by the min-max range in the number of firms covered by analysts covering firm i in year t).
$Day\_elapsed_{kit}$	The scaled number of days elapsed since the forecast by any analyst covering firm i in year t (computed as the days between analyst k's forecast for firm i and the latest preceding forecast for firm i by any analyst, minus the lowest number of days between two adjacent forecasts for firm i by any two analysts in year t, divided by the min-max range of days between 2 adjacent forecasts).

Eststar_arrival$_{kit}$	A dummy variable to indicate whether at least one established star analyst has arrived 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 at least one established analyst has left 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.
Experience$_{kit}$	Analyst k's scaled general experience (computed as the number of years of general experience for analyst k covering firm i in year t minus the lowest number of years of general experience for all analysts covering firm i in year t, divided by the min-max range of years of general experience for all analysts covering firm i in year t).
Frequency$_{kit}$	Analyst k's scaled frequency of forecasts for firm i in year t (computed as the number of forecasts made by analyst k for firm i in year t minus the lowest forecast frequency of all analysts covering firm i in year t, divided by the min-max range of forecast frequency for all analysts covering firm i in year t).
Growth_analyst$_{kit}$	Analyst k's scaled brokerage house size change (computed as the change in number of analysts working for the brokerage house employing analyst k covering firm i in year t minus the smallest change of analysts working for other brokerage houses that have analysts covering firm i in year t, divided by the min-max range of brokerage house size changes for all analysts covering firm i in year t).
Growth_asset$_{kit}$	Analyst k's scaled brokerage house asset change (computed as the change in asset of the broker or parent company of the broker employing analyst k covering firm i in year t minus the smallest change in asset of the brokers or parent companies of the brokers employing other analysts covering firm i in year t, divided by the min-max range of brokerage house asset changes for all analysts covering firm i in year t).
Horizon$_{kit}$	The scaled time from the forecast date to the end of the fiscal period (computed as the forecast horizon (days from the forecast date to the fiscal year-end) for analyst k covering firm i in year t minus the lowest forecast horizon for all analysts covering firm i in year t, divided by the min-max range of forecast horizons for all analysts following firm i in year t).
Indstar_arrival$_{kit}$	A dummy variable to indicate whether at least one star analyst arrives 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 at least one star analyst has left 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.
Industries$_{kit}$	The scaled number of industries analyst k covers in year t (computed as the number of I/B/E/S industries covered by analyst k covering firm i in year t minus the lowest number of I/B/E/S industries covered by all analysts who cover firm i in year t, divided by the min-max range of the number of I/B/E/S industries covered by all analysts covering firm i in year t).
Later_star_arrival$_{kit}$	A dummy variable to indicate whether at least one star analyst arrives 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 who has been ranked in the most recent issue of *Institutional Investor* before the date of the arrival.
$Later\_star\_departure_{kit}$	A dummy variable to indicate whether at least one star analyst has left the brokerage house of analyst k within 12 months after the forecast is made at time t, where a star analyst is an analyst who has been ranked in the most recent issue of *Institutional Investor* before the date of the departure.
$No\_analyst_{kit}$	The total number of analysts working for the broker that employs analyst k covering firm i in year t.
$Star\_arrival_{kit}$	A dummy variable to indicate whether at least one star analyst has arrived 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 who has been ranked in the most recent issue of *Institutional Investor* before the date of the arrival.
$Star\_departure_{kit}$	A dummy variable to indicate whether at least one star analyst has left the brokerage house of analyst k within 12 months before the forecast is made at time t, where a star analyst is an analyst who has been ranked in the most recent issue of *Institutional Investor* before the date of the departure.
$Star_{kit}$	A dummy variable to indicate whether incumbent analyst k is a star analyst in year t, where a star analyst is an analyst who has been ranked in the most recent issue of *Institutional Investor* before the date of the forecast.