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► **To cite this version:**

Tristan Roger. Earnings Forecast Accuracy And Career Concerns. 32nd International Conference of the French Finance Association - AFFI 2015, Jun 2015, Cergy, France. pp.29. hal-01483837

HAL Id: hal-01483837

<https://hal.science/hal-01483837v1>

Submitted on 6 Mar 2017

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Earnings forecast accuracy and career concerns

Tristan Roger *

December 14, 2014

Abstract

Previous studies show that analysts' compensation is not linked to earnings forecast accuracy. We evidence however that analysts have incentives to issue accurate forecasts. We show that brokerage houses reward their best forecasters by assigning them to large, mature firms. Covering such firms increases the potential for future compensation as these firms generate a great deal of investment banking and trading activities. The coverage of such firms also increases analysts' exposure to large buy-side investors. We find that analysts covering large, mature firms are twice as likely to be recognized as star analysts by Institutional Investor. We explain our findings on forecast accuracy as the result of brokerage houses' concerns for reputation.

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1 Introduction

Despite the great interest of both academics and practitioners for earnings forecasts, it is unclear whether financial analysts have strong incentives to issue accurate forecasts. Earnings forecast accuracy has been shown to be linked with job turnover (Mikhail, Walther, and Willis, 1999; Harrison and Kubik, 2003) but not with analysts' compensation (Groysberg, Healy, and Maber, 2011). Mikhail, Walther, and Willis (1999) and Harrison and Kubik (2003) find that analysts who are inaccurate relatively to their peers are more likely to get terminated. Harrison and Kubik (2003) show that forecast accuracy increases the likelihood for an analyst to move to a higher status brokerage house. In contrast, Groysberg, Healy, and Maber (2011), using proprietary data on analysts' remuneration, find that analysts' compensation is related to investment-banking contributions, analysts' star rankings and the average capitalization of analysts' portfolio but not to earnings forecast accuracy. Finally, Emery and Li (2009) show that earnings forecast accuracy has little influence on analysts being recognized as All-star analysts by the *Institutional Investor* (I/I) ranking.

It is somewhat puzzling that forecast accuracy matters for job termination and external hiring but that it is not incentivized by brokerage houses. In an attempt to solve this puzzle, we investigate whether earnings forecast accuracy has an impact on analysts' future compensation through coverage decisions. Analysts' compensation is directly tied to investment banking activities. Therefore, their compensation depends not only on their abilities but also on the number and type of firms they cover. The compensation is likely to increase for analysts covering large firms, firms with high trading volume and firms that generate a lot of investment banking activity. In addition to the potential for investment banking commissions, this type of firms is also the one that attracts the most attention from buy-side investors. As a consequence, covering such firms increases the odds for a financial analyst to obtain votes in the I/I all-star ranking.

In this paper, we investigate the existence of a competition within brokerage houses for the coverage of firms with high potential investment banking fees and high investor recognition. Financial analysts compete for the coverage of these firms because obtaining such coverage increases the potential for future compensation and increases the likelihood of being recognized as a star analyst. Our results indicate that analysts' coverage decisions are constrained by brokerage houses. Successful analysts are assigned to cover large, mature firms while unsuccessful and inexperienced analysts are assigned to small, young,

growth firms. We show that forecast accuracy is the main driver of switching from small, young, growth firms to large, mature firms. Finally, we document that analysts covering large, mature firms are less likely to be terminated and much more likely to be recognized as star analysts.

Our first analysis consists in showing that coverage decisions are constrained by brokerage houses. Because these constraints are not directly observable, we need to establish the existence of a competition within brokerage houses for the coverage of firms with high potential for investment banking activity, high potential for trading commissions and high investor recognition. If our assumption that coverage decisions are constrained, we should observe that successful analysts cover firms that are large, mature and that attract great attention from buy-side investors while unsuccessful analysts follow mainly small, young, growth firms. Following Clement (1999), we use the experience level as a proxy for success. The idea is that experienced analysts tend to be successful analysts as a result of survivorship. Indeed, experienced analysts are analysts that managed to remain in the profession (i.e. they did not get fired).

We introduce a measure that proxy for the potential of firms for investment banking activity, the potential for trading commissions and the investor recognition. Our measure is the result of a Principal Component Analysis on a set of variables that proxy for financial characteristics and fundamentals. We call this new measure the Blue-Chip Index (BCI). We find that there exists a positive and significant relationship between the level of experience and our Blue-Chip Index (BCI). This result indicates that brokerage houses reward successful analysts by assigning them to firms with high potential for investment banking activity, high potential for trading commissions and high investor recognition.

We then investigate whether forecast accuracy influences the likelihood of financial analysts switching to higher BCI firms. We run a panel regression where the dependent variable is the variation between year t and year $t + 1$ of the BCI level of the firms covered by the analysts. We find that forecast accuracy has a positive (negative) significant impact on the probability that an analyst switches to higher (lower) BCI firms. Analysts with low forecast accuracy have 12% less chances to move to higher BCI firms compared to the other analysts. On the contrary, accurate forecasters are 10 percent more likely to move to higher BCI firms. A low (high) accuracy also increases (decreases) the likelihood that an analyst moves to lower BCI firms. Being in the bottom (top) decile of past forecast accuracy increases (decreases) the analyst's chances of switching to lower BCI firms in the

next year by about 25 percent (18 percent).

We find that analysts covering blue-chips are less likely to be terminated by their employer. Analysts who are in the top quintile of firms' BCI see their chances of being terminated decrease by 11 percent compared to other analysts. However, the biggest effect of covering blue-chips is for entering the *Institutional Investor* (I/I) all-star ranking. Non-star analysts who are in the top quintile of firms' BCI have more than twice as many chances of entering the I/I ranking compared to other non-star analysts.

We interpret our findings on forecast accuracy as a result of brokerage houses' concerns for reputation. The structure of analysts' compensation provides them with incentives to generate biased forecasts. However, biased forecasts can potentially hurt the reputation of the brokerage house and, as a consequence, this can reduce the potential for future revenues. For instance, analysts who issue biased forecasts (optimistic forecasts) generate more trading commissions for their brokerage firms. However, this behavior comes at the cost of reputation and decreases long-term gains from building a good reputation. Jackson (2005) shows that market participants assess the analyst reputations with respect to their end-of-period forecast accuracy. Our findings support the idea that brokerage houses provide analysts with short-term incentives (compensation structure) in order to maximize revenues from investment banking and trading commissions, and with long-term incentives (constraints on coverage decisions) in order to maximize reputation and guarantee future streams of revenues. Our findings contribute to the literature on conflict of interests. We document that conflict of interests may be mitigated by the fact that brokerage houses provide analysts with incentives to issue accurate forecasts.

Our study provides a comprehensive analysis of financial analysts' career evolution. Inexperienced analysts start by covering a small number of firms. These firms are typically firms that do not generate a lot of investment banking and trading activity and do not attract a lot of attention from institutional investors. Analysts then gradually switch towards firms that are leaders in their industry. This evolution results from the tournament-like structure of financial analysts' career. Analysts with adverse performance are forced out of the profession and are replaced by better performers. These better performers take over the coverage of the firms previously followed by terminated analysts and they transfer their coverage of small, young, growth firms to analysts who have just arrived in the profession. We evidence that the speed of evolution from small, young, growth firms to blue chips strongly depends on forecast accuracy. The final accomplish-

ment in an analyst's career is to enter then I/I all-star ranking. Our study documents that a prerequisite for becoming an all-star analyst is to cover firms that are leaders in their industry. It follows that experienced analysts are more likely to become all-star analysts as they tend to cover firms that are larger and more mature.

2 Predictions and related research

2.1 Ability and coverage decisions

The earnings of a very able lawyer exceed those of the average lawyer both because he wins more cases and because **he is given the more important cases**. (Mayer, 1960)

Under the assumption that coverage decisions are constrained by brokerage houses, *i.e.* analysts do not have complete discretion regarding which firms to follow, we expect successful analysts to be assigned to more important firms. Therefore, our first hypothesis is

H1: Successful (experienced) analysts are assigned to firms that are large, mature and that attract a lot of attention from buy-side investors.

In the presence of constraints imposed by brokerage houses on coverage decisions, the fact that successful analysts cover firms that are large, mature and that attract a lot of attention from institutional investors (we will denote this firms as blue-chips hereafter) can be seen as the result of two mechanisms.

The first mechanism is that, when deciding to assign an analyst to a blue-chip, brokerage houses have incentives to assign analysts with most abilities. As pointed out by Clement (1999), experience can be used as a proxy for ability. Experienced analysts are more likely to be successful analysts as they managed to remain in the profession (survivorship). Additionally, as the result of a learning process, experienced analysts should have greater skills (Mikhail, Walther, and Willis, 1997; Clement, 1999; Jacob, Lys, and Neale, 1999).

The second mechanism has to do with firm-specific skills and knowledge. When de-

Deciding on which analyst to choose for the coverage of a given firm, brokerage houses have incentives to favor the analyst who is already covering the firm. Analysts with firm-specific experience are superior to analysts who do not cover the firm for numerous reasons. First, analysts with firm-specific experience possess knowledge of the firm's particularities. Their superior knowledge is both qualitative and quantitative. They have a distinct expertise of the legal, regulatory and operational environments of the firm they follow. They have established patterns regarding the firm's strategies and their likely consequences. They have an outstanding understanding of the firm's financial statements and the specific accounting standards followed by the firm. They know what information to look for in financial statements, they know where to look for information and perhaps more importantly, they know how to interpret what is not explicitly disclosed in the financial statements. Second, they have developed contacts with the firm's managers. These contacts provide significantly more information than earnings announcements and financial statements (Rogers and Grant, 1997; Barker, 1998). Third, analysts with firm-specific experience have more insights regarding how to convert qualitative and quantitative information into valuation. The choice of the valuation model chosen by analysts depends both on the firm's characteristics and the industry it belongs to. Finally, these analysts are able to cater to the specific needs of the buy-side clients by providing investment advice tailored to the specific features of the firm under consideration.

With regards to these different elements, assigning a new analyst to a firm appears quite costly. The fixed costs of getting acquainted with firm particularities are high. Acquiring the initial knowledge of the firm, on both qualitative and quantitative issues, is extremely time consuming. The time spent investigating the firm's environment and its business particularities is time not spent generating trading and investment banking revenues. In addition, inexperienced analysts suffer from information asymmetry. Analysts with firm-specific experience possess a track-record which reduces uncertainty regarding their ability to follow a given firm. It follows that the only situation where removing an existing analyst from a firm is a rational choice is the situation where the analyst's covering the firm exhibit subpar performance. When the analyst's performance is sufficiently hurtful to her employer, the brokerage has incentives to dismiss the analyst and to take the risk to appoint a new one.

2.2 Forecast accuracy and coverage assignments

Forecast accuracy matters for job termination and moving to a higher-status brokerage house (Mikhail, Walther, and Willis, 1999; Harrison and Kubik, 2003). However, it has virtually no impact on analysts' compensation. We expect forecast accuracy to matter for future compensation. Accurate forecasters are assigned to more important firms which in turn increases their potential compensation in the next year. Our hypothesis is the following

H2: Accurate forecasters are more likely to be assigned to blue-chips

We expect brokerage houses to value forecast accuracy because it is directly observable by buy-side investors and firm managers (even for market participants that do not have a commercial relationship with the brokerage house). An analyst who is accurate sends a signal to the market that he has a good understanding of the firms she covers and a good knowledge of the industry the firms belong to. By issuing accurate forecasts, the analyst strengthens the reputation of the brokerage house. She sends a message to market participants that they should rely on her brokerage house for their trading and financing needs. Although forecast accuracy does not impact the quality of the relationship between buy-side investors and the brokerage house (or between firm managers and the brokerage house), it may be seen as a prerequisite for trusting the brokerage house (Bradshaw, 2011). Blue chips attract a lot of attention from market participants and generate high revenues for brokerage houses. Therefore, given the stakes at play, the brokerage house needs to make sure that the analysts that are assigned to blue chips do not hurt the reputation of the brokerage house by being inaccurate. These reputation concerns also explain why inexperienced analysts are assigned to small, young, growth firms. When hiring a young analyst, the brokerage cannot evaluate precisely her abilities. Therefore, the brokerage house has incentives to assign the young analyst to firms of lower importance until more information is acquired about the analyst's abilities.

2.3 Coverage assignments and job termination

Analysts are assigned to blue-chips when their brokerage house considers that they have the requisite skills and abilities to provide research of quality and to generate investment banking and trading commissions. Because covering blue-chips is a consequence of being a

successful analyst, we expect analysts covering blue-chips to be less likely to be terminated. Our third hypothesis is

H3: Analysts covering blue-chips are less likely to be terminated (controlling for experience, optimism, forecast boldness, the number of firms covered and forecast accuracy)

2.4 Coverage assignments and star status

Analysts covering blue-chips are analysts whose skills and abilities are recognized by their employer. We therefore expect buy-side investors to recognize their skills as well. In addition, analysts covering blue chips have higher exposure to buy-side investors, especially large buy-side investors. Our fourth hypothesis is

H4: Analysts covering blue-chips are more likely to be recognized as All-star by Institutional Investor (controlling for experience, optimism, forecast boldness, the number of firms covered and forecast accuracy)

As a result of its structure, the I/I ranking represents mainly an assessment of analysts' reputation rather than an assessment of their abilities. Although the I/I ranking is one of the main determinants of analysts' compensation, it is criticized by analysts and institutional investors for being mainly a "popularity contest" (Emery and Li, 2009). The I/I all-star ranking is the result of a survey sent to market participants such as directors of research, equity managers and fund managers. In 2013, to establish the all-star ranking, I/I sent questionnaires covering eight categories and 65 investment sectors to the directors of research and the chief investment officers of major money management firms. Those polled included firms featured in the II300 (I/I ranking of the biggest asset managers in the U.S.) and other significant U.S., European and Asian institutional investors. In addition, they contacted institutional investors from client lists submitted by Wall Street research directors and sent questionnaires to analysts and portfolio managers at many top institutions. The total number of individuals who were contacted amounts to 3,300 individuals from nearly 900 buy-side firms that collectively manage an estimated \$0.5 trillion in U.S. equity assets¹. The ranking of an analyst is the result of the weighted average of the returned scores. Each vote is weighted by the size of the respondent's institution. According to Emery and Li (2009), respondents are asked to name and rank the four best analysts

¹<http://www.institutionalinvestor.com/Research/4556/Overview.html>
<http://www.institutionalinvestor.com/Research/4569/Methodology.html>

in each industry. I/I does not provide the respondents with a list of analysts. Each respondent must recall or look up analyst names (and correct spellings) in order to vote. This mechanism provides an advantage to analysts who have a great exposure to buy-side investors and, in particular, to analysts who have a great exposure to large buy-side investors. Buy-side investors, and especially large buy-side investors, tend to focus more on large, mature firms (as a result of regulatory or internal investment restrictions or as a result of liquidity issues). As a consequence, analysts covering small, young, growth firms tend to have a limited involvement with larger institutions and thus, a lower likelihood to receive votes. Emery and Li (2009) point out that analysts working at regional firms are less likely to be known as they tend to cover local stocks which are typically smaller companies. It follows that covering blue-chips provides the analyst with the opportunity to be familiar with (large) buy-side investors and increases the likelihood that she receives votes for the I/I all-star ranking.

3 Data, measures and descriptive statistics

3.1 Data

Our primary data come from Institutional Brokers Estimate System (I/B/E/S). The data set covers the period from 1981 to 2012 and contains nearly 2.4 million forecasts for the annual earnings of 13,348 firms made by 18,356 analysts. We identify analysts using the code provided by I/B/E/S. We also have, for each forecast, the brokerage affiliation of the analyst. Therefore, we are able to track the analysts when they change brokerage houses. We restrict our sample to the 1990-2012 period in order to be able to compute analysts' experience (in 1990, the most experienced analysts have at least 9 years of experience; in 1991, the most experienced analysts have at least 10 years of experience and so on...). Another reason why we restrict the sample is because of concerns regarding sparse analyst coverage on I/B/E/S previous to 1990 (Harrison Hong and Stein, 2000b; Karl B. Diether and Scherbina, 2002). Our restricted sample contains a little over 2.1 million forecasts for the annual earnings of 12,705 firms made by 15,271 analysts. Our second data set consists of financial and fundamental data obtained from CRSP, Compustat and Thomson Financial.

3.2 Measure of firms' profile

Financial analysts' compensation is tied to the amount of investment banking deals and trading commissions she helps generate. Firms that have a high potential for generating investment banking activity and trading commissions will be deemed more attractive by financial analysts. Indeed, following these firms has a direct impact on analysts' compensation. In addition, financial analysts' compensation is strongly influenced by the outcome of the Institutional Investor All-star ranking. The outcome of this ranking is the result of votes from buy-side investors and especially large buy-side investors (the votes are weighted by the size of the institutions). Hence, covering firms that buy-side investors (and especially large buy-side investors) are interested about increases the odds of being recognized as an All-star analyst.

Anecdotal evidence indicates that firms that have high potential for generating investment banking activity and trading commissions tend to be firms that are large, mature and that have high trading volume. Additionally, these firms are also the ones that attract a lot of attention from institutional investors. These firms are typically called "blue-chips" Our goal here is to create a measure that evaluate to which extent a firm can be classified as a blue-chip.

We turn to Principal Component Analysis (PCA hereafter) in order to build our measure, that we will call the Blue-Chip Index (BCI). This methodology permits to characterize the common factors across firms. Our assumption is that one of these factors, if not the most important factor, is a proxy for the degree to which a firm can be classified as a blue-chip. The purpose of PCA is to reduce the dimensionality of the data space. In the smaller space, interpreting the data is easier. Formally, PCA is a change of basis which permits to locate firms on a meaningful system of coordinates.² The first principal component is the linear combination of the initial variables that maximizes the variance of the projection of the observations on these principal components (*i.e.*, so that it accounts for as much of the variability in the data as possible). The second component is the linear combination of the different variables which maximized the variance under the condition that it is orthogonal to the first component, and so on. If the different variables are perfectly correlated, the first component would explain 100% of the variance. On the contrary, if the different variables are uncorrelated, each component would explain the same amount of the variance (one divided by the number of variables).

²Our PCA is performed on the correlation matrix due to the heterogeneity of the variables.

For our analysis, we define the observations as being the firm-year observations. The variables used for the analysis encompass variables linked to financial characteristics and fundamentals. Our variables are: (1) Capitalization; (2) Book-to-market ratio; (3) Free cash flow scaled by average total assets; (4) External financing scaled by average total assets; (5) Institutional ownership (the fraction of outstanding shares owned by institutional investors); (6) Ownership breadth; (7) Asset growth (average over the past five years); (8) Sales growth (average over the past five years); (9) Accruals (as calculated in Richardson, Sloan, Soliman, and Tuna, 2006); (10) Volume of trading; (11) Momentum; (12) Analyst coverage (number of analysts issuing earnings forecasts for a given firm); (13) Stock return volatility; and, (14) Bid-ask spread. A comprehensive description of the variables is provided in the Appendix.

The first eigenvalue is equal to 3.3012 which implies that 23.58% of the total variation in firm characteristics can be explained by a single common factor. The second component explains about 20.50% of the total variation. Figure 1 shows how the different variables contribute to the first and the second components. We observe that the first component of the PCA is positively correlated with variables that characterize blue chips (Capitalization, analyst coverage, ownership breadth³, volume of trading and free cash flow). This first component is negatively correlated with variables that characterized small, young, growth firms (Stock return volatility, asset growth, sales growth, external financing and bid-ask spread). Note that the contribution of the variables Accruals, Book-to-market, Momentum and Institutional ownership is too small to be taken into account. We define our Blue-Chip Index (BCI) measure as the projection of the firm-year observations on the first component of the PCA.

As an illustration of our methodology, Table 1 provides the year and the name of the firms for the 50 observations with the highest BCI values and the 50 observations with the lowest BCI values. Not surprisingly, we find Dow Jones components like Microsoft, Intel, Cisco, Pfizer and Exxon Mobil among the firms with the highest BCI values.

In order to facilitate the comparisons across sectors, a desirable property for our measure is that the firm which is the leader in a sector A has the same BCI value as a firm that is leader in a sector B. We proceed to the following modification of the measure. For each sector and each year, we sort the firms based on their BCI value. We then assign a ranking based on this sorting; the firm with the highest BCI value receives the first rank,

³Ownership breadth can be used as a proxy for investor recognition (see Scott Richardson and You, 2012)

the second highest receives the second rank, and onward until the firm with the lowest BCI value receives the highest rank. Because the number of firms in each sector varies, we scale the firm's rank by the number of firms that belongs to the sector. Our score measure writes

$$BCI\ score_{i,j,t} = 100 - \left[\frac{BCI\ rank_{i,j,t} - 1}{N_{j,t} - 1} \right] \times 100, \quad (1)$$

where $N_{j,t}$ is the number of firms that belongs to sector j in year t and $BCI\ rank_{i,j,t}$ is the rank of firm i , belonging to sector j , for year t .

For a given sector, the firm with the highest BCI value receives a score of 100 while the firm with the lowest BCI value receives a score of 0.

3.3 Measures of analysts' characteristics

Our analysis uses different analysts' characteristics such as experience, forecast accuracy, forecast boldness and frequency of forecast revisions.

3.3.1 Measure of experience

We build our measure of experience following Clement (1999). We define the *Experience* variable as the number of years for which the analyst has been submitting forecasts to the I/B/E/S database.

3.3.2 Measure of firms' profile covered by analysts

For a given year t , we define the *BCI exposure* of an analyst as the average of the BCI scores of the firms she covers during that year.

3.3.3 Measure of internal promotion and internal demotion

We want to obtain a measure that captures whether an analyst increases (or decreases) over time her BCI exposure, that is, whether an analyst coverage evolves towards high

(low) BCI stocks. The construction of our measure is the following. Each year, we rank analysts with respect to their *BCI exposure*. We then assign the analysts to ten deciles. Our measure of *Internal Promotion* takes the value 1 if the analyst moves from quintile q to quintile $q + 1$ between year t and year $t + 1$. Our measure of *Internal Promotion* takes the value 0 if the previous condition is not met or if the analyst is terminated in year $t + 1$. Note that this measure cannot apply to analysts who are in the top quintile in year t . Our measure of *Internal Demotion* takes the value 1 if the analyst moves from quintile q to quintile $q - 1$ between year t and year $t + 1$ or if she is terminated in year $t + 1$.

3.3.4 Measure of forecast accuracy

We use a relative measure of forecast accuracy to evaluate analysts' forecasting performance. We define our *Accuracy* measure as in Hong, Kubik, and Solomon (2000). For each firm and analyst, we compute the absolute forecast error for the last earnings forecast issued by the analyst before the end of the fiscal year. We then order analysts, for each firm and each year, based on their forecast errors. The analyst with the lowest absolute forecast error receives the first rank, the analyst with the second lowest absolute forecast error receives the second rank and so on. If two or more analysts have the same absolute forecast error, we assign these analysts to the midpoint value of the ranks they take up. We then transform the ranks into scores in order to account for differences in the number of analysts covering the different firms. The score is then obtained by applying the following formula

$$Score_{i,j,t} = 100 - \left[\frac{Rank_{i,j,t} - 1}{n_{j,t} - 1} \right] \times 100 \quad (2)$$

where $n_{j,t}$ is the number of analysts who follow firm j in year t . The relative accuracy measure, $Accuracy_{i,t}$, is the average accuracy scores over all the companies covered by analyst i in year t .

3.3.5 Measure of forecast boldness

Our measure of *Boldness* in earnings forecast is adapted from Hong, Kubik, and Solomon (2000). We define, for firm j in year t , our measure of forecast consensus $\bar{F}_{-i,j,t}$ as the average of the earnings forecasts made by all other analysts except analyst i . We then calculate the deviation from consensus as $|F_{i,j,t} - \bar{F}_{-i,j,t}|$. The process to obtain the *Boldness*

measure is then similar to the one we followed for the *Accuracy* measure. For each firm and each year, we rank analysts with regard to their deviation from consensus. We transform these ranks into scores as in equation 2. The relative boldness measure, $Boldness_{i,t}$, is then the average boldness scores over all companies covered by analyst i in year

3.4 Descriptive statistics

Table 2 provides data on analysts' characteristics and on the characteristics on the firms covered by analysts. We categorize analysts by level of experience and provide the mean value for each characteristic. These descriptive statistics suggest several interesting features. First, we observe that the number of firms covered and the number of industries covered increase with the number of years of experience. We also find that the proportion of all-star analysts is strongly related to the level of experience of analysts. The proportion of all-star analysts among analysts who have just initiated coverage in I/B/E/S is as low as 0.55 percent. This proportion increases to above 17% for the most experienced analysts. Column (4) provides information on the BCI exposure of the analysts in our sample. We observe a positive correlation between the BCI exposure and the level of experience. Columns (5)-(9) give more detailed information about the characteristics of the firms covered by analysts, conditional on their level of experience. The capitalization, ownership breadth and trading volume of the firms covered increase with the analysts' experience. On the contrary, the size of the bid-ask spread and the stock return volatility of the firms' covered is negatively linked with experience. These simple statistics suggest that experienced analysts and inexperienced analysts do not cover the same type of firms.

4 Empirical results

4.1 Analysts' characteristics and profile of covered firms

We run the following regression to analyze the relationship between the characteristics of the firms followed by the analysts and their experience.

$$\begin{aligned} BCI_{i,j,t} = & \beta_0 + \beta_1 Experience_{i,t} \\ & + \beta_2 Number\ of\ stocks\ covered_{i,t} \\ & + \beta_3 Brokerage\ status_{i,t} \\ & + year_t\ effects + industry_{j,t}\ effects + \epsilon_{i,t} \end{aligned} \tag{3}$$

where $BCI_{i,j,t}$ is the Blue Chip Index value of firm j covered by analyst i in year t , $Experience_{i,t}$ corresponds to the number of year the analyst has been reporting forecasts in the I/B/E/S database, $Number\ of\ stocks\ covered_{i,t}$ is the number of stocks covered by analyst i in year t , $Brokerage\ status_{i,t}$ is a dummy variable that takes the value 1 if the analyst works for a high-status brokerage house and 0 otherwise, $year_t\ effects$ is a set of dummies for each year of the sample and $industry_{j,t}\ effects$ is a set of dummies for each industry.

Table 3 provides the regression results. The coefficient for *Experience* is positive (0.4155) and significant, consistent with the fact that successful analysts cover firms that have blue-chips characteristics. The coefficient for the *Number of stocks covered* is not significantly different from 0. The coefficient for *Brokerage status* is positive and significant. The effect of the *Brokerage status* variable is not surprising as analysts working for high-status brokerage houses tend to cover large firms.

4.2 Internal career and forecast accuracy

We look at the influence of past forecast accuracy on the type of firms covered by the analyst. We consider the following probit model specification

$$\begin{aligned} & \Pr(\text{Internal promotion}_{i,t+1}) \\ &= \Phi \left(\begin{array}{l} \beta_0 + \beta_1 \text{Forecast accuracy indicator}_{i,t} + \text{Boldness}_{i,t} \text{ effects} \\ \quad + \text{Optimism}_{i,t} \text{ effects} + \text{Experience}_{i,t} \text{ effects} \\ \quad + \text{Number of firms covered}_{i,t} \text{ effects} + \text{Year}_t \text{ effects} \end{array} \right) \end{aligned} \quad (4)$$

where *Internal promotion*_{*i,t+1*} is an analyst's favorable career outcome within her brokerage firm (*i.e.*, whether analyst *i* moves from quintile *q* of *BCI exposure* in year *t* to quintile *q*+1 in year *t*+1), and *Forecast accuracy indicator*_{*i,t*} is some function of the analyst's past forecast accuracy measured as of year *t*. We control for the analyst's degree of optimism and boldness by including *Boldness*_{*i,t*} *effects* and *Optimism*_{*i,t*} *effects*. We include some additional variables in order to control for the type and number of firms that analysts follow in year *t* as these variables might have an impact on our dependent variable. We add dummy variables to control for the years of experience of the analyst (*Experience*_{*i,t*} *effects*). We also include dummy variables for the number of firms followed by the analyst during year *t* (*Number of firms covered*_{*i,t*} *effects*). Finally, we add a full set of year dummies (*Year*_{*t*} *effects*).

We are also interested in analysts' unfavorable career outcomes within her brokerage firm. We consider this second probit model specification

$$\begin{aligned} & \Pr(\text{Internal demotion}_{i,t+1}) \\ &= \Phi \left(\begin{array}{l} \beta_0 + \beta_1 \text{Forecast accuracy indicator}_{i,t} + \text{Boldness}_{i,t} \text{ effects} \\ \quad + \text{Optimism}_{i,t} \text{ effects} + \text{Experience}_{i,t} \text{ effects} \\ \quad + \text{Number of firms covered}_{i,t} \text{ effects} + \text{Year}_t \text{ effects} \end{array} \right) \end{aligned} \quad (5)$$

where *Internal demotion*_{*i,t+1*} is an analyst's unfavorable career outcome within her brokerage firm (*i.e.*, whether analyst *i* moves from quintile *q* of *BCI exposure* in year *t* to

quintile $q - 1$ in year $t + 1$ or analyst i is terminated in year $t + 1$).⁴

Table 4 presents the results of the estimations of these two probit models. In columns (1)-(3), the dependent variable is whether an analyst experiences an internal promotion, that is, whether the analyst moves to a higher quintile of BCI exposure in year $t + 1$. In column (1), being in the bottom 10 percent of relative accuracy decreases the probability of experiencing this favorable outcome by 3.19 percentage points. This effect is statistically significant at the one percent significance level. In any given year, about 26.48 percent of analysts obtain an internal promotion. Therefore, being inaccurate decreases the likelihood of experiencing an internal promotion by about 12 percent. In column (2), being in the top 10 percent of relative accuracy increases the probability of experiencing an internal promotion by 1.70 percentage point. This effect is significant at the 10 percent significance level. Being among the best forecasters therefore increases an analyst's chances of experiencing a favorable internal career outcome by about 4 percent. In column (3), we compare the effect of being in the 9 bottom deciles of past forecast accuracy on obtaining an internal promotion compared to being in the top accuracy decile. The biggest effect is in the bottom 10 percent. The difference, between the top and bottom deciles of past accuracy, in the probability of obtaining an internal promotion is equal to 4.37 percentage points.

In columns (4)-(6), the dependent variable is whether an analysts experiences an internal demotion, that is, whether the analyst moves to a lower quintile of BCI exposure in year $t + 1$ or whether she is being terminated in year $t + 1$. In column (4), being among the worst forecasters increases the probability of such an unfavorable outcome by 7.05 percentage points. On average, 28.27 percent of analysts experience this unfavorable outcome. It follows that being in the bottom decile of past forecast accuracy increases the analyst's chances of experiencing an internal demotion by about 25 percent. Being in the

⁴One could be concerned with the influence of including analysts who are terminated in year t on our results. In order to make sure that our results describe the impact of forecast accuracy on BCI exposure and not only the impact of forecast accuracy on job termination, we ran the following regression

$$\text{BCI exposure}_{i,t+1} - \text{BCI exposure}_{i,t} \tag{6}$$

$$= \beta_0 + \beta_1 \text{Forecast accuracy indicator}_{i,t} + \text{Boldness}_{i,t} \text{ effects} \\ + \text{Optimism}_{i,t} \text{ effects} + \text{Experience}_{i,t} \text{ effects} \\ + \text{Number of firms covered}_{i,t} \text{ effects} + \text{Year}_t \text{ effects} \tag{7}$$

. The estimation of this additional regression indicates that forecast accuracy has a significant and positive influence on BCI exposure. Being among the best forecasters increases the chances of covering firms with higher BCI values. Our results are similar if we add the variables linearly or non-linearly to the regression specification.

top decile of forecast accuracy, in column (5), decreases the probability that the analyst experiences an unfavorable outcome by about 18 percent. In column (6), we see that being in the bottom decile of past accuracy increases the probability that the analyst faces an internal demotion by 11.24 percentage points compared to an analyst in the top decile of past accuracy.

These results indicate that accurate forecasters are rewarded by brokerage houses which assign their best performers to firms that have more potential for investment banking activity, a higher potential for trading commissions and that attract more attention from investors. It appears that the effect of poor accuracy is larger than the effect of high accuracy. The influence of past accuracy is significant both for internal promotion and internal demotion.

4.3 BCI exposure and job termination

We now investigate whether the profile of firms covered by an analyst impacts the likelihood of job termination. We run the following probit regression

$$\begin{aligned} & \Pr(\text{Job termination}_{i,t+1}) \\ &= \Phi \left(\begin{array}{l} \beta_0 + \beta_1 \text{BCI exposure indicator}_{i,t} + \text{Boldness}_{i,t} \text{ effects} \\ + \text{Optimism}_{i,t} \text{ effects} + \text{Experience}_{i,t} \text{ effects} + \text{Accuracy}_{i,t} \text{ effects} \\ + \text{Number of firms covered}_{i,t} \text{ effects} + \text{Year}_t \text{ effects} \end{array} \right) \quad (8) \end{aligned}$$

where $\text{Job termination}_{i,t+1}$ is a dummy variable that takes the value 1 if the analyst is terminated in year $t + 1$ and 0 otherwise, and $\text{BCI exposure indicator}_{i,t}$ is some function of the analyst's BCI exposure measured as of year t .

Table 5 presents the results of the estimation of this probit model. In column (1), being in the bottom 20 percent of BCI exposure increases the probability of being terminated by 0.0064 percentage points. However, this effect is not significantly different from 0. In column (2), being in the top quintile of BCI exposure decreases the probability of termination by 1.46 percentage point. This effect is significant at the 5 percent significance level. In any given year, about 13.05 percent of analysts are terminated. Therefore, covering high BCI firms decreases the likelihood of facing this unfavorable career outcome by about 11 percent. In column (3), we compare the effect of being in the 4 bottom

quintiles of BCI exposure on the likelihood of termination compared to being in the top BCI exposure quintile. The difference, between the top and bottom quintiles of BCI exposure, in the probability of being terminated is equal to 1.77 percentage points and is statistically different from 0 at the 5 percent significance level.

4.4 BCI exposure and *Institutional Investor* ranking

$$\begin{aligned} & \Pr(All-star_{i,t+1}) \\ &= \Phi \left(\begin{array}{l} \beta_0 + \beta_1 BCI \text{ exposure indicator}_{i,t} + Boldness_{i,t} \text{ effects} \\ + Optimism_{i,t} \text{ effects} + Experience_{i,t} \text{ effects} + Accuracy_{i,t} \text{ effects} \\ + Number \text{ of firms covered}_{i,t} \text{ effects} + Year_t \text{ effects} \end{array} \right) \quad (9) \end{aligned}$$

where $All-star_{i,t+1}$ is a dummy variable that takes the value 1 if the analyst is classified as all-star analyst by the *Institutional Investor* ranking in year $t + 1$ and 0 otherwise, and $BCI \text{ exposure indicator}_{i,t}$ is some function of the analyst's BCI exposure measured as of year t .

The results are presented in Table 6. Columns (1)-(3) correspond to the estimation of the probit specification using the entire sample. In column (1), being in the bottom 20 percent of BCI exposure decreases the probability of being in the all-star I/I ranking by 9.44 percentage points. This effect is statistically significant at the one percent significance level. In any given year, about 13.31 percent of analysts are being classified as all-star analysts. Therefore, covering low BCI firms decreases the likelihood of facing this favorable career outcome by about 71 percent. In column (2), being in the top quintile of BCI exposure in year t increases the probability of being in the all-star I/I ranking in year $t + 1$ by 11.44 percentage point compared to other analysts. This effect is significant at the 1 percent significance level. Being among the analysts who cover blue-chips thus increases an analyst's chances of being in the all-star I/I ranking by about 86 percent. In column (3), we compare the effect of being in the 4 bottom quintiles of BCI exposure on the likelihood of termination compared to being in the top BCI exposure quintile. The biggest effect is in the bottom 20 percent. The difference, between the top and bottom quintiles of BCI exposure, in the probability of being terminated is equal to 17.69 percentage points. In columns (4)-(6), we examine the impact of BCI exposure on the probability for a non

all-star analyst to become an all-star analyst. The proportion of non all-stars in one year who become all-stars in the next year is 2.86%. In column (4), covering low BCI firms decreases the probability of becoming an all-star analyst by 1.95 percentage points. This effect is highly significant. Compared to other analysts, the analysts in the first quintile of BCI exposure are about 68% less likely to enter the I/I all-star ranking. In column (5), being in the top quintile of BCI exposure increases the likelihood of becoming an all-star analyst by 3.27 percentage points. Being among the analysts who cover blue-chips thus increases an analyst's chances of entering the I/I all-star ranking by as much as 114 percent. In column (6), we observe that the probability of becoming an all-star analyst increases monotonically with the BCI exposure. The difference, between the top and bottom quintiles of BCI exposure, in the probability of becoming an all-star analyst is equal to 4.40 percentage points and is statistically different from 0 at the 1 percent significance level.

In columns (7)-(9), we examine the impact of BCI exposure on the probability for an all-star analyst to stay in the I/I all-star ranking. We observe that the type of firms covered matters less for analysts who are already in the ranking. The only significant effect that we observe is for analysts in the bottom quintile of BCI exposure. In column (7), being in the bottom quintile of BCI exposure decreases the likelihood of repeating by 3.55 percentage points. This effect is significant at the 10% significance level.

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Appendix

Variable	Description
Capitalization	Market capitalization of common equity (in billions of dollars).
Book-to-market ratio	Book-to-market ratio, calculated as the ratio of the book value to the market value of common equity.
Free cash flow	Free cash flow scaled by average total assets.
External financing	External financing scaled by average total assets.
Institutional ownership	Fraction of outstanding shares owned by institutional investors.
Ownership breadth	Ratio of the number of institutional investors who hold a long position in the stock to the total number of institutional investors covered in the Thomson database for that quarter.
Asset growth	Average asset growth over the past five years.
Sales growth	Average sales growth over the past five years.
Accruals	Total accrual as calculated in Richardson, Sloan, Soliman, and Tuna (2006).
Analyst coverage	Number of analysts issuing earnings forecasts for a given firm.
Stock return volatility	6-month historical stock return volatility.
Bid-ask spread	Bid-ask spread divided by bid-ask midpoint.

Figure 1
Projection of firms' characteristics variables on the two first components of the PCA

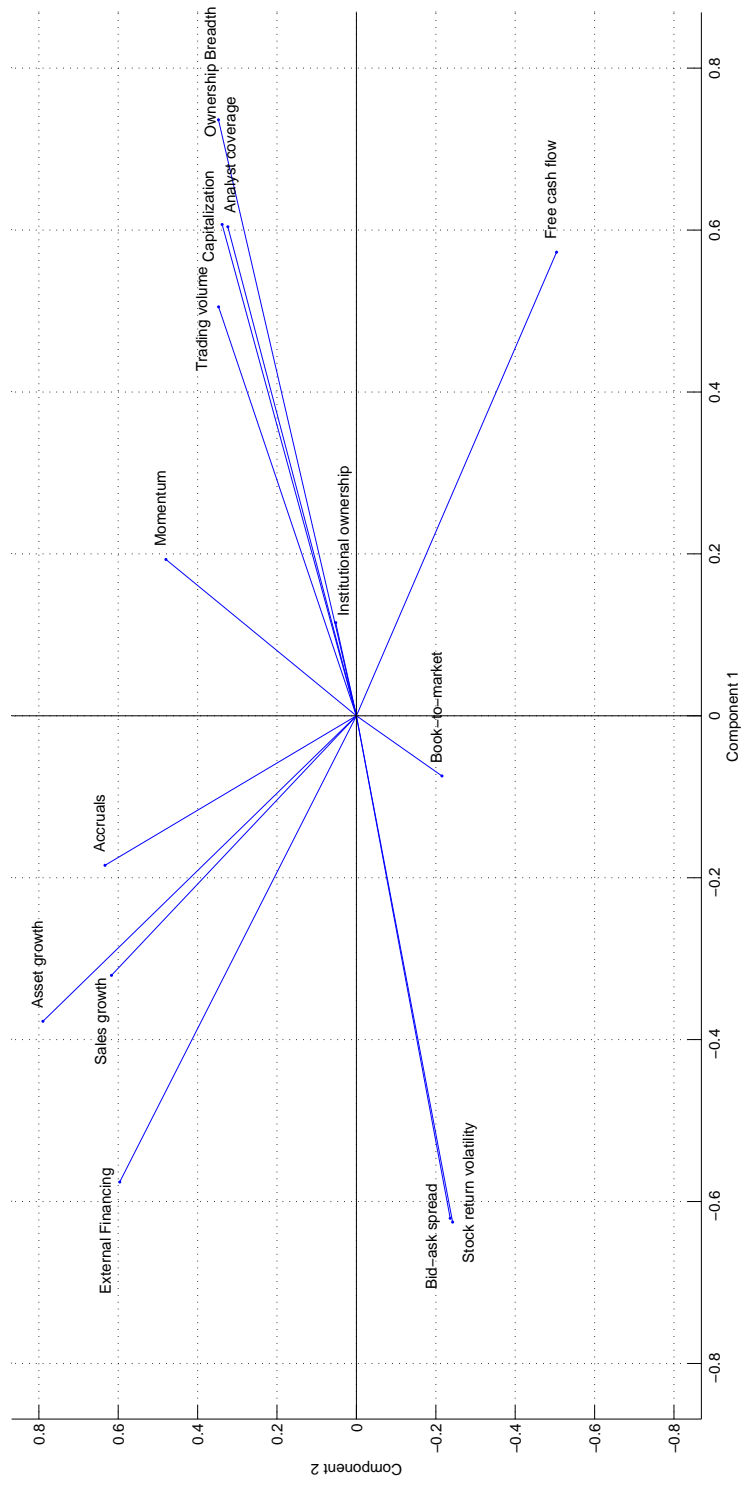


Table 1

Firms-years with the highest and the lowest BCI values

Firm-year with highest BCI values		Firm-year with lowest BCI values	
Firm-year	BCI measure	Firm-year	BCI measure
APPLE INC (2012)	45.99160568	VARSITY GROUP (2000)	-13.18691848
APPLE INC (2011)	29.65385129	INTERWAVE COMM (2000)	-12.10245051
APPLE INC (2010)	24.70290872	HARRIS INTRACTVE (2000)	-11.91810518
CISCO SYS INC (2000)	21.70325068	SAVVIS COMM. (2000)	-11.59715578
MICROSOFT CP (1999)	21.18254596	APROPOS TECH INC (2000)	-11.40728097
MICROSOFT CP (2000)	21.15638507	EMERGE INTERACT (2000)	-11.25900391
EXXON MOBIL CORP (2008)	21.14954315	NAVISITE INC (2000)	-11.23185115
EXXON MOBIL CORP (2007)	20.92929815	TURNSTONE SYS. (2000)	-11.15639538
INTEL CP (2000)	20.4310431	SEMGROUP ENERGY (2008)	-11.06291543
APPLE INC (2008)	19.27608689	NETRO CORP. (2000)	-10.84815119
MICROSOFT CP (2001)	18.68995169	WITNESS SYSTEMS (2000)	-10.70836076
EXXON MOBIL CORP (2011)	17.77343431	ELOQUENT INC (2000)	-10.57225074
MICROSOFT (2007)	17.71837319	FTD.COM INC (2000)	-10.44042356
EXXON MOBIL CORP (2009)	17.51268426	CDNOW INC (1998)	-10.11009346
EXXON MOBIL CORP (2006)	17.43958681	FIREPOND INC (2000)	-9.901368889
MICROSOFT CP (2005)	17.43704919	IMAGEX.COM INC (2000)	-9.854255991
EXXON MOBIL CORP (2012)	17.36941927	CHORDIANT SFTWRE (2000)	-9.828481503
APPLE INC (2007)	17.18062059	LANTE CORP (2000)	-9.757036943
MICROSOFT CP (2004)	17.0363242	AVENUE A INC (2000)	-9.742939215
MICROSOFT CP (2002)	17.02760588	CONCUR TECH (1999)	-9.705361663
MICROSOFT (2006)	16.75500053	SONIC FOUNDRY (2000)	-9.611391026
MICROSOFT CP (2003)	16.66279467	EVOLVE SOFTWARE (2001)	-9.532969179
EXXON MOBIL CORP (2005)	16.27057437	M-SYSTEMS FLASH (2000)	-9.32317083
MICROSOFT (2008)	16.05089744	SYCAMORE NTKWS. (2000)	-9.322773063
EXXON MOBIL CORP (2010)	16.04964434	DIGITAL ISLAND (2000)	-9.284253202
MICROSOFT (2010)	15.30308887	EFFICIENT NTKWS (2000)	-9.257961507
INTEL CP (1999)	14.82095271	INFORTE CORP. (2000)	-9.183962402
MICROSOFT (2012)	14.39019844	NET2PHONE INC (2000)	-9.070227392
MICROSOFT (2011)	14.22928495	KOS PHARMA INC (1999)	-9.05091443
AGILYSYS INC. (2007)	14.13164575	TUT SYSTEMS INC (1999)	-9.023965516
APPLE INC (2009)	13.96911077	AUDIO BOOK CLUB (1998)	-8.816635274
MICROSOFT CP (1998)	13.45538756	ASK JEEVES INC (2000)	-8.732505732
EXXON MOBIL CORP (2004)	13.44391551	ALTEON WEBSYSTEMS (2000)	-8.719032056
INTEL CP (2004)	13.42859075	CELGENE CP (2000)	-8.661539404
ORACLE CORP (2000)	13.35309568	BROADBASE SOFT (2000)	-8.59141528
EXXON MOBIL CORP (2000)	13.24378147	ABGENIX INC (2000)	-8.588369579
GOOGLE (2007)	13.17267958	NATL ENVTL GRP (1991)	-8.586890101
PFIZER INC (2004)	13.08650459	CIMA LABS (2000)	-8.568752826
MICROSOFT (2009)	13.06158823	CLARUS CORP (2000)	-8.537760564
GOOGLE (2012)	13.01663351	METRICOM INC (1999)	-8.447082197
EXXON MOBIL CORP (2001)	12.93541356	RECYCLING INDUS (1998)	-8.428312621
INTEL CP (2005)	12.84385996	SILVERSTREAM SFW (2000)	-8.411445663
INTEL CP (2001)	12.80095742	VA LINUX SYS (2000)	-8.398931922
CISCO SYS INC (1999)	12.61005955	LIFEMINDERS INC (2000)	-8.37901466
INTEL CP (1997)	12.52627002	BAM! ENTERAIN (2002)	-8.34723282
PFIZER INC (2001)	12.42221456	BUY.COM INC (2000)	-8.330007112
GOOGLE (2008)	12.25370127	PHOTON DYNAMICS (2000)	-8.314189234
INTEL CP (2003)	12.24820887	PEAPOD INC (2000)	-8.289794196
GOOGLE (2011)	12.1822726	DYNAVAX TECH (2008)	-8.214197009
INTL BUS MACH (2012)	12.15829686	VIRATA (2000)	-8.18918788

This table provides the name and year of the 50 observations (firm-year) with the highest BCI values and the 50 observations with the lowest BCI values. The BCI values are computed using the first component from an Principal Component Analysis performed on the following firm characteristics: (1) Capitalization; (2) Book-to-market ratio; (3) Free cash flow scaled by average total assets; (4) External financing scaled by average total assets; (5) Institutional ownership (the fraction of outstanding shares owned by institutional investors); (6) Ownership breadth; (7) Asset growth (average over the past five years); (8) Sales growth (average over the past five years); (9) Accruals (as calculated in Richardson, Sloan, Soliman and Tuna, 2006); (10) Volume of trading; (11) Momentum; (12) Analyst coverage (number of analysts issuing earnings forecasts

Table 2
Descriptive statistics

Years of experience	Analysts' characteristics				Characteristics of the firms covered by analysts				
	Nb firms covered	Nb industries covered	Proportion of all-star	BCI exposure	Capitalization	Ownership breadth	Trading volume	Bid ask spread	Volatility
1 year	4.9259	2.2233	0.0055	0.5924	7556.3810	0.0933	16327.8193	0.0428	0.0334
2 years	7.6318	2.9548	0.0160	0.6066	7471.2556	0.0950	15729.3788	0.0420	0.0329
3 years	9.3561	3.2920	0.0374	0.6278	7752.1157	0.0985	16414.1762	0.0414	0.0324
4 years	10.5464	3.4997	0.0640	0.6355	8166.6544	0.1019	16374.4507	0.0412	0.0322
5 years	11.5996	3.6749	0.0879	0.6527	8776.3520	0.1061	18142.2669	0.0402	0.0315
6 years	12.3686	3.7790	0.1096	0.6619	9064.0283	0.1090	18985.0487	0.0393	0.0307
7 years	12.8442	3.9263	0.1114	0.6680	9307.2191	0.1109	19160.9097	0.0385	0.0300
8 years	13.4566	4.0527	0.1361	0.6772	9955.1017	0.1136	20503.8556	0.0373	0.0291
more than 8 years	14.4631	4.1685	0.1748	0.6927	10467.5453	0.1165	20471.5986	0.0361	0.0283

This table presents descriptive statistics for analysts conditioned to their level of experience. Column 2 indicates the average number of firms covered per analyst. Column 3 indicates the average of industries covered per analyst. Column 4 gives the proportion of all-star analysts among analysts with the given level of experience. Column 5 gives the average BCI exposure per analyst. Column 6 indicates the average level of capitalization covered by analysts with the given level of experience. Column 7 indicates the average ownership breadth of the firms covered by analysts with the given level of experience. Column 8 indicates the average trading volume of the firms covered by analysts with the given level of experience. Column 9 indicates the average bid-ask spread of the firms covered by analysts with the given level of experience. Column 10 indicates the average level of stock return volatility of the firms covered by analysts with the given level of experience.

Table 3
Experience and profile of firms covered

	Blue Chip Index (BCI) of firms covered			
	Coefficient	Robust standard error	t-statistic	p-value
<i>Experience</i>	0.415535***	0.055054	7.55	0.000
<i>Number of stocks covered</i>	0.001591	0.030321	0.05	0.958
<i>Brokerage status</i>	6.487799***	0.412828	15.72	0.000
Year dummies		Yes		
Industry dummies		Yes		
Number of observations		1,609,275		
R-squared		0.0901		

This table shows the coefficient estimates (Coefficients) from the following OLS regression: $BCI_{i,j,t} = \alpha + \beta_1 Experience_{i,t} + \beta_2 Number\ of\ stocks\ covered_{i,t} + \beta_3 Brokerage\ status_{i,t} + year_t\ effects + industry_{j,t}\ effects + \epsilon_{i,j,t}$, where $BCI_{i,j,t}$ is the Blue Chip Index value of firm j covered by analyst i in year t , $Experience_{i,t}$ corresponds to the number of year the analyst has been reporting forecasts in the IBES database, $Number\ of\ stocks\ covered_{i,t}$ is the number of stocks covered by analyst i in year t , $Brokerage\ status_{i,t}$ is a dummy variable that takes the value 1 if the analyst works for a high-status brokerage house and 0 otherwise, $year_t\ effects$ is a set of dummies for each year of the sample and $industry_{j,t}\ effects$ is a set of dummies for each industry. ***/**/* correspond to 1%/5%/10% significance levels. P-values are computed using robust analyst-clustered standard errors.

Table 4

The effect of past accuracy on internal promotion and demotion

	Internal Promotion			Internal Demotion		
	(1)	(2)	(3)	(4)	(5)	(6)
Bottom 10% of accuracy	-0.1008*** (0.0316) [-0.0319]		-0.1345*** (0.0401) [-0.0437]	0.2015*** (0.0265) [0.0705]		0.3114*** (0.0349) [0.1124]
2 nd decile dummy			-0.0888** (0.0385) [-0.0293]			0.2143*** (0.0345) [0.0758]
3 rd decile dummy			-0.0270 (0.0382) [-0.0091]			0.1708*** (0.0347) [0.0598]
4 th decile dummy			-0.0376 (0.0383) [-0.0126]			0.1122*** (0.0351) [0.0387]
5 th decile dummy			-0.0438 (0.0387) [-0.0147]			0.1373*** (0.0351) [0.0473]
5 th decile dummy			0.0260 (0.0381) [0.0087]			0.1155*** (0.0351) [0.0372]
7 th decile dummy			-0.0532 (0.0385) [-0.0177]			0.1251*** (0.0350) [0.0433]
8 th decile dummy			-0.0533 (0.0382) [-0.0178]			0.0637* (0.0350) [0.0217]
9 th decile dummy			-0.0316 (0.0380) [-0.0106]			0.0814** (0.0348) [0.0278]
Top 10% of accuracy		0.0516* (0.0289) [0.0170]			-0.1553*** (0.0264) [-0.0500]	
Forecast Optimism Effects	Yes	Yes	Yes	Yes	Yes	Yes
Forecast Boldness Effects	Yes	Yes	Yes	Yes	Yes	Yes
Average coverage Effects	Yes	Yes	Yes	Yes	Yes	Yes
Experience Effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of Firms covered Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Effects	Yes	Yes	Yes	Yes	Yes	Yes
Log Likelihood	-14,590.20	-14,593.75	-14,584.07	-18,058.98	-18,070.12	-18,033.28
Number of observations	25,597	25,597	25,597	31,254	31,254	31,254

Financial analysts are tracked to examine if past forecast accuracy affects the likelihood that an analyst sees her BCI exposure increase or that an analyst see her BCI exposure decrease. We consider that the analyst experiences an internal promotion in year $t + 1$ if she moves from quintile q of BCI exposure to quintile. We consider that the analyst experiences an internal demotion in year $t + 1$ if she moves from quintile q of BCI exposure to quintile $q - 1$ between year t and year $t + 1$ or if she is terminated in year $t + 1$. The probit specifications are in equations 4 and 5. Standard errors are in parenthesis. The entries in brackets are the marginal probabilities that an analyst with the various accuracy scores experiences an internal promotion (or demotion) compared to other analysts. ***/**/* correspond to 1%/5%/10% significance levels.

Table 5

The effect of BCI exposure on job termination

	Job termination		
	(1)	(2)	(3)
Bottom 20% of BCI exposure	0.0309 (0.0272) [0.0064]		0.0878*** (0.0340) [0.0177]
2 nd quintile dummy			0.1188*** (0.0308) [0.2430]
3 rd quintile dummy			0.0821*** (0.0305) [0.0165]
4 th quintile dummy			0.0106 (0.0309) [0.0020]
Top 20% of BCI exposure		-0.0730*** (0.0253) [-0.0146]	
Forecast Optimism Effects	Yes	Yes	Yes
Forecast Boldness Effects	Yes	Yes	Yes
Experience Effects	Yes	Yes	Yes
Number of Firms covered Effects	Yes	Yes	Yes
Year Effects	Yes	Yes	Yes
Log Likelihood	-10,558.18	-10,554.61	-10,547.38
Number of observations	28,045	28,045	28,045

Financial analysts are tracked to examine if their BCI exposure affects their likelihood of being terminated. The probit specification is in equation 8. Standard errors are in parenthesis. The entries in brackets are the marginal probabilities that an analyst with the various levels of BCI exposure gets terminated compared to other analysts. ***/**/* correspond to 1%/5%/10% significance levels.

Table 6
The effect of BCI exposure on all-star recognition

	Entire Sample			Non-star analysts			Star analysts		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Bottom 20% of BCI exposure	-0.7400*** (0.0468) [-0.0944]		-1.0874*** (0.0503) [-0.1769]	-0.4089*** (0.0737) [-0.0195]		-0.7662*** (0.0789) [-0.0440]	-0.1274* (0.0665) [-0.0335]		-0.1457* (0.0873) [-0.0380]
2 nd quintile dummy			-0.8930*** (0.0372) [-0.1619]			-0.6899*** (0.0625) [-0.0421]			-0.0685 (0.0865) [-0.0172]
3 rd quintile dummy			-0.5165*** (0.0316) [-0.1149]			-0.4893*** (0.0542) [-0.0351]			0.0083 (0.0869) [0.0020]
4 th quintile dummy			-0.1645*** (0.0292) [-0.0435]			-0.1793*** (0.0468) [-0.0166]			-0.0061 (0.0855) [-0.0015]
Top 20% of BCI exposure		0.5218*** (0.0249) [0.1144]			0.4419*** (0.0400) [0.0327]			0.0498 (0.0699) [0.0125]	
Forecast Optimism Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Forecast Boldness Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Experience Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of Firms covered Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Log Likelihood	-8,582.28	-8,526.16	-8,196.92	-2,662.48	-2,629.81	-2,575.49	-1,478.63	-1,480.19	-1,478.10
Number of observations	24,557	24,557	24,557	21,278	21,278	21,278	3,279	3,279	3,279

Financial analysts are tracked to examine if their BCI exposure affects their likelihood of becoming an all-star analyst. The probit specification is in equation 9. In columns (1)-(3), we consider the entire sample. In columns (4)-(6), we examine the influence of non-star analysts' BCI exposure on the likelihood that they enter the all-star I/I ranking. In columns (7)-(9), we examine the influence of star analysts' BCI exposure on the likelihood that they stay in the all-star I/I ranking. Standard errors are in parenthesis. The entries in brackets are the marginal probabilities that an analyst with the various levels of BCI exposure is classified as an all-star analyst. ***/**/* correspond to 1%/5%/10% significance levels.