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Analyzing the analysts: The effect of technical and social skills on analyst career

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ABSTRACT

This paper investigates how technical and social skills of financial analysts affect their performance and career advancement. Using a sample of LinkedIn profiles of financial analysts, we document that analysts with good social skill, proxied by the number of social connections, generate more accurate earnings forecasts and produce more informative stock recommendations. These analysts are also more likely to be voted as All-Star analysts and to move to high-status brokers when changing jobs. However, the effect of technical skills, proxied by the quantitative skills disclosed on LinkedIn, only affect earnings forecast accuracy. The analysts with technical skills are indifferent in the likelihood of being voted as star analysts and job separations comparing with other analysts. These findings provide the first large sample evidence that social skills are more important than technical skills in analyst career advancement.

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1. Introduction

Every year buy-side institutions are solicited to vote for the Institutional Investor All-American Research Teams and provide opinions on the most valuable attributes of analysts. These attributes are both "soft" (such as industry knowledge, accessibility and responsiveness, and special service) and "hard" (such as financial models and earnings estimates).[1] Institutions always rank those "soft" attributes at the top and far ahead of "hard" ones, suggesting that there is a huge demand for "soft" attributes. Prior academic research has identified the value of analysts to investors in both their depth of information analysis and the breath of information search (Bradshaw 2011, Brown et al. 2015). While we have identified many determinants of analyst performance and career outcome over last two decades, we haven't explored the effect of analyst technical and social skills on their career. These skills, particularly social skills, may be highly associated with the "soft" features valued by institutional investors. The recent emergence of social media such as LinkedIn makes such an inquiry possible. Using self-disclosed quantitative skills as the proxy for technical skills and the size of social connections as the proxy for social skills, in this paper we examine how technical and social skills of financial analysts affect their performance such as forecast accuracy and stock recommendation informativeness and their career outcome.

Technical and social skills are both important for an individual's success on the labor market. A number of prior studies find that employees' technical skills are positively associated with performance and productivity. For example, Abraham and Spletzer (2009) provide evidence

[1] Institutional Investor Magazine holds voting every year and publishes the results in October.

that technical skills are highly rewarded in the labor market based on U.S. Census Bureau's Current Population Survey (CPS). Technical skills are also the basic qualification for a financial analyst. Financial analyst job listings usually require the candidates to have certain level of technical skills, for example, financial modelling, or equity valuation. Surveys and interviews with financial analysts suggest that technical skills are components of client or institutional investor votes which are highly related to analysts' compensation (Brown et al. 2015, Groysberg et al. 2011, Yin and Zhang 2014).

People with good social skills often establish a sizable social network. Social connections are widely studied in the economic and psychology literature. For example, Karlan et al. (2009) find that social connections smooth and secure information transfer. Baker (2000) shows that social connections are an important source of social capital which is critical for information acquisition. Analysts with broad social connections have more information sources which include senior officers from target firms, peers, financial journalists, customers, suppliers, and competitors. The information received from various social connections can potentially help financial analysts make better assessment about the firms and improve their performance. Social connections may also help advance analysts' career directly in two channels. First, social connections reduce the information asymmetry between employers and potential employees. Second, prior labor market literature suggests that the size of social connections reflects a person's social skills which play a significant role in communicating with others. Theses social skills have been perceived more and more important in the analyst profession. For example, Hong and Kubik (2003) describe All-Star voting as "beauty contest" and indicate that financial analysts heavily lobby institutional investor before the vote. Brown et al. (2015) show that winning client or broker's votes is the most important attribute in an analyst's career opportunities. Overall, these studies imply that analysts with more social connections are more likely to have better performance and favorable career outcomes.

We obtain the names of all U.S. financial analysts who have issued at least one stock recommendation in the I/B/E/S database in 2014. We manually collect the LinkedIn profiles of these analysts and extract data on several analyst attributes, including social connections, skill sets, and other individual characteristics (e.g., age, gender, experience). We use the number of connections that analysts have reported on their LinkedIn profiles to proxy for social skills. We proxy technical skills as the number of quantitative skills (e.g., financial modelling, equity valuation, derivatives) reported within their top five endorsed types of expertise on LinkedIn profiles.

We first examine whether analysts' forecast accuracy varies across their technical skills and social connections. The results show that analysts with technical skills or more social connections have lower earnings forecast errors, suggesting that both attributes significantly improve analyst forecast accuracy. We further examine whether technical skills and social connections affect the informativeness of analyst stock recommendations. We find that both buy and sell recommendations from analysts with more social connections have a greater price impact on stock returns. Specifically, market reaction is up to 0.65% (-0.80%) on their upgrade (downgrade) stock recommendation when they have more than 396 LinkedIn connections.[2] Interestingly, we find no evidence that analysts with strong technical skills are associated with a more informative stock recommendation. This result suggests that the broad connection of analysts may play a more important role in stock selection.

[2] 396 is the median value of the number of connections. Our results are robust when we use an alternative cutoff value 500. For any connections more than 500, LinkedIn reports the connections as 500+.

We next investigate whether technical skills and social connections affect analyst career outcome. We focus on two primary career outcomes; namely, whether the analyst is voted as All-Star by institutional investors, and whether the analyst moves from a low-status brokerage house to a high-status brokerage house (Hong and Kubik 2003). Our results suggest that financial analysts with more social connections are more likely to be voted as star analysts, and are more likely to be promoted to high-status brokers. In contrast, we find that technical skills have no effect on helping analysts become All-Stars and the evidence on the effect of technical skills on analysts' job switch is mixed. This evidence is consistent with the fact that the features associated with social skills are becoming more important in Institutional Investor's surveys in recent years and also supports the argument that one's social network is beneficial to career advancement.

Our results persist after controlling for a host of widely documented analyst, brokerage, and firm characteristics including forecast frequency, forecast horizon, experience, lagged forecast error, number of firms and number of industries that the analyst follows, brokerage size, firm size, market-to-book, and return on assets. We also perform several additional tests. Our results are robust for using alternative analyst forecast error measures and excluding analysts without available LinkedIn profiles. Our results are also consistent if we use the highest number of endorsement on LinkedIn profile as an alternative measure of social skills. Taken together, our results suggest that both technical skills and social connections are important in determining analyst performance but connections play a more significant role in the career outcome.

Our study makes contributions to several streams of literature. First, it expands our knowledge about the linkage between analysts' characteristics and their performance. Based on the information available on LindedIn, we propose two measures to proxy for technical and social skills, respectively. We find that analysts with technical skills and social connections generate more accurate forecasts while only social connection has a direct impact on analyst career outcome such as being voted as All-star analysts. These results show a new angle to understand the nature of analysts' professional expertise.

Second, our study contributes to the labor economics literature. We decompose analysts' skills into technical and social components. This decomposition enables us to see how these skills are valued by investors and brokers. Our study is the first large sample empirical study showing that financial analysts with better social skills proxied by the number of connections are more likely to be voted as All-stars by institutional investors or to be promoted to a more resourceful brokerage house. Out study thus suggests both investors and employers value social skills more than technical skills. The findings may be generalizable and thus highlight the importance of training in school and hiring practice in the corporate world.

Third, our study adds to the growing literature about the impact of social networks on the capital markets. Prior research has focused on the role of a specific social tie (e.g., alumni tie, work tie) in information transfer among managers, mutual funds, and financial analysts (Cohen et al. 2008, 2010, Gu et al. 2014, Fang and Huang 2015). We investigate a broader definition of social network, namely, the size of the social network. Our results suggest that the size of the social network affect both analyst performance and career advancement.

The rest of the paper is organized as follows. Section 2 discusses the related literature and develops the hypotheses. Section 3 describes the sample and the key variables. Section 4 discusses the research design, and Section 5 presents the empirical results. Section 6 concludes.

2. Related Literature and Hypotheses

2.1 Performance of Financial Analysts and Skills

Financial analysts are among the most important information intermediary in revealing information in the capital market. A large part of a financial analyst's job is to research, produce, and report forecast on firms' future performance, and translate their forecasts into stock recommendations (Cohen et al. 2010). Prior research on the performance of financial analysts examines whether analyst attributes, brokerage house traits, and firm characteristics affect forecast accuracy and the profitability of stock recommendation. For example, Stickel (1992) shows that star analysts have better forecast accuracy. Clement (1999) finds that analysts' experience, their portfolio complexity, and brokerage size have a positive association with their forecasts' accuracy. Malloy (2005) and Bae et al. (2008) find that local analysts are significantly more accurate than other non-local analysts. Kumar (2010) documents that female analysts issue bolder and more accurate forecasts. Clement and Law (2014) suggest that analysts who begin their career in an economic recession are more conservative in their forecasts.[3] A number of studies also find that analysts with alumni or work ties with managers or directors have better forecast performance and enjoy other benefits in their career outcome (Cohen et al 2010, Gu et al. 2014, Fang and Huang 2015). Although these studies advance our understanding of the determinants of the financial analyst performance, we are not clear which type of skills help analysts improve their performance. The skills do not limit to technical skills such as financial modelling and equity valuation, but also include social skills such as an expanding social network and communicating with others. According to the annual Institutional Investor surveys over the last decade, all top ranked features

[3] Brown et al. (2010) find that financial analysts with background disclosure events (e.g., criminal actions, customer complaints, bankruptcies, regulatory actions) have less accurate forecast. Chang et al. (2016a, 2016b) find that the complexity of derivatives reduces analyst forecast accuracy.

are more or less social skills based, for example, industry knowledge, special service, responsiveness. Stock selection and earnings forecasts were ranked as high as second and fifth in 1998, but have been falling out of the top 10 features in the ranks during the recent years. These perceptions suggest that both social and technical skills may affect the performance and the career outcome of financial analysts. While practitioners consider social skills important, few prior academic studies look into the effect of such skills on their performance with a large sample.

Social connections reflect one aspect of social skills. A large body of work in social psychology and economics suggests that social connections play a crucial role in labor market outcomes. Social connections are perceived to be correlated with intelligence and social skills. Individuals who have better social skills are more confident in communicating with others and thus build a broader social network. Meanwhile, wider social connections help individuals broaden information source, generate ideas, acquire knowledge, and identify opportunities (Baker 2000). All of these benefits, in return, help individuals build confidence as well as social and communication skills (Mobius and Rosenblat 2006), and as a result, a job candidate with a broader social network is more likely to be employed with higher pay (Munshi 2003).

Financial analysts can benefit from social connections in both performance and career opportunities. Karlan et al. (2009) suggests that social connections between individuals can be used as social collateral to secure information borrowing. In their model, social connections build trust which enforces an informal contract between individuals. Prior studies have identified the value of analysts to the capital market in assembling the mosaic of information available to them (Huang et al. 2015, Bradshaw et al. 2014, Chen et al. 2010). Social connections can expand the breadth of analysts' information mosaic search which includes peers, financial journalists, a firm's customers, a firm's suppliers, and a firm's competitors in addition to access to management. Two recent studies document that analysts revise their forecasts based on the tone of the financial press, suggesting that analysts incorporate information from financial journalists (Huang and Mamo 2014, Bradshaw et al. 2014). Bradshaw (2011) shows that firms' suppliers, customers, and competitors play a crucial role in analysts' information search process. Hugon et al. (2016) find that analysts who are exposed to macroeconomists have better forecast accuracy and their forecast revisions are perceived to be more credible by investors.[4] Overall, these findings suggest that social connections can improve analyst performance, namely, forecast accuracy and profitability of stock recommendation, by broadening the sources of information.

Technical skills are the required qualification for the labor market. The job postings for financial analyst usually require a certain level of technical skills, for example, financial modelling, or equity valuation. These skills can be acquired by taking courses or having relevant work experience. A number of studies find that the level of workers' technical skills is positively associated with performance and productivity (Abraham and Spletzer 2009), so we conjecture that financial analysts with strong technical skills have more accurate earnings forecast and more informative stock recommendations.

Summarizing the above discussions, we have the following hypothesis:

H1A: Analysts with technical skills and social connections have better forecast accuracy.

H1B: Analysts with technical skills and social connections issue more informative stock recommendation.

Establishing social connections could also be costly. Maintaining social connections need effort and time and can cause distractions from work and impair the investment in technical skills. Indeed, social psychology studies find that students participating in many clubs are observed to

[4] Luo and Nagarajan (2015) find that analysts following both a supplier and its major customer have better forecast accuracy.

have weak academic performance. In addition, it is possible that financial analysts produce information by independent research without reaching out to their connections, for example, googling and analyzing the reports from firms' suppliers and customers instead of direct interaction with them. These counter arguments would weaken the effect of social connections on financial analyst performance.

2.2. Career Outcome of Financial Analysts and Skills

Social connections can influence the career outcome of financial analysts through two channels. First, more social connections imply more potential referrals. These potential referrals can provide job candidates with information about job opportunities that they otherwise would not have. Moreover, these referrals help reduce the information asymmetry in the labor market and benefit both firms and new hires. Dustmann et al. (2015) derive a theoretical model suggesting that referrals provide hiring information through the network instead of formal hiring channels. New workers hired through referrals are better matched to the firms than workers hired through the external market. Burks et al. (2015) indicate that referred workers have a lower turnover rate than nonreferred workers.

Second, social connections are perceived to correlate with confidence, social skills and intelligence which can generate labor market premiums for job candidates (Litecky et al. 2004, Mobius and Rosenblat 2006, Biddle and Hamermesh 1994, 1998). Prior labor economic literature finds that job candidates with better social skills are more likely to be hired and to be favorably treated by employers. In a recent survey conducted by Brown et al. (2015), 83% of financial analysts indicate that broker or client votes are the most important trait for analyst career opportunities. Their finding suggests that building good client relationships is crucial for analyst career advancement. Overall, our conjecture is that analysts with more social connections are more likely to be voted as All-Star analysts and are more likely to be promoted from smaller or less accurate to larger or more accurate brokerage houses.

A growing body of work examines the alumni or work tie and information transfer. For example, Cohen et al. (2010) document that analysts with alumni ties with mangers have more accurate forecasts and more informative stock recommendations. Gu et al. (2014) find that work ties among mutual fund managers and financial analysts can benefit both parties. Fang and Huang (2015) introduce gender differences into the effect of alumni ties and suggest that alumni ties between managers and analysts only improve male analysts' performance and their career outcome. Our social connections measure is different from these alumni or work ties in two aspects: first, our social connections capture the breadth of information search. It does not imply private information transfer from managers to financial analysts. Second, our social connections also reflect one type of qualitative skills - social skills of financial analysts. While there is some consensus in the literature on the association between technical skills and performance, the role of technical skills in analysts' career advancement is less clear. On the one hand, a body of research documents that technical skills lead to better career outcomes. For example, Abraham and Spletzer (2009) provide evidence that technical skills are highly rewarded on the labor market based on U.S. Census Bureau's Current Population Survey (CPS). Tambe (2014) finds that the labor market has a high demand of employees with technical skills because this intellectual capital is the determinant of firm productivity. On the other hand, technical skills are usually the necessary rather than sufficient qualification that helps the job candidate achieve certain type of career advancement. Prior studies suggest that strong technical skills are not sufficient for career advancement even for high-tech industries (Baron and Markman 2000, Litecky et al. 2004, 2009). Consistent with these studies, the ranks of financial modelling, earnings estimate, and stock selection have been declining in the Institutional Investor ranking surveys during recent years. Taken together, the evidence on the association between technical skills and career advancement is mixed. We conjecture that analysts with technical skills are more likely to be voted as All-Star analysts, and are more likely to be promoted from smaller or less accurate brokerage houses to larger or more accurate brokerage houses.

To summarize, we generate our second hypothesis:

H2A: Analysts with technical skills and social connections are more likely to be voted as All-Star.

H2B: Analyst with technical skills and social connections are more likely to be promoted from low-status brokers to high-status brokers.

3. SAMPLE SELECTION AND KEY VARIABLES

3.1. Sample Selection

Table 1 summarizes the sample selection. We start with an initial sample of 7,112 U.S. financial analysts who have issued at least one earnings forecasts over the January 2014 to December 2015 period. We collect analyst annual earnings forecasts and stock recommendations from I/B/E/S, stock return data from CRSP, financial statement data from the Compustat Annual database, and All-American Research Team status from the Institutional Investor magazine. We exclude observations without I/B/E/S actual earnings information, stock return or financial statement data to calculate control variables. The final sample consists of 62,035 observations, with 3,241 unique firms and 4,627 unique analysts.

3.2. LinkedIn Analyst Data

We manually collect the LinkedIn profiles of these financial analysts. We focus on LinkedIn because it is the world's largest professional networking website (Chen et al. 2015). We then use a Perl program to parse these LinkedIn profiles and extract data on several analyst attributes, including social connections, skills set, age, gender, education background, and employment history. Table 2 reports on the I/B/E/S analysts' LinkedIn connections and technical skill set. In particular, Panel A of Table 2 shows that analysts' LinkedIn connections range from 0 to 500+, with a median of 396 connections. Panel B of Table 2 and Figure 1 present the frequency of each skill reported as top five skills on analyst LinkedIn profiles. Note that these skills have to be endorsed by their LinkedIn connections. A higher rank in analysts' skill sets means this skill has more endorsements from their connections. We focus on the top five skills because these skills have more endorsements and thus are more credible. Not surprisingly, equity research, financial modelling, equities, and valuation are among the most commonly recognized skills of financial analysts. 47% and 43% of financial analysts have financial modelling and valuation in their skills set, respectively.

3.3. Key Variables

3.3.1. Analyst connections and technical skills

Our key variables of interest include analysts' connections and technical skills reported on LinkedIn. Since LinkedIn does not report the actual number of connections beyond 500, to address the potential measurement error problem of raw connections (*Connect*), we define well-connected analysts as those who have more than 396 LinkedIn connections and create an indicator variable (*Connect*) accordingly. We use 396 as a cutoff because it is the median value of social connections reported in Table 2. In our additional analyses, we repeat the same tests using 500 as an alternative cutoff point. Our results are all robust.

We proxy technical skills (*Tech_Skills*) as the number of technical skills reported within analysts' top five endorsed expertise on LinkedIn profiles. Technical skills include financial modelling, equity valuation, valuation, derivatives, and comparative analysis.

3.3.2. Analyst performance measures

We construct two proxies for analyst performance, namely, earnings forecast accuracy and the price impact of stock recommendation. Earnings forecast accuracy is measured by earnings forecast error (*AFE*) which is defined as the absolute value of the analyst's annual earnings forecast minus actual annual EPS for the firm-year, and then scaled by the stock price at the beginning of the year. Following Janakiraman et al. (2007) and Hugon et al. (2016), we focus on the analyst's first earnings forecast and the stock recommendations in a firm-year because an information advantage of well-connected financial analysts could be timely access to information, which is likely more beneficial to earnings forecasts and recommendations made early in the year. The price impact of financial analysts' stock recommendation is measured by the three-day cumulative abnormal size-adjusted returns surrounding the announcement date of the stock recommendation (*CAR* [-1,+1]).

3.3.3. Analyst career outcome measures

To examine the effect of technical skills and social connections on analysts' career advancement, we rely on Institutional Investor's All-Star analyst award status and a promotion measure constructed based on Institutional Investor's rankings of brokerage firms. Each year, the Institutional Investor magazine polls institutional investors to vote for the top sell-side equity analysts and brokerage firms. We create an indicator variable (*AA_Award*) which is set to one if the analyst is ranked in the top three in their respective industries or as a runner-up by Institutional Investor in year t, and zero otherwise. As for the analyst promotion, we follow Hong and Kubik (2003) by creating an indicator variable (*Promotion*) which is set to one if the analyst moves from a unranked brokerage firm to a brokerage firm ranked by Institutional Investor in year t, and zero otherwise.

3.3.4. Control variables

Based on the earnings forecast accuracy literature (e.g., Clement 1999; Jacob et al. 1999; Lim 2001; Clement and Tse 2003), we control for earnings forecast frequency, *Freq*, forecast horizon, *Horizon*, brokerage firm size, *BSize*, number of firms followed, *NFirm*, number of industries followed, *NInd*, and firm experience, *Exp*. Regarding firm characteristics, we use firm size, *Size*, to proxy for the general information environment and market-to-book ratio, *MTB*, to proxy for growth firm. We control for firm performance, *ROA*, as better performing firms are presumably less difficult to forecast. In our tests for career outcome, we control for the analyst performance measures such as earnings forecast accuracy and analyst stock return profitability. A complete list of variable definitions are shown in the Appendix.

4. RESEARCH DESIGN

4.1. Analysts' Connections and Earnings Forecast Accuracy

Our hypothesis H1A asserts that analysts' technical skills and social connections have a positive relationship with earnings forecast accuracy. To test this hypothesis, we regress earnings forecast error (*AFE*) on technical skills and social connections, controlling for forecast frequency, forecast horizon, brokerage firm size, number of firms followed, number of industries followed, firm experience, firm size, market-to-book, and firm performance. Specifically, we estimate the following OLS model:

$$\begin{aligned} AFE_{i,t} = \; & \beta_0 + \beta_1 \cdot Connect_{i,t} + \beta_2 \cdot Tech\_Skills_{i,t} + \beta_3 \cdot Freq_{i,t} + \beta_4 \cdot Horizon_{i,t} \\ & + \beta_5 \cdot BSize_{i,t} + \beta_6 \cdot NFirm_{i,t} + \beta_7 \cdot NInd_{i,t} + \beta_8 \cdot Exp_{i,t} + \beta_9 \cdot Size_{i,t} \\ & + \beta_{10} \cdot MTB_{i,t} + \beta_{11} \cdot ROA_{i,t} + Year\ Effects + Industry\ Effects + \varepsilon_{i,t}, \end{aligned} \tag{1}$$

4.2. Analysts' Connections and the Informativeness of Stock Recommendations

Our hypothesis H1B asserts that analysts' technical skills and social connections have a positive relationship with the informativeness of their stock recommendations. To test this hypothesis, we estimate the following OLS model:

$$\begin{aligned} CAR[-1,+1] = \; & \beta_0 + \beta_1 \cdot Connect_{i,t} + \beta_2 \cdot Tech\_Skills_{i,t} + \beta_3 \cdot BSize_{i,t} + \beta_4 \cdot NFirm_{i,t} \\ & + \beta_5 \cdot NInd_{i,t} + \beta_6 \cdot Exp_{i,t} + \beta_7 \cdot Size_{i,t} + \beta_8 \cdot MTB_{i,t} + Year\ Effects \\ & + Industry\ Effects + \varepsilon_{i,t}, \end{aligned} \tag{2}$$

We classify I/B/E/S' strong buy and buy stock recommendations into the *Buy* category and I/B/E/S' hold, sell, and strong sell recommendations into the *Sell* category. We also identify the recommendations upgraded (downgraded) from the same analysts' most recent recommendations issued within one year and classify those recommendations into the *Upgrade* (*Downgrade*) category. Then, we estimate Equation (2) separately for each category. We expect incremental positive stock market reactions to well-connected analysts' buy and upgraded recommendations, and incremental negative stock market reactions to well-connected analysts' sell and downgraded recommendations.

4.3. Analysts' Connections and the All-Star Analyst Awards

Our hypothesis H2A asserts a positive relationship between analysts' technical skills and social connections and the likelihood of receiving the All-American Research Team status. To test this hypothesis, we estimate the following Probit model:

$$\begin{aligned} AA\_Award = \; & \beta_0 + \beta_1 \cdot Connect_{i,t} + \beta_2 \cdot Tech\_Skills_{i,t} + \beta_3 \cdot Avg\_AFE_{i,t} \\ & + \beta_4 \cdot Avg\_CAR[-1,+1]_{i,t} + \beta_5 \cdot Avg\_Freq_{i,t} + \beta_6 \cdot BSize_{i,t} \\ & + \beta_7 \cdot NFirm_{i,t} + \beta_8 \cdot NInd_{i,t} + \beta_9 \cdot AA\_Award_{i,t-1} + \beta_{10} \cdot Avg\_Exp_{i,t} \\ & + \beta_{11} \cdot Avg\_Size_{i,t} + \beta_{12} \cdot Avg\_MTB_{i,t} + \varepsilon_{i,t} \, , \end{aligned} \tag{3}$$

where *AA_Award* denotes All-American Research Team status, an indicator variable set to one if the analyst is ranked in the top three or as a runner-up by Institutional Investor in their respective industries in year t, and zero otherwise, and other variables are as previously defined. Note that for some control variables, we take the average of all firms in the analyst's research portfolio during the year.

4.4. Analysts' Connections and Promotion to more Resourceful Brokerage Firm

Our hypothesis H2B asserts a positive relationship between analysts' technical skills and social connections and the likelihood of advancing to a high-status brokerage firm. To test this hypothesis, we estimate the following Probit model:

$$\begin{aligned} Promotion = \; & \beta_0 + \beta_1 \cdot Connect_{i,t} + \beta_2 \cdot Tech\_Skills_{i,t} + \beta_3 \cdot Avg\_AFE_{i,t} \\ & + \beta_4 \cdot Avg\_CAR[-1,+1]_{i,t} + \beta_5 \cdot Avg\_Freq_{i,t} + \beta_6 \cdot BSize_{i,t} + \beta_7 \cdot NFirm_{i,t} \\ & + \beta_8 \cdot NInd_{i,t} + \beta_9 \cdot Avg\_Exp_{i,t} + \beta_{10} \cdot Avg\_Size_{i,t} + \beta_{11} \cdot Avg\_MTB_{i,t} \\ & + \varepsilon_{i,t} \, , \end{aligned} \tag{4}$$

where *Promotion* proxies for analyst promotion from a low-status brokerage firm to a high-status brokerage firm, an indicator variable set to one if the analyst moves to a non-I.I. ranked brokerage firm to a I.I.-ranked brokerage firm during year t, and zero otherwise. As in the test of All-Star analyst awards, for some control variables, we take the average of all firms in the analyst's research portfolio during the year.

5. Empirical Results

5.1. Analyst Skills and Earnings Forecast Accuracy

Table 3 presents descriptive statistics for the variables in Equation (1). The mean of *Connect* is 0.338, suggesting 33.8% of the earnings forecasts are issued by well-connected analysts (those with connections more than 396). The median value of *Tech_Skills* is zero, indicating that over 50% of analysts do not have technical skills reported and endorsed within their top five types of expertise on LinkedIn. Consistent with prior literature, the median financial analyst issues four earnings forecasts, follows 16 firms within three industries, and has four years of firm specific experience. We winsorize the continuous variables at the top and bottom 1%.

Table 4 reports the results from the estimation of Equation (1). In Table 4, column 1, where we only include the proxy for analysts' social connections, the coefficient estimates on *Connect* is negative and significant (p-value < 0.01), suggesting that well-connected analysts issue more accurate earnings forecasts than other analysts. In column 2, where we only include the proxy for analysts' technical skills, we find a negative and significant coefficient estimate on *Tech_Skills* (p-value < 0.01), suggesting that the technical skills reported on the analysts' LinkedIn profiles provide some indication of their research quality. In column 3, we continue to find the negative and significant coefficient estimates on *Connect* and *Tech_Skills* (both p-values < 0.01) when they are simultaneously included in the model. In economic terms, based on the median beginning stock price ($39.77) in the sample, the presence of *Connect* is associated with a $0.06 decrease in forecast error, and each reported technical skill is on average associated with a $0.02 decrease in forecast error. Finally, in column 4, we control for analysts' earnings forecast error for the firm in the previous year, and our inferences remain unchanged. For all regressions in this study, the t-statistics or z-statistics are reported in parentheses and calculated based on standard errors clustered at broker level. Overall, these results are consistent with our hypothesis H1A that analysts with technical skills and social connections have better forecast accuracy.

5.2. Analyst Skills and the Informativeness of Stock Recommendations

Table 3 also reports descriptive statistics for the additional variables in Equation (2). Consistent with prior literature, in our stock recommendation sample, the mean and median recommendation levels are 3.607 and 4, respectively, indicating that analysts tend to issue favorable recommendations for the firms they follow.

Table 5 reports the results from the estimation of Equation (2). In Table 5, column 1, when we focus on analysts' strong buy and buy recommendations, we find a positive and significant coefficient estimate on *Connect* (p-value < 0.1), suggesting that the buy stock recommendations issued by well-connected analysts on average are associated with 0.18% more positive stock returns. In column 2, when we focus on analysts' hold, sell, and strong sell recommendations, we find a negative and significant coefficient estimate on *Connect* (p-value < 0.01), suggesting that the sell stock recommendations issued by well-connected analysts on average are associated with 0.6% more negative stock returns. In columns 3 and 4, when we focus on recommendations upgraded or downgraded from the same analysts' prior recommendations, we find well-connected analysts' stock recommendation upgrades are associated with 0.65% more positive and their downgrades are associated with 0.80% more negative stock returns. Interestingly, investors do not perceive the incremental benefit of analysts' technical skills, as the coefficient on *Tech_Skills* is insignificant in all four columns. Overall, the results are consistent with our hypothesis H1B that analysts with more social connections issue more informative stock recommendations.[5]

5.3. Analyst Skills and All-Star Award Status

Table 6 reports descriptive statistics for the variables in Equation (3). In our analyst career outcome sample, 6.4% of the analysts are awarded the All-Star status at the end of year t, and 0.9% of the analysts are promoted from a non-I.I. ranked brokerage firm to a I.I. ranked brokerage firm. Based on our variable definitions, 27.8% of the analysts are well-connected. Our analyst career outcome sample is at the analyst-year level. The median financial analyst issues 3.6 earnings forecasts, follows 10 firms in a single industry, and has 3.3 years of firm specific experience.

Table 7 reports the results from the estimation of Equation (3). In Table 7, column 1, where we only include the proxy for analysts' connections, the coefficient estimate on *Connect* is positive and significant (p-value < 0.01), suggesting that well-connected analysts are more likely to be voted as All-Star analysts relative to other analysts. In column 2, where we only include the proxy for analysts' technical skills, we find an statistically insignificant coefficient estimate on *Tech_Skills*, suggesting that after controlling analysts' average forecast accuracy, the incremental

[5] To address the concern of confounding information events, we exclude stock recommendations issued within the (five-day) earnings announcement windows of the firms and the re-estimate Equation (2). The results highly similar and our inference remains unchanged.

benefit of technical skills is not valued by institutional investors. In column 3, when both social connections and technical skills variables are simultaneously included in the model, we continue to find a positive and significant coefficient estimate on *Connect* (p-value < 0.05). In terms of economic significance, the marginal effect at means for *Connect* is approximately 0.4%, which is approximately 6.3% of the mean of *AA_Award*. Finally, in column 4, we control for the average firm characteristics of an analyst's research portfolio, and our inferences remain unchanged. Importantly, to address the concern that analysts may become well-connected *after* being awarded the All-Star status, we control for analysts' award status in year t-1 in all empirical specifications. Overall, the results on analysts' social connections are consistent with our hypotheses H2A that financial analysts with more social connections are more likely to be voted as All-Star analysts.

5.4. Analyst Skills and Promotion to High-Status Brokerage Firms

Table 6 reports that 0.9% of the analysts in our sample are promoted from non-I.I. brokerage firms to I.I. brokerage firms. Table 8 reports the results from the estimation of Equation (4). In column 1, where we only include the proxy for analysts' social connections, the coefficient estimate on *Connect* is positive and significant (p-value < 0.01), suggesting that well-connected analysts are more likely to advance to high-status brokerage firms relative to other analysts. In column 2, where we only include the proxy for analysts' technical skills, we find that after controlling analysts' average forecast accuracy, analyst technical skills also provide incremental benefits in job separation, as the coefficient estimate on *Tech_Skills* is positive and significant (p-value < 0.05). In column 3, when both the social connection and technical skills variables are simultaneously included in the model, we find a positive and significant coefficient estimate on

Connect (p-value < 0.01) but an insignificant coefficient estimate on *Tech_Skills*. The evidence suggests that social connection dominates technical skills in job separation. In terms of economic significance, the marginal effect at means for *Connect* is approximately 0.9%, which is approximately the mean of *Promote*. Finally, in column 4, when we control for the average firm characteristics of an analyst's research portfolio, our inferences remain unchanged.

5.5. Additional Analyses

5.5.1 Addressing Measurement Error of Analyst Connections

For analysts whose LinkedIn pages cannot be found, we set the value of their connections to zero. However, this would introduce measurement errors to our connection variable, as those analysts may have some sorts of connections outside LinkedIn. To address this issue, we repeat the main analysis on a subsample which only contains the analysts with LinkedIn information, and we report the results in Table 9. The results based on this subsample are generally consistent with our main results: We continue to find that well-connected analysts issue more accurate earnings forecasts and more informative buy, sell, upgrade and downgrade recommendations; compared with other analysts, well-connected analysts are also more likely to be awarded the All-Star status and advance to a high-status brokerage firm.

5.5.2 Alternative Earnings Forecast Measures

To address the omitted variable problem for the earnings forecast accuracy test, we rely on two approaches to control for firm effects by (1) standardizing earnings forecast error and the determinants of forecast error to between 0 to 1, and by (2) measuring earnings forecast error and the determinants of forecast error after subtracting the corresponding firm-year mean (e.g., Clement 1999; Jacob et al. 1999; Lim 2001; Clement and Tse 2003). By doing so, firm-level variables are dropped out of the empirical models. We then estimate an augmented version of Equation 1 and report the results in Table 10. Even when the alternative earnings forecast error measures are used, we still find that well-connected analysts are able to issue more accurate earnings forecasts.

5.5.3 Analysts' last earnings forecasts and stock recommendations

We also re-estimate Equations (1) and (2) using the last (most recent) earnings forecast and stock recommendations issued by an analyst for a firm-year, and we report the estimation results in Table 11. We continue to find that both analysts' social connections and technical skills contribute to earnings forecast accuracy and that well-connected analysts are able to issue more informative buy, sell, upgrade and downgrade recommendations.

5.5.4 Alternative definition of social connections and technical skills

We repeat the main analyses using an alternative cutoff of social connection, *Connect_500+,* which is equal to one if the analyst has more than 500 connections, and zero otherwise. Our results are generally robust (see Table 12). We continue to find that analysts with more connections issue relatively more accurate earnings forecasts and more informative stock recommendations, and are also more likely to be awarded the All-Star status and advance to a high-status brokerage firm.

To address the concern that LinkedIn network includes inactive connections or only reflects self-aggressiveness, we use the highest number of endorsements on analyst skills as an alternative measure of social skills. In untabulated tests, we find consistent results that analysts with more endorsements have better performance and career advancement.

In addition, we find that the results are robust to alternative definition of technique skills in untabulated analyses. The results are similar unaffected when we exclude comparative analysis or derivatives from technique skills.

6. Conclusion

In this paper we investigate whether technical skills and social connections of financial analysts affect their performance and career advancement. Using a sample of LinkedIn profiles of financial analysts, we find that analysts with more social connections have lower forecast errors and more informative stock recommendation. Both buy and sell recommendations from analysts with more social connections have greater price impact on stock return. We further find that financial analysts with more social connections are more likely to be voted as All-Star, and are more likely to be promoted to high-status brokers. However, the effect of strong technical skills only appears in analyst earnings forecast accuracy. Technical skills have little impact on analysts' career advancement. We find no evidence that analysts with strong technical skills are associated with more informative stock recommendation. In our opinion, the number of social connections should well reflect social skills of an analysts. In this regard, the above findings highlight the important role of social skills in career development of financial analysts.

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Appendix: Variable Definition

Variable	Definition
Dependent variables	
AFE	Earnings forecast error, calculated as the absolute value of the analyst's earnings forecast for firm i minus firm i's actual EPS in year t, and then scaled by the stock price at the beginning of year t.
CAR[-1,+1]	Three-day cumulative abnormal size-adjusted returns surrounding the announcement date of the analyst's stock recommendation for firm i in year t.
AA_Award	All-Star analyst award, an indicator variable set to one if the analyst is ranked in the top three or as a runner-up by Institutional Investor in year t, and zero otherwise.
Promote	Analyst promotion from a low-status brokerage firm to a high-status brokerage firm, an indicator variable set to one if the analyst moves from a non-I.I. ranked brokerage firm to an I.I. ranked brokerage firm during year t, and zero otherwise.
Key independent variables	
Raw Connect	Number of the analyst's LinkedIn connections.
Connect	Well-connected analysts, an indicator variable set to one if the analyst has more than 396 LinkedIn connections, and zero otherwise.
Connect_500+	An indicator variable set to one if the analyst has more than 500 LinkedIn connections, and zero otherwise.
Tech_Skills	Number of technical skills (i.e., see Table 2 for details) within the top five skills reported by the analyst and endorsed by the analyst's LinkedIn connections.
Control variables	
Freq	Earnings forecast frequency, calculated as the number of earnings forecasts issued by the analyst for firm i in year t.
Horizon	Earnings forecast horizon, defined as the number of days between the analyst's earnings forecast for firm i and the announcement date of firm i's actual EPS in year t.
BSize	Brokerage firm size, calculated as the natural logarithm of the number of analysts employed by the sell-side firm in year t.
NFirm	Number of firms that the analyst follows in year t.
NInd	Number of 2-digit SIC industries that the analyst follows in year t.
Exp	Firm-specific experience, defined as the number of years that the analyst has issued at least one earnings forecast for firm i prior to year t.
Size	Firm size, measured as the natural logarithm of market value of firm i at the end of year t.
MTB	Market-to-book ratio, calculated as market value of common equity divided by book value of common equity of firm i at the end of year t.
ROA	Return on assets, measured as income before extraordinary items divided by total assets at the end of year t.

Figure 1 Analyst Skills Reported on LinkedIn

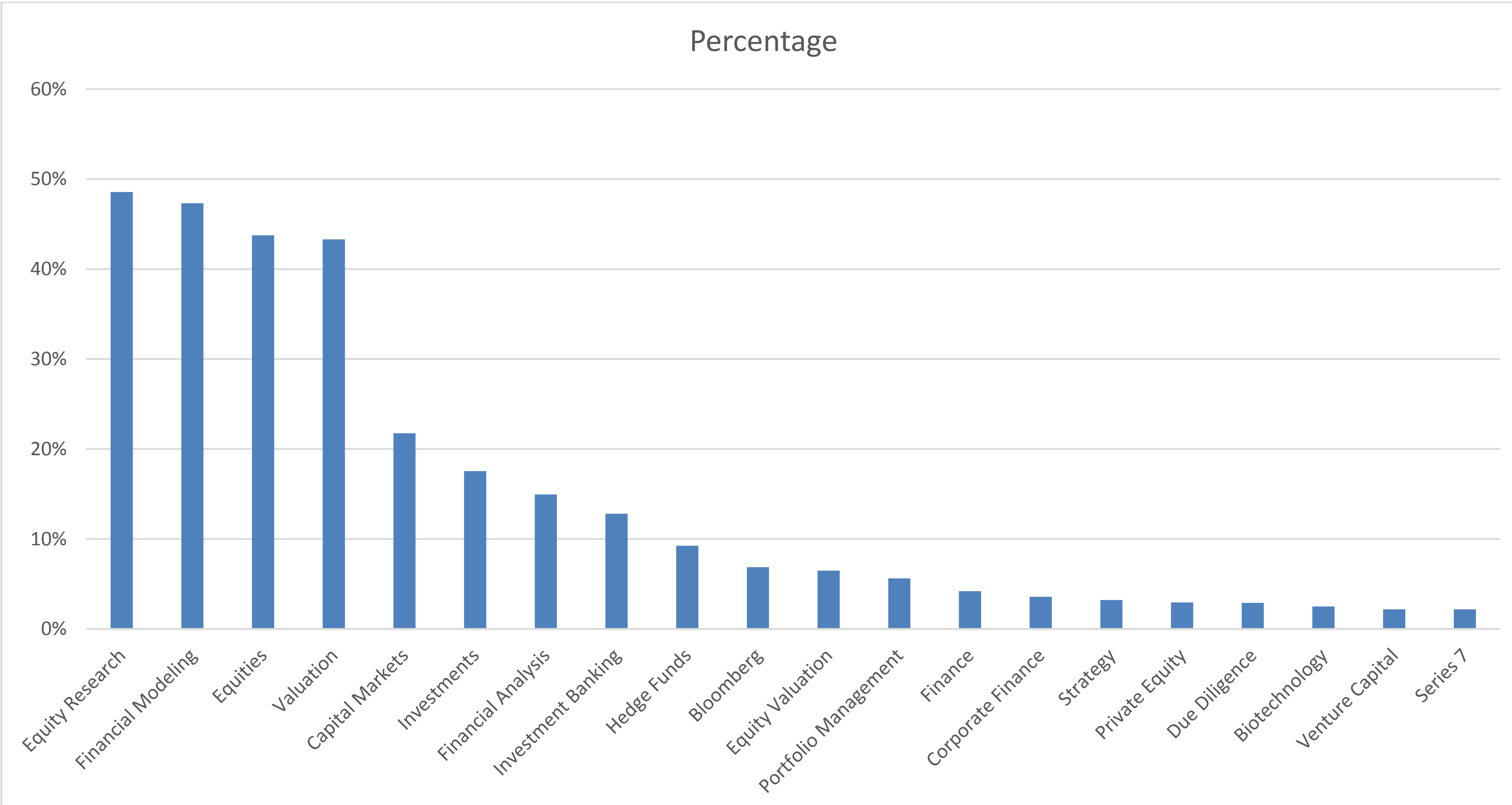

Table 1
Sample Selection

Sample selection criteria	Number of analyst-firm-years	Number of firms	Number of analysts
Analyst-firm-years with EPS forecasts and unique I/B/E/S analyst IDs, 2014/1 - 2015/12	103,912	5,698	7,112
With I/B/E/S actual earnings information to calculate earnings forecast errors	96,707	5,069	6,943
With stock price information at the beginning of year t	73.114	4,028	4,794
With financial data to calculate control variables	62,035	3,241	4,627
Final earnings forecast sample	62,035	3,241	4,627

This table presents the procedures to construct the sample for the analyst performance test.

Table 2
Analyst Skills Reported on LinkedIn

Panel A: Analysts' connections

Variable	Min	Q1	Median	Q3	Max
Raw Connect	0	222	396	500+	500+

Panel B: Analysts' skills

Skill	Percentage	Skill	Percentage
Equity Research	49%	Microsoft Excel	2%
Financial Modelling	47%	Competitive Analysis	2%
Equities	44%	Fixed Income	2%
Valuation	43%	Research	1%
Capital Markets	22%	Corporate Development	1%
Investments	18%	Banking	1%
Financial Analysis	15%	Mining	1%
Investment Banking	13%	Strategic Planning	1%
Hedge Funds	9%	Microsoft Office	1%
Bloomberg	7%	Financial Markets	1%
Equity Valuation	6%	Securities	1%
Portfolio Management	6%	Derivatives	1%
Finance	4%	Telecommunications	1%
Corporate Finance	4%	Trading	1%
Strategy	3%	Alternative Investments	1%
Private Equity	3%	Market Research	1%
Due Diligence	3%	Energy	1%
Biotechnology	3%	Risk Management	1%
Venture Capital	2%	Financial Services	1%
Series 7	2%	Business Analysis	1%
Management	2%	Healthcare	1%
Asset Management	2%	PowerPoint	1%
Emerging Markets	2%	Pharmaceutical Industry	1%
Analysis	2%	Investor Relations	1%
Business Strategy	2%	Economics	1%

This table presents the analysts' connections and skills reported on LinkedIn. *Raw Connect* = Raw number of the analyst's LinkedIn connections.

Table 3
Descriptive Statistics - Analyst Performance Tests

Variable	Mean	Stdev	Q1	Median	Q3
Earnings forecast accuracy tests (n = 62,035)					
AFE	0.016	0.037	0.002	0.005	0.014
Connect	0.338	0.473	0.000	0.000	1.000
Tech_Skills	0.656	0.892	0.000	0.000	1.000
Freq	4.168	2.479	2.000	4.000	5.000
Horizon	5.657	0.484	5.659	5.886	5.900
BSize	3.792	1.062	3.045	3.970	4.605
NFirm	16.676	9.286	11.000	16.000	21.000
NInd	3.232	2.368	1.000	3.000	4.000
Exp	4.966	4.044	2.000	4.000	7.000
Size	8.461	1.711	7.282	8.477	9.626
MTB	4.820	6.341	1.818	3.005	5.158
ROA	0.030	0.122	0.010	0.046	0.084
Stock recommendation price impact tests (n = 17,697)					
Recom_Level	3.607	0.889	3.000	4.000	4.000
CAR[-1,+1]	-0.003	0.062	-0.022	0.000	0.023

This table presents descriptive statistics for the sample used in the tests of earnings forecast errors and market reactions to stock recommendation. *AFE* = Earnings forecast error, calculated as the absolute value of the analyst's earnings forecast minus actual EPS for firm i in year t, and then scaled by the stock price at the beginning of year t. *Connect* = Well-connected analysts, an indicator variable set to one if the analyst has more than 396 LinkedIn connections, and zero otherwise. *Tech_Skills* = Number of technical skills (i.e., see Table 2 for details) within the top five skills reported by the analyst and endorsed by the analyst's LinkedIn connections. *Freq* = Earnings forecast frequency, calculated as the number of earnings forecasts issued by the analyst for firm i in year t. *Horizon* = Earnings forecast horizon, defined as the natural logarithm of the number of days between the analyst's earnings forecast for firm i and the announcement date of firm i's actual EPS in year t. *BSize* = Brokerage firm size, calculated as the natural logarithm of the number of analysts employed by the sell-side firm in year t. *NFirm* = Number of firms that the analyst follows in year t. *NInd* = Number of 2-digit SIC industries that the analyst follows in year t. *Exp* = Firm-specific experience, defined as the number of years that the analyst has issued at least one earnings forecast for firm i prior to year t. *AA_Award* = All-Star analyst, an indicator variable set to one if the analyst is ranked in the top three or as a runner-up by Institutional Investor in year t, and zero otherwise. *Size* = Firm size, measured as the natural logarithm of market value of firm i at the end of year t. *MTB* = Market-to-book ratio, calculated as market value of common equity divided by book value of common equity of firm i at the end of year t. *ROA* = Return on assets, measured as income before extraordinary items divided by total assets at the end of year t. *Recom_Level* = Analyst's I/B/E/S recommendation, where strong buy is set to 5, buy is set to 4, hold is set to 3, sell is set to 2, and strong sell is set to 1. *CAR*[-1,+1] = Three-day cumulative abnormal size-adjusted returns surrounding the announcement date of the analyst's stock recommendation for firm i in year t.

Table 4
Analyst Skills and Earnings Forecast Accuracy

Variable	(1) *AFE*	(2) *AFE*	(3) *AFE*	(4) *AFE*
Intercept	0.0499***	0.0502***	0.0501***	0.0396**
	(6.11)	(6.15)	(6.12)	(2.38)
Connect	-0.0019***		-0.0016***	-0.0005*
	(-7.98)		(-6.05)	(-1.73)
Tech_Skills		-0.0008***	-0.0004***	-0.0003*
		(-5.44)	(-2.68)	(-1.92)
Freq	0.0009**	0.0009**	0.0009**	0.0010***
	(2.32)	(2.26)	(2.33)	(2.92)
Horizon	0.0033***	0.0033***	0.0033***	0.0025***
	(6.78)	(6.81)	(6.91)	(2.64)
BSize	-0.0006**	-0.0006**	-0.0006**	-0.0004**
	(-1.99)	(-2.14)	(-2.04)	(-2.05)
NFirm	-0.0001	-0.0001	-0.0001	-0.0001
	(-0.52)	(-0.57)	(-0.53)	(-0.61)
NInd	-0.0001	-0.0001	-0.0001	-0.0001
	(-0.36)	(-0.31)	(-0.34)	(-0.39)
Exp	-0.0002**	-0.0002**	-0.0002**	-0.0001
	(-2.14)	(-2.17)	(-2.18)	(-1.59)
Size	-0.0044***	-0.0044***	-0.0044***	-0.0032***
	(-43.74)	(-43.10)	(-43.59)	(-15.49)
MTB	-0.0003**	-0.0003**	-0.0003**	-0.0003**
	(-2.41)	(-2.45)	(-2.41)	(-2.01)
ROA	-0.0669***	-0.0665***	-0.0668***	-0.0545***
	(-5.99)	(-5.93)	(-5.97)	(-6.85)
Lag_AFE				0.7630***
				(8.22)
Year Fixed Effect	Included	Included	Included	Included
Industry Fixed Effect	Included	Included	Included	Included
N	62,035	62,035	62,035	44,666
Adj. R-squared	0.161	0.161	0.161	0.314

This table presents the results from estimating the OLS regression of Equation (1). *AFE* = Earnings forecast error, calculated as the absolute value of the analyst's earnings forecast minus actual EPS for firm i in year t, and then scaled by the stock price at the beginning of year t. *Connect* = Well-connected analysts, an indicator variable set to one if the analyst has more than 396 LinkedIn connections, and zero otherwise. *Tech_Skills* = Number of technical skills (i.e., see Table 2 for details) within the top five skills reported by the analyst and endorsed by the analyst's LinkedIn connections. All remaining variables are defined in the Appendix. *t*-statistics (in parenthesis) are calculated based on standard errors clustered at the broker level. *, **, ***, indicate two-tailed significance at the 10%, 5%, and 1% levels, respectively.

Table 5
Analyst Skills and the Informativeness of Stock Recommendations

	Buy	*Sell*	*Upgrade*	*Downgrade*
	(1)	(2)	(3)	(4)
Variable	*CAR*[-1,+1]	*CAR*[-1,+1]	*CAR*[-1,+1]	*CAR*[-1,+1]
Intercept	0.0798***	-0.0569***	-0.0243**	-0.0684***
	(3.73)	(-5.88)	(-2.18)	(-3.26)
Connect	0.0018*	-0.0060***	0.0065***	-0.0080*
	(1.76)	(-2.79)	(2.78)	(-1.82)
Tech_Skills	0.0004	0.0001	-0.0029	-0.0024
	(0.93)	(0.05)	(-1.02)	(-1.37)
BSize	0.0022***	-0.0000	0.0043***	-0.0062***
	(3.97)	(-0.03)	(4.72)	(-4.32)
NFirm	-0.0001**	-0.0001	0.0002**	-0.0006***
	(-2.57)	(-0.82)	(2.17)	(-3.20)
NInd	-0.0003*	-0.0008	-0.0013***	0.0013*
	(-1.70)	(-1.53)	(-3.48)	(1.78)
Exp	0.0005***	-0.0001	0.0004*	0.0001
	(3.39)	(-0.69)	(1.83)	(0.27)
Size	-0.0051***	0.0061***	-0.0091***	0.0089***
	(-8.92)	(8.50)	(-7.70)	(5.96)
MTB	-0.0001**	-0.0002**	-0.0001	-0.0010***
	(-1.99)	(-2.42)	(-1.29)	(-3.79)
Year Fixed Effect	Included	Included	Included	Included
Industry Fixed Effect	Included	Included	Included	Included
N	8,894	8,803	1,557	1,404
Adj. R-squared	0.043	0.038	0.065	0.088

This table presents the results from estimating the OLS regression of Equation (2). *Buy* = analysts' strong buy and buy recommendations. *Sell* = analysts' hold, sell, and strong sell recommendations. *Upgrade* = upgrade from the same analysts' recommendations issued within one year. *Downgrade* = downgrade from the same analysts' recommendations issued within one year. *CAR*[-1,+1] = Three-day cumulative abnormal size-adjusted returns surrounding the announcement date of the analyst's stock recommendation for firm i in year t. *Connect* = Well-connected analysts, an indicator variable set to one if the analyst has more than 396 LinkedIn connections, and zero otherwise. *Tech_Skills* = Number of technical skills (i.e., see Table 2 for details) within the top five skills reported by the analyst and endorsed by the analyst's LinkedIn connections. All remaining variables are defined in the Appendix. *t*-statistics (in parenthesis) are calculated based on standard errors clustered at the broker level. *, **, ***, indicate two-tailed significance at the 10%, 5%, and 1% levels, respectively.

Table 6
Descriptive Statistics - Analyst Career Path Tests

Variable	Mean	Stdev	Q1	Median	Q3
n = 7,465					
AA_Award	0.064	0.245	0.000	0.000	0.000
Promote	0.009	0.096	0.000	0.000	0.000
Connect	0.278	0.448	0.000	0.000	1.000
Tech_Skills	0.547	0.842	0.000	0.000	1.000
Avg_AFE	0.031	0.075	0.005	0.010	0.023
Avg_CAR[-1,+1]	-0.002	0.042	-0.008	0.000	0.008
Avg_Freq	3.843	1.967	2.500	3.615	4.714
BSize	3.709	1.156	2.931	3.888	4.605
NFirm	10.684	8.012	3.000	10.000	16.000
NInd	2.101	1.738	1.000	1.000	3.000
Avg_Exp	4.003	2.676	1.875	3.308	5.550
Avg_Size	8.880	1.560	7.906	9.046	9.966
Avg_MTB	5.229	7.141	1.842	3.312	5.634

This table presents descriptive statistics for the sample used in the tests of analysts' career paths. *AA_Award* = All-Star analyst, an indicator variable set to one if the analyst is ranked in the top three or as a runner-up by Institutional Investor in year t, and zero otherwise. *Promote* = Analyst promotion to a high-status broker, an indicator variable set to one if the analyst moves from a non-I.I. ranked broker to an I.I. ranked broker during year t, and zero otherwise. *Connect* = Well-connected analysts, an indicator variable set to one if the analyst has more than 396 LinkedIn connections, and zero otherwise. *Tech_Skills* = Number of technical skills (i.e., see Table 2 for details) within the top five skills reported by the analyst and endorsed by the analyst's LinkedIn connections. *Avg_AFE* = Average earnings forecast accuracy, calculated as the mean of the analyst's price-deflated earnings forecast errors in year t. *Avg_CAR*[-1,+1] = Average price impact of stock recommendations, calculated as the mean of the three-day cumulative abnormal market-adjusted stock returns surrounding the analyst's stock recommendations in year t. *Avg_Freq* = Average earnings forecast frequency, calculated as the mean of the number of earnings forecasts issued by the analyst for the firms followed in year t. *BSize* = Brokerage firm size, calculated as the natural logarithm of the number of analysts employed by the sell-side firm in year t. *NFirm* = Number of firms that the analyst follows in year t. *NInd* = Number of 2-digit SIC industries that the analyst follows in year t. *Avg_Exp* = Average firm-specific experience, defined as the mean of the number of years that the analyst has followed the firms in his or her portfolio in year t. *Avg_Size* = Average firm size, measured as the mean of the natural logarithm of market value of the firms that the analyst follows in year t. *Avg_MTB* = Average market-to-book ratio, calculated as the mean of the market-to-book ratios of the firms that the analyst follows in year t.

Table 7
Analyst Skills and All-Star Analyst Awards

Variable	(1) *AA_Award*	(2) *AA_Award*	(3) *AA_Award*	(4) *AA_Award*
Intercept	-4.8170***	-4.7487***	-4.7824***	-6.1026***
	(-9.57)	(-9.32)	(-9.11)	(-19.93)
Connect	0.1939*		0.2392**	0.2207**
	(1.78)		(2.51)	(2.51)
Tech_Skills		0.0011	-0.0592	-0.0618
		(0.02)	(-1.37)	(-1.38)
Avg_AFE	-1.1174***	-1.0683***	-1.1207***	-0.1824***
	(-17.54)	(-5.29)	(-7.63)	(-3.01)
Avg_CAR[-1,+1]	-0.8001*	-0.8664**	-0.8037*	-0.7914*
	(-1.85)	(-1.99)	(-1.81)	(-1.70)
Avg_Freq	0.1059***	0.1062***	0.1052***	0.0991***
	(25.31)	(18.60)	(20.48)	(14.57)
BSize	0.2592***	0.2618***	0.2572***	0.2522***
	(3.42)	(3.33)	(3.35)	(3.05)
NFirm	0.0426***	0.0433***	0.0426***	0.0454***
	(5.50)	(5.93)	(5.48)	(6.51)
NInd	0.0619***	0.0620***	0.0629***	0.0603***
	(4.00)	(4.04)	(4.13)	(3.87)
Lag_AA_Award	2.8227***	2.8285***	2.8153***	2.7484***
	(32.21)	(31.47)	(32.46)	(35.19)
Avg_Exp	0.0389***	0.0347***	0.0379***	0.0298***
	(5.47)	(4.41)	(4.91)	(2.83)
Avg_Size				0.1395***
				(3.26)
Avg_MTB				0.0071
				(1.44)
N	7,465	7,465	7,465	7,179
Pseudo R-squared	0.700	0.699	0.701	0.704

This table presents the results from estimating the Probit regression of Equation (3). *AA_Award* = All-Star analyst, an indicator variable set to one if the analyst is ranked in the top three or as a runner-up by Institutional Investor in year t, and zero otherwise. *Connect* = Well-connected analysts, an indicator variable set to one if the analyst has more than 396 LinkedIn connections, and zero otherwise. *Tech_Skills* = Number of technical skills (i.e., see Table 2 for details) within the top five skills reported by the analyst and endorsed by the analyst's LinkedIn connections. *Avg_AFE* = Average earnings forecast accuracy, calculated as the mean of the analyst's price-deflated earnings forecast errors in year t. *Avg_CAR*[-1,+1] = Average price impact of stock recommendations, calculated as the mean of the three-day cumulative abnormal market-adjusted stock returns surrounding the analyst's stock recommendations in year t. *Avg_Freq* = Average earnings forecast frequency, calculated as the mean of the number of earnings forecasts issued by the analyst for the firms followed in year t. *Avg_Exp* = Average firm-specific experience, defined as the mean of the number of years that the analyst has followed the firms in his or her portfolio in year t. *Avg_Size* = Average firm size, measured as the mean of the natural logarithm of market value of the firms that the analyst follows in year t. *Avg_MTB* = Average market-to-book ratio, calculated as the mean of the market-to-book ratios of the firms that the analyst follows in year t. All remaining variables are defined in the Appendix. *z*-statistics (in parenthesis) are calculated based on standard errors clustered at the broker level. *, **, ***, indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 8
Analyst Skills and Promotion to High-Status Brokerage Firms

Variable	(1) *Promote*	(2) *Promote*	(3) *Promote*	(4) *Promote*
Intercept	-3.1813***	-3.1455***	-3.1848***	-6.0947***
	(-28.64)	(-27.96)	(-27.74)	(-13.65)
Connect	0.3887***		0.3812***	0.3679***
	(4.14)		(3.37)	(2.97)
Tech_Skills		0.1032**	0.0092	0.0359
		(2.13)	(0.15)	(0.53)
Avg_AFE	0.1417	0.1132	0.1412	1.3538***
	(0.24)	(0.19)	(0.24)	(2.80)
Avg_CAR[-1,+1]	-0.5010	-0.5744	-0.4950	-0.0635
	(-0.51)	(-0.58)	(-0.51)	(-0.05)
Avg_Freq	0.0373*	0.0392*	0.0373*	0.0105
	(1.77)	(1.91)	(1.78)	(0.46)
BSize	0.1737***	0.1762***	0.1739***	0.1802***
	(8.31)	(8.56)	(8.18)	(7.04)
NFirm	-0.0279***	-0.0248***	-0.0280***	-0.0292***
	(-3.80)	(-3.64)	(-3.89)	(-3.72)
NInd	-0.0175	-0.0164	-0.0177	-0.0148
	(-0.54)	(-0.52)	(-0.54)	(-0.37)
Avg_Exp				
Avg_Size	0.0349**	0.0337**	0.0351**	0.0079
	(2.03)	(2.01)	(2.04)	(0.43)
Avg_MTB				0.3226***
				(7.35)
N	7,465	7,465	7,465	7,179
Pseudo R-squared	0.062	0.046	0.062	0.151

This table presents the results from estimating the Probit regression of Equation (4). *Promote* = Analyst promotion to a high-status broker, an indicator variable set to one if the analyst moves from a non-I.I. ranked broker to an I.I. ranked broker during year t, and zero otherwise. *Connect* = Well-connected analysts, an indicator variable set to one if the analyst has more than 396 LinkedIn connections, and zero otherwise. *Tech_Skills* = Number of technical skills (i.e., see Table 2 for details) within the top five skills reported by the analyst and endorsed by the analyst's LinkedIn connections. *Avg_AFE* = Average earnings forecast accuracy, calculated as the mean of the analyst's price-deflated earnings forecast errors in year t. *Avg_CAR*[-1,+1] = Average price impact of stock recommendations, calculated as the mean of the three-day cumulative abnormal market-adjusted stock returns surrounding the analyst's stock recommendations in year t. *Avg_Freq* = Average earnings forecast frequency, calculated as the mean of the number of earnings forecasts issued by the analyst for the firms followed in year t. *Avg_Exp* = Average firm-specific experience, defined as the mean of the number of years that the analyst has followed the firms in his or her portfolio in year t. *Avg_Size* = Average firm size, measured as the mean of the natural logarithm of market value of the firms that the analyst follows in year t. *Avg_MTB* = Average market-to-book ratio, calculated as the mean of the market-to-book ratios of the firms that the analyst follows in year t. All remaining variables are defined in the Appendix. *z*-statistics (in parenthesis) are calculated based on standard errors clustered at the broker level. *, **, ***, indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 9
Alternative Sample: Excluding Non-LinkedIn Analysts

Panel. A: Analyst skills and earnings forecast accuracy

Variable	(1) *AFE*	(2) *AFE*	(3) *AFE*	(4) *AFE*
Intercept	0.0508***	0.0510***	0.0510***	0.0399***
	(6.78)	(6.78)	(6.79)	(3.29)
Connect	-0.0013***		-0.0012***	-0.0004*
	(-5.16)		(-4.27)	(-1.66)
Tech_Skills		-0.0004***	-0.0002	-0.0003*
		(-3.20)	(-1.30)	(-1.73)
Lag_AFE	No	No	No	Yes
Controls	Yes	Yes	Yes	Yes
N	56,392	56,392	56,392	41,723
Adj. R-squared	0.159	0.159	0.159	0.310

Panel B: Analyst skills and the informativeness of stock recommendations

	Buy	*Sell*	*Upgrade*	*Downgrade*
	(1)	(2)	(3)	(4)
Variable	*CAR*[-1,+1]	*CAR*[-1,+1]	*CAR*[-1,+1]	*CAR*[-1,+1]
Intercept	0.0801***	-0.0552***	-0.0239*	-0.0650***
	(3.75)	(-5.63)	(-1.89)	(-3.02)
Connect	0.0018*	-0.0058***	0.0068***	-0.0082*
	(1.71)	(-2.66)	(2.88)	(-1.88)
Tech_Skills	0.0003	0.0002	-0.0029	-0.0024
	(0.78)	(0.13)	(-1.06)	(-1.33)
Controls	Yes	Yes	Yes	Yes
N	8,659	8,607	1,541	1,389
Adj. R-squared	0.044	0.038	0.068	0.089

Panel C: Analyst Skills and All-Star Analyst Awards

Variable	(1) *AA_Award*	(2) *AA_Award*	(3) *AA_Award*	(4) *AA_Award*
Intercept	-4.7057***	-4.6133***	-4.6541***	-6.1164***
	(-8.47)	(-8.16)	(-7.98)	(-20.83)
Connect	0.1476		0.2019**	0.1791**
	(1.32)		(2.11)	(2.06)
Tech_Skills		-0.0273	-0.0753*	-0.0791*
		(-0.49)	(-1.70)	(-1.74)
Firm Controls	No	No	No	Yes
Analyst and Broker Controls	Yes	Yes	Yes	Yes
N	5,968	5,968	5,968	5,807
Pseudo R-squared	0.685	0.684	0.685	0.690

Panel D: Analyst promotion to high-status brokerage firms

Variable	(1) *Promote*	(2) *Promote*	(3) *Promote*	(4) *Promote*
Intercept	-3.1304***	-3.0438***	-3.1344***	-5.7114***
	(-7.75)	(-6.79)	(-7.32)	(-7.35)
Connect	0.3848***		0.3805***	0.3464***
	(3.95)		(3.02)	(2.91)
Tech_Skills		0.0841*	0.0062	0.0203
		(1.77)	(0.10)	(0.34)
Firm Controls	No	No	No	Yes
Analyst and Broker Controls	Yes	Yes	Yes	Yes
N	5,968	5,968	5,968	5,807
Pseudo R-squared	0.062	0.044	0.062	0.134

This table presents the results of re-estimating Equations (1) to (4) on an alternative sample where all analysts have information available on LinkedIn. *AFE* = Earnings forecast error, calculated as the absolute value of the analyst's earnings forecast minus actual EPS for firm i in year t, and then scaled by the stock price at the beginning of year t. *CAR*[-1,+1] = Three-day cumulative abnormal size-adjusted returns surrounding the announcement date of the analyst's stock recommendation for firm i in year t. *AA_Award* = All-Star analyst, an indicator variable set to one if the analyst is ranked in the top three or as a runner-up by Institutional Investor in year t, and zero otherwise. *Promote* = Analyst promotion to a high-status broker, an indicator variable set to one if the analyst moves from a non-I.I. ranked broker to an I.I. ranked broker during year t, and zero otherwise. *Connect* = Well-connected analysts, an indicator variable set to one if the analyst has more than 396 LinkedIn connections, and zero otherwise. *Tech_Skills* = Number of technical skills (i.e., see Table 2 for details) within the top five skills reported by the analyst and endorsed by the analyst's LinkedIn connections. Analyst, broker, and firm-level controls are as specified in Equations (1) to (4), respectively. *t- or z*-statistics (in parenthesis) are calculated based on standard errors clustered at the broker level. *, **, ***, indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 10
Robustness Checks: Alternative Earnings Forecast Error Measures

Panel. A: Standardized earnings forecast errors

Variable	(1) *RAFE*	(2) *RAFE*	(3) *RAFE*	(4) *RAFE*
Intercept	0.2179***	0.2153***	0.2172***	0.2682***
	(28.13)	(26.73)	(26.76)	(37.06)
Connect	-0.0186***		-0.0198***	-0.0212***
	(-4.71)		(-5.95)	(-5.80)
Tech_Skills		-0.0028	0.0016	0.0009
		(-1.32)	(0.87)	(0.76)
Lag_RAFE	No	No	No	Yes
Controls	Yes	Yes	Yes	Yes
N	60,578	60,578	60,578	43,812
Adj. R-squared	0.079	0.078	0.079	0.027

Panel B: Mean-adjusted earnings forecast errors

Variable	(1) *MAFE*	(2) *MAFE*	(3) *MAFE*	(4) *MAFE*
Intercept	-0.0000	-0.0001	-0.0000	0.0001***
	(-0.20)	(-1.10)	(-0.44)	(3.04)
Connect	-0.0002*		-0.0003***	-0.0002*
	(-1.92)		(-2.90)	(-1.73)
Tech_Skills		0.0000	0.0001	-0.0000
		(0.09)	(1.52)	(-0.24)
Lag_MAFE	No	No	No	Yes
Controls	Yes	Yes	Yes	Yes
N	62,043	62,043	62,043	44,666
Adj. R-squared	0.042	0.042	0.042	0.012

This table presents the results of re-estimating Equation (1) using alternative earnings forecast error measures. *RAFE* = Standardized earnings forecast error, calculated as the analyst's earnings forecast error minus the minimum earnings forecast error of analysts following firm i in year t, and then scaled by the range of earnings forecast error of analysts following firm i in year t. *MAFE* = Mean-adjusted earnings forecast accuracy, calculated as the analyst's earnings forecast error minus the mean earnings forecast error of analysts following firm i in year t, and then scaled by the stock price at the beginning of year t. *Connect* = Well-connected analysts, an indicator variable set to one if the analyst has more than 396 LinkedIn connections, and zero otherwise. *Tech_Skills* = Number of technical skills (i.e., see Table 2 for details) within the top five skills reported by the analyst and endorsed by the analyst's LinkedIn connections. Analyst and broker-level controls are included and standardized/mean-adjusted. *t*-statistics (in parenthesis) are calculated based on standard errors clustered at the broker level. *, **, ***, indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 11
Robustness Checks: Analysts' Last Earnings Forecasts and Stock Recommendations

Panel. A: Analyst skills and earnings forecast accuracy

	(1)	(2)	(3)	(4)
Variable	*AFE*	*AFE*	*AFE*	*AFE*
Intercept	0.0363***	0.0365***	0.0366***	0.0261**
	(3.05)	(3.08)	(3.08)	(1.99)
Connect	-0.0011***		-0.0007***	-0.0000
	(-5.81)		(-4.41)	(-0.07)
Tech_Skills		-0.0006***	-0.0005***	-0.0004***
		(-6.25)	(-5.55)	(-3.22)
Lag_AFE	No	No	No	Yes
Controls	Yes	Yes	Yes	Yes
N	62,014	62,014	62,014	44,654
Adj. R-squared	0.122	0.122	0.122	0.261

Panel B: Analyst skills and the informativeness of stock recommendations

	Buy	*Sell*	*Upgrade*	*Downgrade*
	(1)	(2)	(3)	(4)
Variable	*CAR*[-1,+1]	*CAR*[-1,+1]	*CAR*[-1,+1]	*CAR*[-1,+1]
Intercept	0.0841***	-0.0719***	0.0868***	-0.0670***
	(4.56)	(-5.63)	(5.20)	(-7.50)
Connect	0.0030***	-0.0050**	0.0071***	-0.0063***
	(2.87)	(-1.98)	(3.28)	(-3.54)
Tech_Skills	-0.0003	0.0004	-0.0039**	0.0035*
	(-0.61)	(0.44)	(-2.51)	(1.67)
Controls	Yes	Yes	Yes	Yes
N	8,801	8,908	2,402	2,386
Adj. R-squared	0.043	0.049	0.058	0.094

This table the results of re-estimating Equations (1) and (2) using analysts' last earnings forecasts and recommendations, respectively, for firm i in year t. *AFE* = Earnings forecast error, calculated as the absolute value of the analyst's earnings forecast minus actual EPS for firm i in year t, and then scaled by the stock price at the beginning of year t. *CAR*[-1,+1] = Three-day cumulative abnormal size-adjusted returns surrounding the announcement date of the analyst's stock recommendation for firm i in year t. *Connect* = Well-connected analysts, an indicator variable set to one if the analyst has more than 396 LinkedIn connections, and zero otherwise. *Tech_Skills* = Number of technical skills (i.e., see Table 2 for details) within the top five skills reported by the analyst and endorsed by the analyst's LinkedIn connections. Analyst, broker, and firm-level controls are as specified in Equations (1) and (2), respectively. *t*-statistics (in parenthesis) are calculated based on standard errors clustered at the broker level. *, **, ***, indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 12
Alternative Connection Measure

Panel. A: Analyst skills and earnings forecast accuracy

	(1)	(2)	(3)	(4)
Variable	*AFE*	*AFE*	*AFE*	*AFE*
Intercept	0.0496***	0.0502***	0.0499***	0.0349*
	(6.09)	(6.15)	(6.12)	(1.89)
Connect_500+	-0.0017***		-0.0013***	-0.0005**
	(-6.82)		(-4.56)	(-1.97)
Tech_Skills		-0.0008***	-0.0005***	-0.0004**
		(-5.44)	(-3.58)	(-2.30)
Lag_AFE	No	No	No	Yes
Controls	Yes	Yes	Yes	Yes
N	62,035	62,035	62,035	44,666
Adj. R-squared	0.161	0.161	0.161	0.334

Panel B: Analyst skills and the informativeness of stock recommendations

	Buy	*Sell*	*Upgrade*	*Downgrade*
	(1)	(2)	(3)	(4)
Variable	*CAR*[-1,+1]	*CAR*[-1,+1]	*CAR*[-1,+1]	*CAR*[-1,+1]
Intercept	0.0803***	-0.0578***	-0.0244**	-0.0694***
	(3.78)	(-5.97)	(-2.21)	(-3.29)
Connect_500+	0.0015	-0.0065***	0.0057**	-0.0085***
	(1.21)	(-3.32)	(2.48)	(-2.80)
Tech_Skills	0.0005	-0.0002	-0.0023	-0.0029
	(1.47)	(-0.17)	(-0.92)	(-1.56)
Controls	Yes	Yes	Yes	Yes
N	8,894	8,803	1,557	1,404
Adj. R-squared	0.043	0.038	0.065	0.088

Panel C: Analyst Skills and All-Star Analyst Awards

	(1)	(2)	(3)	(4)
Variable	*AA_Award*	*AA_Award*	*AA_Award*	*AA_Award*
Intercept	-4.8430***	-4.7487***	-4.8036***	-6.0551***
	(-9.46)	(-9.32)	(-9.05)	(-21.30)
Connect_500+	0.2640**		0.3135***	0.2805***
	(2.14)		(2.81)	(2.63)
Tech_Skills		0.0011	-0.0678*	-0.0678
		(0.02)	(-1.68)	(-1.64)
Firm Controls	No	No	No	Yes
Analyst and Broker Controls	Yes	Yes	Yes	Yes
N	7,465	7,465	7,465	7,179
Pseudo R-squared	0.701	0.699	0.702	0.704

Panel D: Analyst promotion to more accurate brokerage firms

Variable	(1) *Promote*	(2) *Promote*	(3) *Promote*	(4) *Promote*
Intercept	-3.1498***	-3.1455***	-3.1640***	-5.9948***
	(-29.50)	(-27.96)	(-28.02)	(-13.73)
Connect_500+	0.3813***		0.3562***	0.2780**
	(3.85)		(3.17)	(2.27)
Tech_Skills		0.1032**	0.0326	0.0705
		(2.13)	(0.57)	(1.12)
Firm Controls	No	No	No	Yes
Analyst and Broker Controls	Yes	Yes	Yes	Yes
N	7,465	7,465	7,465	7,179
Pseudo R-squared	0.059	0.046	0.059	0.145

This table presents the results of re-estimating Equations (1) to (4) on an alternative sample where all analysts have information available on LinkedIn. *AFE* = Earnings forecast error, calculated as the absolute value of the analyst's earnings forecast minus actual EPS for firm i in year t, and then scaled by the stock price at the beginning of year t. *CAR*[-1,+1] = Three-day cumulative abnormal size-adjusted returns surrounding the announcement date of the analyst's stock recommendation for firm i in year t. *AA_Award* = All-Star analyst, an indicator variable set to one if the analyst is ranked in the top three or as a runner-up by Institutional Investor in year t, and zero otherwise. *Promote* = Analyst promotion to a high-status broker, an indicator variable set to one if the analyst moves from a non-I.I. ranked broker to an I.I. ranked broker during year t, and zero otherwise. *Connect_500+* = Well-connected analysts, an indicator variable set to one if the analyst has more than 500 LinkedIn connections, and zero otherwise. *Tech_Skills* = Number of technical skills (i.e., see Table 2 for details) within the top five skills reported by the analyst and endorsed by the analyst's LinkedIn connections. Analyst, broker, and firm-level controls are as specified in Equations (1) to (4), respectively. *t- or z*-statistics (in parenthesis) are calculated based on standard errors clustered at the broker level. *, **, ***, indicate significance at the 10%, 5%, and 1% levels, respectively.