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# The effect of social skills on analyst performance

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## Abstract

Social skills are important but difficult to measure. So far, few empirical studies have examined the effect of social skills on the performance of professionals. Using the number of LinkedIn connections as a proxy for social skills, we investigate the effect of financial analysts' social skills on their performance. We use multiple ways to validate the measure of social skills and show that analysts with better social skills produce more accurate earnings forecasts and that their stock recommendations elicit stronger market reactions. Furthermore, these socially skilled analysts are more likely to be voted as All-Star Analysts. This study provides the first large-sample evidence highlighting the importance of social skills on financial analysts' performance.

KEYWORDS
analysts, connections, labor market, social media, social skills

## L'effet des compétences sociales sur la performance des analystes

## Résumé

Les compétences sociales sont importantes, mais difficiles à mesurer. Jusqu'à présent, peu d'études empiriques ont examiné l'effet des compétences sociales sur la performance des professionnels. En utilisant le nombre de relations sur LinkedIn comme indicateur des compétences sociales, les auteurs étudient l'effet des compétences sociales des analystes financiers sur leur performance. Ils utilisent plusieurs moyens pour valider la mesure des compétences sociales et montrent que les analystes ayant de meilleures compétences sociales produisent des prévisions de résultats plus précises et que leurs recommandations en matière d'actions suscitent des réactions plus fortes du marché. De

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plus, ces analystes socialement compétents sont plus susceptibles d'être élus analystes All-Star. Les auteurs exposent les conclusions d'une première étude portant sur un vaste échantillon soulignant l'importance des compétences sociales sur la performance des analystes financiers.

**MOTS-CLÉS**
analystes, compétences sociales, marché du travail, médias sociaux, relations

# 1 | INTRODUCTION

The job duties of financial analysts include such activities as issuing research reports, arranging non-deal roadshows, hosting investor conferences, and providing one-on-one meetings and other high-touch services. These responsibilities require effective gathering and analysis of information and smooth communication with investors and corporate management. Based on its annual surveys, *Institutional Investor*, an influential business magazine, highlights some of the analyst attributes that are most valued by fund managers: industry knowledge, management access, and special services, among others (Bagnoli et al., 2008). Research in accounting and finance supports the view that these attributes are associated with the quality of services performed by analysts (Green et al., 2014; Kadan et al., 2012). Much remains unknown, however, about the fundamental factors that drive the variation in these attributes and performance across analysts. This study focuses on this issue by examining whether and how analysts' social skills affect their performance.

Social skills have been defined as comprising two elements: (1) specific proficiencies or behaviors that play a role in establishing relationships with others and (2) competencies that assist individuals to interact effectively with others (Baron, 2004; Baron & Markman, 2000; Baron & Tang, 2009; Segrin & Kinney, 1995). Recent studies suggest that social skills are important in the labor market (Adhvaryu et al., 2018; Deming, 2017a). According to employment growth figures from the US Census, jobs that require high levels of social skills grew by 11.8% between 1980 and 2012. Consistently, a growing body of literature suggests that better social skills are associated with greater labor market returns. This finding is related to the inability of newer technologies to replace the jobs that require social skills (Adhvaryu et al., 2018; Deming, 2017a; Deming & Kahn, 2018). Despite the important role of social skills in the labor market, there is no systematic evidence that social skills matter for performance in a competitive equity research industry that demands a high degree of quantitative skills.

Social skills can play an important role in analysts' performance. Analysts with better social skills are likely to have broader social connections, such as industry peers, financial journalists, and the customers, suppliers, and competitors of covered companies (Bradshaw, 2011; C. Li, 2018; Call et al., 2021; SEC, 2000). These connections serve as information sources and can provide analysts with information to improve their industry knowledge, an important determinant of analyst performance (Bradley et al., 2017; Brown et al., 2015; Kadan et al., 2012). Analysts with better social skills also can improve their performance by communicating more effectively with information sources and investors. For example, socially skilled analysts are more likely to be favored by managers, enabling them to gain the information needed to understand their covered companies through private communication, earnings conference calls, or site visits (Brown et al., 2015; Cheng et al., 2016, 2019; Mayew, 2008; Soltes, 2014).

Social skills are difficult for researchers to observe directly. This may be the reason why little empirical research has tested the role of social skills in the financial industry. Prior literature in psychology uses survey-based data to measure social skills, but such research generally has been limited to small samples and is difficult to apply in other settings. Because establishing relationships and facilitating interaction and communication with others are the key functions of social skills, we argue that the size of social connections can proxy for social skills. Prior studies in psychology support this argument. For example, Riggio (1986) and Riggio and Zimmerman (1991) show high correlations between their survey-based measures of social skills and the size of social connections. Pollet et al. (2011) and Lans et al. (2015) find that the size of social connections is associated with the determinants of social skills such as social competence and extraversion.

We thus start by constructing a measure of analysts' social skills based on their profiles on LinkedIn, the world's largest professional networking platform. Specifically, we obtained the names of all US financial analysts who issued at least one earnings forecast in 2014 from the I/B/E/S stock recommendation file. Then, in November 2015, we collected the LinkedIn profiles of these analysts manually and extracted relevant information, including the number of connections, skill sets, and education. Social skills are measured based on the number of analysts' connections.

We conduct three tests to validate our measure of social skills. First, we evaluate the concurrent validity as a facet of construct validity by examining the correlations between our measure of social skills and several analyst and broker attributes that are likely to be related to social skills.[1] The results show that analysts with better social skills are more likely to have an MBA degree, more general experience, and higher perceived sociability, measured by analysts' facial appearance as perceived by Amazon Mechanical Turk (MTurk) raters. In addition, their brokerage firms tend to have a higher demand for social skills, proxied by the percentage of financial analyst job postings that require social skills. Second, as an evaluation of the predictive validity of our measure, we use the earnings conference call setting to examine whether analysts with better social skills have better management access (Mayew, 2008; Mayew et al., 2013; Milian et al., 2017). Consistent with analysts with better social skills having better relationships with the management of covered companies, we find that these analysts are treated more favorably by managers during earnings conference calls. They are more likely to ask questions and be invited to ask questions earlier in Q&A sessions as well as receive longer answers from managers to their questions. Third, prior studies suggest that social skills are essential for effective leadership and teamwork (Goleman, 2009; Karp, 2013; Morgeson et al., 2005; Riggio & Reichard, 2008). Consistent with this literature, we find that analysts with better social skills also are more likely to lead an analyst team, proxied by the presence of multiple authors in their research reports. All these results lend support to the use of our measure of social skills.

Using a sample of 38,875 analyst-company-year observations from 2014 to 2015, we find that analysts with better social skills, defined as the number of connections above the sample median, have lower earnings forecast errors, suggesting that social skills significantly improve analyst forecast accuracy.[2] Furthermore, analysts with better social skills issue more profitable "buy" stock recommendations and receive stronger market reactions to their "buy" and "sell" recommendations. Overall, our findings indicate that social skills have significant effects on analyst performance, presumably through easier access to information sources and more effective communication with investors. We further explore the moderating role of the information environment of analysts' covered companies. We find that the effect of social skills on analyst performance tends to be more pronounced for companies with a poorer information environment. Again, these findings are consistent with the view that social skills enable analysts to gather more information through more channels. Finally, we find that, after controlling for quantitative research output, analysts with better social skills are more likely to be voted All-Star Analysts, consistent with social skills as correlated with some qualitative analyst attributes that are valued by fund managers.

[1] Concurrent validity is the extent to which an operationalized construct correlates with theoretically related measures. Predictive validity is related to the ability of operationalized construct to predict an outcome that will result from the underlying theoretical construct (Bochkay et al., 2022).

[2] Throughout the paper, "year" refers to the fiscal year when it is mentioned in conjunction with a company; otherwise, "year" refers to the calendar year.

In additional analyses, we address the correlated-omitted-variable problem and alternative explanations. Specifically, we consider (1) analysts without LinkedIn profiles, the exclusion of which may introduce a sample selection bias; (2) the relationships between analysts and managers, which may subsume the effect of social skills on analyst performance; (3) physical appearance, which may be correlated with social skills; and (4) the possibility that stronger market reactions to stock recommendations of analysts with better social skills stem from these analysts' choosing to piggyback on corporate news to a greater extent than do analysts with poorer social skills. In all tests, our results for social skills are robust.

Our study makes several contributions. First, our study provides the first and timely large-sample evidence to support the important role of social skills in analysts' performance. Although prior studies focus extensively on the top-ranked attributes across analysts, it is unclear whether there are certain fundamental factors that drive the variations in these attributes. For example, Green et al. (2014) find that access to management is an important source of analysts' informational advantage, but the study is silent on why some analysts gain management access while others cannot. We fill this gap in the literature by suggesting that social skills contribute to different analyst attributes and performance.

Second, although recent studies in labor economics provide evidence on the returns to social skills (Adhvaryu et al., 2018; Autor, 2015; Deming, 2017a; Deming & Kahn, 2018), little is known about the role of social skills within a profession. Our study adopts a novel measure of an individual's social skills and applies this measure to the profession of financial analysts. We believe that our measure of social skills may be generalized to other professions. Whereas prior psychology literature has used survey-based data to measure social skills in small samples, our measure is based on LinkedIn data, which enables us to conduct large-sample empirical analyses. Our evidence supports the significance of social skills in the development of professional careers.

Third, our study has implications for education and corporate hiring and training. There has been concern over the sustainability of the financial analyst profession, given the potential threat of replacement by artificial intelligence. Many investment banks have started to use robots to automate their operations, based on advanced data analytics.[3] Although robot advisers are likely to be better users of technical tools than are humans, financial analysts' social skills cannot be easily replaced by computers (Autor, 2015). Our findings thus support the need to consider social skills in the corporate hiring process. Furthermore, because social skills can be developed further in practice (Adhvaryu et al., 2018; Dimitriadis & Koning, 2022; Riggio & Reichard, 2008), our findings highlight the importance of training employees to foster social skills.

# 2 | LITERATURE AND HYPOTHESES

## 2.1 | Background on social skills and how to measure them

Social or interpersonal skills include the ability to get along with people, form and maintain friendships, comfort and help others, show sensitivity to the feelings of others, and express feelings, ideas, and opinions in a positive way (Dow & Tierney, 2005; Neidell & Waldfogel, 2010). Recent studies suggest that social skills are highly valued in the labor market (Adhvaryu et al., 2018; Deming, 2017a; Deming & Kahn, 2018). The US Census survey shows that the fastest-growing professional occupations all require massive interpersonal interactions and social skills (Deming, 2017b). In contrast, the jobs that require high technical skills but low

[3]https://iscjobs.com/man-vs-machine-financial-analysts-in-an-age-of-automation/
https://www.finextra.com/newsarticle/30236/capital-markets-jobs-on-the-line-as-banks-raise-ai-spend

social skills declined by 3.3% between 1980 and 2012, and the decline was more pronounced after 2000. Jobs with social skills pay higher wages as the labor markets respond to automation (Deming, 2017b). This evidence suggests the importance of social skills for which there is still no good substitute (Autor, 2015). In recent years, many investment banks have started to use artificial intelligence to automate their operations. Although these robots can assist investment banks to assess investment deals and form future strategies, it is impossible for robots to engage in any teamwork that requires significant interaction and communication.

Social skills facilitate interaction and communication with others and can help individuals to establish relationships and build broader social networks. As such, the size of social connections can proxy for social skills. Riggio (1986) shows high correlations between social skills and the size of social connections. His measure of social skills, Social Skills Inventory (SSI), has the highest positive correlations with the number of close friends and the number of daily acquaintances, among many self-reported social behaviors. Moreover, the number of close friends and the number of daily acquaintances are significantly positively related to four dimensions of social skills: emotional expressivity, emotional sensitivity, social expressivity, and social control. Similarly, Riggio and Zimmerman (1991) document a positive correlation between the SSI and the size of an individual's social network. Consistent with Riggio (1986), Pollet et al. (2011) and Lans et al. (2015) find that the size of social connections is associated with the determinants of social skills, such as social competence and extraversion. Overall, prior literature suggests that the size of social connections is highly related to social skills.

Prior studies have developed several survey-based measures for social or interpersonal skills. For example, Lowe and Cautela (1978) design a 100-item survey, Social Performance Survey Schedule, to assess an adult's positive and negative social behavior. Riggio (1986) develops a 105-item survey that pertains to seven basic social abilities and constructs the SSI, an index of global social skills, by summing the seven basic social skill scores. Clark and Patton (1997) develop an instrument that comprises several items that relate directly or indirectly to social skills in the workplace: whether participants establish and maintain close and/or casual friendships; and whether they demonstrate skills for getting along with coworkers or supervisors. Lindsey and Rice (2015), using a 20-item situational test of emotional management, survey 856 undergraduates from colleges of business regarding their interpersonal skills. Deming (2017a) constructs a measure based on two self-reported items from the National Longitudinal Survey of Youth in 1979 and 1997. Overall, these measures are generally limited to small samples and are difficult to apply in other settings.

## 2.2 | Hypothesis development

Financial analysts are important information intermediaries in collecting, analyzing, and disseminating information in the capital market. Analysts can gain industry- and company-specific information by interacting with a company's customers, suppliers, and competitors, and other information sources (Bradshaw, 2011; Bradshaw et al., 2021; Brown et al., 2015; Call et al., 2021; C. Li, 2018). Bradshaw (2011) notes that the suppliers, customers, and competitors of covered companies play critical roles in analysts' information search processes. Brown et al. (2015) suggest that analysts incorporate pieces of private and public information from management and other sources into their own industry knowledge. C. Li (2018) reports that financial journalists use direct quotes from financial analysts. Call et al. (2021) report that 57% of financial journalists in their sample are very likely to have direct interaction with financial analysts. Consistently, in a comment letter from the Association for Investment Management and Research (AIMR) to the US SEC, AIMR states, "Analysts also go beyond company contacts and speak to customers, contractors, suppliers and competitors in order to find as many pieces of the puzzle as possible with the goal of developing the most accurate and complete picture of a company under review."[4] In this regard, social skills help analysts to establish broad connections that can expand the breadth of their information search. As a result, analysts with better social skills are likely to have more information sources and be more capable of incorporating pieces of private and public information into their industry- and company-specific knowledge.

Financial analysts with better social skills are likely to have better relationships and more effective communication with others. Deming (2017a) shows that social skills help to reduce the cost of information exchange. The reduced cost further facilitates information transfer and allows these sociable analysts to receive more information from various sources. For example, better social skills may enable analysts to have better and more communication with management during corporate site visits, earnings conference calls, and one-on-one phone calls. Prior studies suggest that management access is not equally available to all analysts (Francis et al., 2004; Francis & Philbrick, 1993; S. Chen & Matsumoto, 2006). Mayew (2008) shows that managers use their discretion to discriminate among analysts by granting more conference call participation to analysts who issue more favorable stock recommendations. Therefore, analysts with better social skills may yield valuable new interpretations based on their existing private information and the information disseminated by managers. Furthermore, better social skills may help analysts to communicate and disseminate their research more effectively to investors, resulting in a larger market impact of their research.

Based on the above discussion, we expect social skills to be associated positively with analyst performance. Thus, we form the following hypothesis in the alternative form:

**Hypothesis.** Analysts with better social skills perform better than other analysts.

# 3 | SAMPLE SELECTION AND KEY VARIABLES

## 3.1 | LinkedIn analyst data and sample selection

We obtained the names of all US financial analysts who issued at least one earnings forecast during 2014 from the I/B/E/S stock recommendation file and manually collected the profiles of these analysts from LinkedIn, the world's largest professional social network, in November 2015. We then used a Perl program to parse these LinkedIn profiles and extract data on analyst attributes, including the number of connections, skill sets, and other individual characteristics (e.g., education).

Table 1 provides a summary of the sample selection procedures. Our sample period is from 2014 to 2015. We obtain analysts' annual earnings forecasts and stock recommendations from I/B/E/S and retain their most recent earnings forecasts and stock recommendations within a company's fiscal year (Clement, 1999; Clement & Tse, 2003). We obtain stock return data from CRSP, financial statement data from the Compustat Annual database, and All-Star Analyst award status from *Institutional Investor* magazine. We also collect information about the education of the covered companies' top executives and directors from BoardEx. We exclude analysts whose names are not available in I/B/E/S or whose LinkedIn profiles could not be identified. After excluding observations with missing information to calculate control variables, the final sample consists of 38,875 analyst-company-years (2,767 unique companies and 2,280 unique analysts).

[4]The comment letter also states, "They (analysts) speak with everyone and anyone who might provide more pieces of the puzzle: customers, employees, competitors, and suppliers, to name a few. The more discussions analysts have about a company, the greater their ability to ask the right questions or fill in the gaps. For example, an analyst may discover something unusual or incongruous in a company's financial statements and look for someone to discuss this with. Questions about revenue-generating ability or inventory problems, for example, might be addressed to key customers." See https://www.sec.gov/rules/proposed/s73199/zeikel1.htm

**TABLE 1** Sample selection.

| Sample selection criteria | Number of analyst-company-years | Number of companies | Number of analysts |
|---|---|---|---|
| Analyst-company-years with EPS forecasts, January 2014 to December 2015 | 103,912 | 5,698 | 7,112 |
| Retain: with analyst name in the I/B/E/S recommendation file | 87,537 | 5,198 | 3,522 |
| Retain: with LinkedIn profile | 61,122 | 4,931 | 2,410 |
| Retain: with I/B/E/S actual earnings information to calculate earnings forecast error | 57,195 | 4,569 | 2,401 |
| Retain: with stock price information at the beginning of fiscal year $t$ | 46,545 | 3,824 | 2,347 |
| Retain: with financial data to calculate market value and market-to-book ratio | 38,875 | 2,767 | 2,280 |
| Final earnings forecast sample | 38,875 | 2,767 | 2,280 |

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

## 3.2 | Key variables

### 3.2.1 | Analyst social skills

Our key variable of interest is analysts' social skills, proxied by the number of connections reported on LinkedIn. We define analysts with better social skills as those who have above the median (i.e., 396) number of LinkedIn connections, and we create an indicator variable (*Social_Skills*) accordingly.[5] We empirically validate the *Social_Skills* measure in Section 4. In our sample period, 65% of financial analysts in I/B/E/S who issue both earnings forecasts and stock recommendations for the US companies have a LinkedIn profile.

### 3.2.2 | Analyst performance measures

We measure analyst performance by earnings forecast error (*AFE*), defined as the absolute value of the analyst's most recent earnings forecast minus the actual earnings per share for the company-year, scaled by the beginning-of-year stock price (Clement, 1999; Clement & Tse, 2003; Merkley et al., 2020). Following Clement and Tse (2003), *AFE* is standardized to range from zero to one to control for company-year effects. Specifically, the standardized *AFE* for analyst $i$ who follows company $j$ in fiscal year $t$ is calculated as $[AFE_{i,j,t} - \min(AFE_{j,t})]/[\max(AFE_{j,t}) - \min(AFE_{j,t})]$, where $\max(AFE_{j,t})$ and $\min(AFE_{j,t})$ denote the largest and smallest earnings forecast errors, respectively, of all of the analysts who follow company $j$ in fiscal year $t$. The standardized *AFE* is calculated based on all available and most recent 1-year-ahead earnings forecasts for company $j$ in fiscal year $t$, including those issued by analysts without LinkedIn profiles.

We also use the profitability and informativeness of stock recommendations to proxy for analyst performance. Specifically, we examine the longer window return ($CAR[-1,90]$) of analyst $i$'s most recent stock recommendation for company $j$ during fiscal year $t$ as a proxy for

[5]LinkedIn reports 500+ for the number of connections larger than 500. In untabulated tests, we repeat the empirical analyses, using 500 as an alternative cutoff point, tercile ranking of LinkedIn connections, and normalized ranking of LinkedIn connections to measure social skills; our findings are unchanged.

recommendation profitability and the short-window market reaction ($CAR[-1,1]$) to the stock recommendation as a proxy for recommendation informativeness. $CAR[-1,90]$ is measured as the cumulative market-adjusted return during the [−1,90] days of stock recommendations. $CAR[-1,1]$ is measured as the 3-day cumulative market-adjusted return that surrounds the announcement date of stock recommendations.[6] For "hold," "sell," and "strong sell" stock recommendations, we multiply *CAR* by −1 for ease of result interpretation (Hope et al., 2021; Stephan et al., 2021; Yezegel, 2015).[7]

### 3.2.3 | Control variables

A stream of literature studies specific social ties among financial analysts and their connections (Cohen et al., 2010; L. Fang & Huang, 2017; Gu et al., 2019). Cohen et al. (2010) suggest that selective disclosure is the main mechanism of information transfer along social ties such as school connections. Although they document that the effect of the ties existed before Reg FD but disappeared after Reg FD, one concern is that our measure of social skills may still capture the effect of specific social ties, as analysts with more connections may have such specific social ties. To address this concern, we control for specific observable social ties in all of our tests. Following Cohen et al. (2010) and L. Fang and Huang (2017), we measure the existence of school ties between an analyst and the top executives and directors of a covered company. Specifically, we identify analysts who graduated from the top 100 universities in the United States and the top five universities in Canada and collect the education backgrounds of all top executives and directors of the companies followed by these analysts. The ranking of top universities in the United States is taken from *US News & World Report* (2015). We create an indicator variable (*Alumni_Ties*), which is set to one if the analyst and the executive or director attended the same educational institution and zero otherwise.

Following prior literature, we include brokerage firm size (*BSize*) to control for the analyst's brokerage firm resources, number of companies followed (*NFirm*) and number of industries followed (*NInd*) to control for the analyst's portfolio complexity, and company-specific experience (*Exp*) to control for the analyst's forecasting ability (Clement, 1999; Clement & Tse, 2003; Jacob et al., 1999; Lim, 2001). In the tests of earnings forecast accuracy, we also include earnings forecast frequency (*Freq*) and forecast horizon (*Horizon*) to control for the analyst's forecasting effort and forecast timeliness, respectively. In the tests of stock recommendation profitability and informativeness, we further control for the characteristics of the analyst's covered companies, including size (*Size*) and market-to-book ratio (*MTB*).[8] The definitions of variables are provided in the Appendix.

## 3.3 | Descriptive statistics

Panel A of Table 2 presents the descriptive statistics for the variables used in the regression analyses. Here, *AFE* is the unstandardized, price-deflated earnings forecast error. The number of connections (*Raw_Connect*) ranges from 0 to 500+, with a median of 396 connections. The mean of *Social_Skills* is 0.525, indicating that 52.5% of the earnings forecasts are issued by analysts with better social skills (those with more than 396 connections). Fourteen percent of

[6]We derive inferentially similar results based on $CAR[-1,180]$ (untabulated). In these windows, −1 and 1 represent trading days, while 90 and 180 represent calendar days.

[7]We follow previous studies and treat "hold" as sell recommendations (Barber et al., 2001; Loh & Mian, 2006). The results reported in Section 5.2 are robust to excluding "hold" recommendations (untabulated).

[8]In an untabulated test, we further include the number of times of media coverage as an additional measure to proxy for analyst reputation or celebrity (Bonner et al., 2007) and find consistent results.

**TABLE 2** Descriptive statistics and correlations.

| Panel A: Descriptive statistics | | | | | | |
|---|---|---|---|---|---|---|
| **Variable** | ***N*** | **Mean** | **SD** | **Q1** | **Median** | **Q3** |
| **Dependent variables** | | | | | | |
| *AFE* (*price-deflated*) | 38,875 | 0.008 | 0.023 | 0.001 | 0.002 | 0.005 |
| *CAR*[−1,90] | 9,857 | 0.018 | 0.163 | −0.069 | 0.014 | 0.099 |
| *CAR*[−1,1] | 9,857 | 0.017 | 0.050 | −0.007 | 0.011 | 0.036 |
| *CAR*[2,90] | 9,857 | 0.000 | 0.153 | −0.077 | 0.001 | 0.079 |
| *NParticipation* | 9,531 | 1.531 | 1.441 | 0.000 | 1.000 | 3.000 |
| *Q&A_Priority* | 6,153 | −5.336 | 3.248 | −7.000 | −4.750 | −3.000 |
| *Answers_Length* | 6,153 | 5.549 | 1.240 | 5.409 | 5.822 | 6.174 |
| *Team* | 6,812 | 0.720 | 0.449 | 0.000 | 1.000 | 1.000 |
| **Independent variables** | | | | | | |
| *Raw_Connect* | 2,280 | – | – | 222 | 396 | 500+ |
| *Social_Skills* | 38,875 | 0.525 | 0.499 | 0.000 | 1.000 | 1.000 |
| *Alumni_Ties* | 38,875 | 0.140 | 0.346 | 0.000 | 0.000 | 0.000 |
| *BSize* | 38,875 | 3.794 | 1.015 | 2.996 | 3.892 | 4.663 |
| *NFirm* | 38,875 | 17.107 | 8.826 | 11.000 | 16.000 | 21.000 |
| *NInd* | 38,875 | 3.353 | 2.346 | 2.000 | 3.000 | 5.000 |
| *Exp* | 38,875 | 4.934 | 3.883 | 2.000 | 4.000 | 7.000 |
| *Freq* | 38,875 | 4.297 | 2.387 | 3.000 | 4.000 | 6.000 |
| *Horizon* | 38,875 | 4.448 | 0.906 | 4.277 | 4.595 | 4.779 |
| *Size* | 38,875 | 8.448 | 1.668 | 7.284 | 8.447 | 9.579 |
| *MTB* | 38,875 | 4.946 | 6.409 | 1.911 | 3.084 | 5.298 |
| **Additional independent variables for tests of earnings conference call participation** | | | | | | |
| *Recom_Level* | 9,531 | 3.622 | 0.903 | 3.000 | 4.000 | 4.000 |
| *NAnalyst* | 9,531 | 2.864 | 0.678 | 2.398 | 2.996 | 3.401 |
| *NCall* | 9,531 | 3.585 | 0.890 | 3.000 | 4.000 | 4.000 |
| *AA_Award* | 9,531 | 0.112 | 0.316 | 0.000 | 0.000 | 0.000 |
| **Additional independent variables for test of likelihood of working in a team** | | | | | | |
| *ROA* | 6,812 | 0.029 | 0.129 | 0.008 | 0.049 | 0.089 |
| *NAnalyst* | 6,812 | 20.274 | 11.819 | 10.000 | 18.000 | 29.000 |

(Continues)

**TABLE 2** (Continued)

| Panel A: Descriptive statistics | | | | | | |
|---|---|---|---|---|---|---|
| **Variable** | ***N*** | **Mean** | **SD** | **Q1** | **Median** | **Q3** |
| *NSector* | 6,812 | 1.282 | 0.615 | 1.000 | 1.000 | 1.000 |
| *RetVol* | 6,812 | 0.022 | 0.010 | 0.015 | 0.019 | 0.027 |

**Panel B: Correlation matrix**

| Variable | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) | (13) | (14) | (15) | (16) | (17) | (18) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| (1) *Social_Skills* | 1 | | | | | | | | | | | | | | | | | |
| (2) *AFE* | **−0.02** | 1 | | | | | | | | | | | | | | | | |
| (3) *CAR*[−1,90] | 0.01 | −0.01 | 1 | | | | | | | | | | | | | | | |
| (4) *CAR*[−1,1] | **0.03** | 0.01 | **0.41** | 1 | | | | | | | | | | | | | | |
| (5) *CAR*[2,90] | −0.00 | −0.01 | **0.90** | 0.00 | 1 | | | | | | | | | | | | | |
| (6) *NParticipation* | **0.03** | **−0.02** | **0.04** | **0.06** | **0.02** | 1 | | | | | | | | | | | | |
| (7) *Q&A_Priority* | −0.00 | **0.09** | **0.03** | **0.10** | −0.01 | **0.13** | 1 | | | | | | | | | | | |
| (8) *Answers_Length* | **0.03** | 0.00 | **0.02** | **0.05** | −0.00 | **0.20** | **0.16** | 1 | | | | | | | | | | |
| (9) *Team* | **0.06** | **−0.05** | −0.03 | **0.04** | **−0.05** | **0.08** | −0.03 | −0.02 | 1 | | | | | | | | | |
| (10) *AA_Award* | **0.04** | **−0.02** | −0.01 | **−0.02** | 0.01 | **0.13** | **0.06** | **0.05** | **0.18** | 1 | | | | | | | | |
| (11) *Alumni_Ties* | **0.07** | **−0.03** | −0.01 | **−0.02** | 0.01 | **0.02** | **−0.05** | 0.00 | 0.02 | **0.03** | 1 | | | | | | | |
| (12) *BSize* | **0.08** | **−0.02** | 0.01 | −0.01 | 0.01 | **0.15** | 0.02 | **0.03** | **0.50** | **0.27** | **0.04** | 1 | | | | | | |
| (13) *NFirm* | **0.04** | **−0.04** | **0.03** | **0.03** | **0.02** | **0.04** | **0.08** | **0.03** | **0.23** | **0.26** | **−0.01** | **0.16** | 1 | | | | | |
| (14) *NInd* | **−0.05** | **0.02** | 0.01 | 0.01 | 0.01 | **0.07** | **0.06** | **0.05** | **0.05** | **0.18** | −0.00 | 0.00 | **0.41** | 1 | | | | |
| (15) *Exp* | **−0.05** | **−0.04** | −0.01 | −0.01 | −0.00 | **0.16** | −0.00 | **0.06** | **0.08** | **0.11** | **0.05** | 0.00 | **0.07** | **0.02** | 1 | | | |
| (16) *Freq* | 0.00 | **−0.19** | 0.00 | **0.03** | −0.01 | **0.26** | **−0.02** | **0.07** | **0.13** | **0.05** | **0.02** | **0.11** | **0.12** | 0.01 | **0.10** | 1 | | |
| (17) *Horizon* | 0.01 | **0.21** | 0.00 | **0.04** | −0.01 | **−0.06** | **0.05** | **0.00** | **−0.05** | **−0.08** | **−0.02** | **−0.06** | **−0.05** | **−0.07** | **0.01** | **−0.46** | 1 | |
| (18) *Size* | **0.01** | **−0.14** | **−0.08** | **−0.18** | −0.01 | **−0.10** | **−0.40** | **−0.04** | **0.16** | **0.10** | **0.20** | **0.13** | −0.00 | **−0.06** | **0.21** | **0.14** | **−0.14** | 1 |
| (19) *MTB* | **0.06** | −0.00 | 0.00 | 0.00 | 0.00 | 0.00 | **−0.07** | **−0.05** | 0.01 | **−0.01** | **0.01** | **0.01** | **−0.03** | **−0.04** | **−0.07** | **−0.07** | **0.04** | **0.07** |

*Note*: Panel A presents descriptive statistics for the variables used in the regression analyses. *Raw_Connect* is the raw number of the analyst's LinkedIn connections. See the Appendix for the variable definitions. Panel B presents the Pearson correlation coefficients between the dependent variables and independent variables, where bold type indicates significance at the 10% level.

earnings forecasts are issued by analysts with school ties. The average financial analyst in our sample issues four earnings forecasts, follows 17 companies within three 2-digit SIC industries, and has 5 years of company-specific experience.

Panel B of Table 2 presents the Pearson correlation coefficients of the main variables used in the analyst-company-year-level analyses. *Social_Skills* has a negative correlation with standardized *AFE* and a positive correlation with $CAR[-1,1]$. This provides preliminary evidence that analysts with better social skills issue more accurate earnings forecasts and more informative stock recommendations.

# 4 | VALIDATION OF SOCIAL SKILLS MEASURE

## 4.1 | Correlations with other attributes related to social skills

We examine the construct validity of the *Social_Skills* measure through multiple tests. In our first test, we evaluate the concurrent validity of the *Social_Skills* measure, which is a facet of construct validity (Bochkay et al., 2022). Specifically, we examine the correlations between *Social_Skills* and several analyst and broker attributes that are likely to be related to social skills, including an analyst's perceived sociability (*Perceived_Sociability*), MBA degree (*MBA*), general experience (*GExp*), and her brokerage firm's demand for social skills (*Broker_Demand_for_Social_Skills*).

Motivated by prior studies that measure competence, trustworthiness, or personality based on facial appearance, we construct a measure of perceived sociability (*Perceived_Sociability*) based on the analyst's facial appearance (Oosterhof & Todorov, 2008).[9,10] The measure attempts to capture the analyst's perceived skills to seek out companionship and engage in interpersonal relations. This is calculated as the mean value of the sociability ratings (ranging from 1 to 4; *below average* = 1, *average* = 2, *sociable* = 3, *very sociable* = 4) submitted by the human raters for the analyst.[11] We employ the Amazon MTurk service to rate the analyst photographs from LinkedIn profiles. Each photograph is rated by 10 MTurk raters. For analysts without a high-quality photograph in their LinkedIn profile, we set *Perceived_Sociability* to the value of the first quartile (i.e., 1.89).[12] The sample mean of *Perceived_Sociability* is 1.99.

We expect that financial analysts with an MBA degree have better social skills than do those without an MBA degree for the following reasons. One of the goals of MBA programs is to hone students' interpersonal skills. Prior survey evidence suggests that most MBA programs in the United States conduct interpersonal skills assessment for their applicants and require coursework that covers interpersonal skills topics (Beenen et al., 2018; Navarro, 2008). These MBA programs promote group projects, team presentations, and public speeches to improve students' social skills. Moreover, MBA programs provide students with an opportunity to expand their networks and develop leadership skills.[13] We create an indicator variable (*MBA*)

[9]For example, Graham et al. (2017) construct four measures of the facial traits of CEO—attractiveness, competence, trustworthiness, and likeableness—based on ratings from graduate and undergraduate students. Using Amazon's MTurk service, Blankespoor et al. (2017) construct a composite measure of investors' overall perceptions of management competence, trustworthiness, and attractiveness. Similarly, Duarte et al. (2012) elicit judgments about a borrower's trustworthiness based on a photograph alone, using MTurk raters. Fink et al. (2006) use ratings from college students on facial pictures to construct measures of sociability, intelligence, liveliness, self-confidence, and balance.

[10]The literature in biology and psychology suggests that both nature (i.e., the inborn part) and nurture (i.e., the acquired part) contribute to the development of facial features (C. Chen & Jack, 2017; Moore, 2013). We thus argue that perceived sociability based on facial traits captures both nature (i.e., the inborn social skills that remain unchangeable) and nurture (i.e., the acquired social skills that were built and developed over time) to some extent, even though we are unable to separate them empirically.

[11]The results based on the quantitative measures (ranging from 1 to 100) are similar (untabulated).

[12]A significant number of analysts do not have a high-quality photograph in their LinkedIn profile. The correlation between *Social_Skills* and an indicator variable for missing profile photo (*No_Photo*) is −0.304 (untabulated). This negative correlation suggests that analysts without a profile photo are less sociable or at least less active on social media.

[13]https://www.skillsyouneed.com/rhubarb/interpersonal-skills-from-mba.html

that is set to one if the analyst has an MBA degree, and zero otherwise. Thirty-two percent of the analysts in our sample have an MBA degree.

Analysts with more experience could have better social skills because they receive training in social skills at their workplace. For example, Guile and Griffiths (2001) note that work experience can provide an opportunity to develop social skills through various forms of social interactions. Analysts have job responsibilities that include interacting with coworkers and clients, and these social interactions could serve as training in social skills. Moreover, brokerage firms have training seminars to help employees improve their social skills. We thus expect that general experience is positively correlated with social skills. We measure the analyst's general experience (*GExp*) as the number of years since the analyst first appeared in the I/B/E/S database. The sample mean of *GExp* is 7.74 years.

Finally, the preference for financial analysts with better social skills may vary across brokerage firms. We use the percentage of financial analyst job postings that require social skills in a broker-year (*Broker_Demand_for_Social_Skills*) to proxy for such a preference. The job postings data are obtained from Burning Glass. Following Deming and Kahn (2018) and Deming and Noray (2020), we consider a financial analyst job posting to require social skills if it includes any of the following terms: communication skills, corporate/business communications, effective communications, oral/verbal communication, stakeholder/employee communications, team building, team management, teamwork, collaboration, customer relationship management, social networking, or leadership. For brokerage firms without any financial analyst job posting during the year, we set *Broker_Demand_for_Social_Skills* to zero. The sample mean of *Broker_Demand_for_Social_Skills* is 17.82%.

Panel A of Table 3 presents the correlations of the above variables at the analyst-year level. Consistent with our expectations, *Social_Skills* is positively correlated with all four analyst and broker attributes. These results provide support for the view that *Social_Skills* captures the desired underlying construct.

## 4.2 | Relationships with covered companies' management

Next, we evaluate the predictive validity of the *Social_Skills* measure, which is another facet of construct validity, using the earnings conference call setting (Mayew, 2008; Mayew et al., 2013; Milian et al., 2017). Because social skills help individuals to establish relationships and interact effectively with others, we expect that analysts with better social skills maintain good relationships with the covered companies' management and, therefore, have better management access during conference calls. We collected from Thomson StreetEvents all earnings call transcripts for our sample period and matched the conference call participants to our sample companies and analysts. We then estimate the following model:

$$\begin{aligned} Mgmt\_Access_{i,j,t} = {} & \beta_0 + \beta_1 Social\_Skills_i + \beta_2 Alumni\_Ties_{i,j,t} + \beta_3 Recom\_Level_{i,j,t} + \beta_4 NAnalyst_{j,t} \\ & + \beta_5 NCall_{j,t} + \beta_6 AA\_Award_{i,t-1} + \beta_7 AFE_{i,j,t} + \beta_8 Exp_{i,j,t} + \beta_9 NFirm_{i,t} \\ & + \beta_{10} NInd_{i,t} + \beta_{11} Freq_{i,j,t} + \beta_{12} BSize_{i,t} + \beta_{13} Size_{j,t-1} + \beta_{14} MTB_{j,t-1} + \varepsilon_{i,j,t}, \end{aligned} \tag{1}$$

where *Mgmt_Access* denotes *NParticipation*, *Q&A_Priority*, or *Answers_Length*.

*NParticipation* is the number of company *j*'s earnings conference calls in fiscal year *t* in which analyst *i* participates by asking questions. *Q&A_Priority* is the analyst's priority in asking questions, calculated by averaging the order the analyst appears in the Q&A sessions of company *j*'s earnings conference calls in year *t*, multiplied by −1 so that a higher value indicates

**TABLE 3** Validation of social skills measure.

**Panel A: Correlations between social skills measure and other analyst and broker characteristics**

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| (1) *Social_Skills* | 1 | | | |
| (2) *Perceived_Sociablity* | **0.27** | 1 | | |
| (3) *MBA* | **0.20** | **0.03** | 1 | |
| (4) *GExp* | **0.04** | **−0.04** | **0.09** | 1 |
| (5) *Broker_Demand_for_Social_Skills* | **0.02** | **0.02** | **0.03** | 0.01 |

**Panel B: Analyst social skills and earnings conference call participation**

| Variable | (1) *NParticipation* | (2) *Q&A_Priority* | (3) *Answers_Length* |
|---|---|---|---|
| *Social_Skills* | 0.171*** | 0.176** | 0.095*** |
| | (3.90) | (2.38) | (9.78) |
| *Alumni_Ties* | 0.157** | 0.044 | −0.013 |
| | (2.26) | (0.33) | (−0.57) |
| *Recom_Level* | 0.140*** | 0.191*** | −0.028*** |
| | (6.53) | (7.07) | (−28.80) |
| *NAnalyst* | −0.939*** | −2.068*** | −0.165*** |
| | (−14.84) | (−11.81) | (−5.87) |
| *NCalls* | 0.645*** | −0.510*** | 0.027 |
| | (22.06) | (−5.30) | (1.54) |
| *AA_Award* | 0.633*** | 0.984*** | 0.014 |
| | (19.79) | (8.31) | (0.89) |
| *AFE* | −0.656 | 3.135*** | −0.911** |
| | (−1.09) | (12.92) | (−2.33) |
| *Exp* | 0.087*** | 0.044*** | 0.010* |
| | (25.96) | (3.79) | (1.77) |
| *NFirm* | −0.018*** | 0.035*** | −0.001 |
| | (−9.11) | (6.98) | (−1.40) |
| *NInd* | 0.029* | −0.074*** | 0.011*** |
| | (1.67) | (−4.79) | (4.11) |
| *Freq* | 0.211*** | 0.008 | 0.014*** |
| | (34.48) | (0.39) | (6.73) |
| *BSize* | 0.278*** | 0.349*** | 0.023 |
| | (10.25) | (12.20) | (1.19) |
| *Size* | −0.065** | −0.206*** | 0.025*** |
| | (−2.29) | (−4.54) | (2.58) |
| *MTB* | 0.010** | −0.017*** | −0.007*** |
| | (2.01) | (−3.88) | (−4.38) |
| *NParticipation* | | 0.385*** | 0.185*** |
| | | (25.45) | (27.23) |
| *Q&A_Priority* | | | 0.041*** |
| | | | (7.34) |
| Intercept(s) | Included | Included | Included |
| *N* | 9,531 | 6,153 | 6,153 |
| Pseudo/Adj. $R^2$ | 0.091 | 0.326 | 0.064 |

(Continues)

**TABLE 3** (Continued)

**Panel C: Analyst social skills and likelihood of leading an analyst team**

| **Variable** | **(1)** *Team* |
|---|---|
| *Social_Skills* | 0.083** |
| | (2.14) |
| *Alumni_Ties* | −0.046 |
| | (−0.78) |
| *Freq* | 0.042*** |
| | (3.74) |
| *Horizon* | 0.003 |
| | (0.12) |
| *BSize* | 0.015*** |
| | (20.05) |
| *NFirm* | 0.033*** |
| | (9.99) |
| *NInd* | −0.006 |
| | (−0.53) |
| *Exp* | 0.026*** |
| | (4.73) |
| *AA_Award* | 0.181* |
| | (1.91) |
| *Size* | 0.057** |
| | (2.54) |
| *MTB* | 0.001 |
| | (0.23) |
| *ROA* | −0.190 |
| | (−1.09) |
| *NAnalyst* | 0.002 |
| | (0.55) |
| *NSector* | −0.052 |
| | (−1.48) |
| *RetVol* | 0.509 |
| | (0.20) |
| Industry FE | Yes |
| *N* | 6,812 |
| Pseudo $R^2$ | 0.239 |

*Note*: Panel A presents the Pearson correlation coefficients between the *Social_Skills* measure and some analyst and brokerage firm characteristics related to the underlying social skills construct. *Perceived_Sociability* is the analyst's sociability as perceived by Amazon MTurk raters and ranges from 1 to 4. *MBA* is an indicator variable set to one if the analyst has an MBA degree, and zero otherwise. *GExp* is the number of years since the analyst first appeared in the I/B/E/S database. *Broker_Demand_for_Social_Skills* is the percentage of financial analyst job postings that require social skills in a broker-year, and zero otherwise. Bold type indicates significance at the 10% level. Panel B presents the results from estimating Equation (1) by ordered logit (column (1)) or OLS (columns (2) and (3)) regression. The *t*-statistics and *z*-statistics (in parentheses) are calculated based on the standard errors clustered at the analyst level. Panel C presents the results from estimating the probit regression of Equation (2). The *z*-statistics (in parentheses) are calculated based on standard errors and are clustered at the analyst level. All variables are defined in the Appendix.
*, **, and *** represent two-tailed significance levels of 10%, 5%, and 1%, respectively.

higher priority. *Answers_Length* is the length of management's answers to the analyst's questions, calculated by the natural logarithm of the average number of words that company *j*'s management replies to the analyst. Following Mayew (2008), we use the level of the analyst's first stock recommendation for company *j* in fiscal year *t* (*Recom_Level*) to proxy for the analyst's view of the company, where strong buy, buy, hold, sell, and strong sell recommendations are coded as 5, 4, 3, 2, and 1, respectively. We control for the constraints to the analyst's participation, such as the number of analysts following (*NAnalyst*) and the number of earnings conference calls held by company *j* in year *t* (*NCall*). We include *NFirm* and *NInd* because analysts who cover more industries and companies have less time to expend to cover a particular company (Mayew, 2008). We also control for the analyst's reputation as proxied by All-Star Analyst award status (*AA_Award*) in calendar year $t-1$, initial earnings forecast accuracy for company *j* in fiscal year *t* (*AFE*), company-specific experience (*Exp*), and other known determinants of analyst performance, as defined in Section 3.2.3 (Clement, 1999; Clement & Tse, 2003; Jacob et al., 1999; Lim, 2001). The *t*-statistics or *z*-statistics are reported in parentheses and calculated based on standard errors clustered at the analyst level.

The results of univariate analysis in panel B of Table 2 show that *Social_Skills* is positively correlated with *NParticipation* and *Answers_Length*. Panel B of Table 3 presents the results from estimating Equation (1) by ordered logit (column (1)) or OLS regression (columns (2) and (3)). The coefficient on *Social_Skills* is positive and significant (*z*-value = 3.90) in column (1), suggesting that analysts with better social skills tend to gain more access to management through earnings calls participation. The significantly positive coefficient on *Social_Skills* (*t*-value = 2.38) in column (2) suggests that analysts with better social skills are granted higher priority in asking questions. In column (3), after further controlling for analysts' priority in Q&A sessions, the significantly positive coefficient on *Social_Skills* (*t*-value = 9.78) suggests that managers provide longer answers to socially skilled analysts' questions and that these analysts are more effective in digging out information through communication. Overall, these results are consistent with social skills helping analysts to build better relationships with management and suggest that *Social_Skills* captures the desired underlying construct.

## 4.3 | Leading an analyst team

We further evaluate the predictive validity of our social skills measure by testing the conjecture that analysts with better social skills are more likely to lead an analyst team because social skills are essential for effective leadership and teamwork (Goleman, 2009; Karp, 2013; Morgeson et al., 2005; Riggio & Reichard, 2008). We estimate the following probit model:

$$\begin{aligned} Team_{i,j,t} = {} & \beta_0 + \beta_1 Social\_Skills_i + \beta_2 Alumni\_Ties_{i,j,t} + \beta_3 Freq_{i,j,t} + \beta_4 Horizon_{i,j,t} + \beta_5 BSize_{i,t} \\ & + \beta_6 NFirm_{i,t} + \beta_7 NInd_{i,t} + \beta_8 Exp_{i,t} + \beta_9 AA\_Award_{i,t-1} + \beta_{10} Size_{j,t-1} + \beta_{11} MTB_{j,t-1} \\ & + \beta_{12} ROA_{j,t-1} + \beta_{13} NAnalyst_{j,t} + \beta_{14} NSector_{j,t} + \beta_{15} RetVol_{j,t-1} + Industry\ FE + \varepsilon_{i,j,t}, \end{aligned} \tag{2}$$

where *Team* is an indicator variable set to one if analyst *i* issues a research report with multiple authors for company *j* in fiscal year *t*, and zero otherwise. Following B. Fang and Hope (2021), we also include the number of sectors (*NSector*) to control for task complexity, return on assets (*ROA*) to control for company performance, and stock return volatility (*RetVol*) to control for company uncertainty. Panel C of Table 3 provides the results. We find that the coefficient on *Social_Skills* is positive and significant (*z*-value = 2.14), suggesting that analysts with better social skills are more likely to lead a team. The result thus lends further support to the use of our measure of social skills.

# 5 | SOCIAL SKILLS AND ANALYSTS' PERFORMANCE

## 5.1 | Social skills and earnings forecast accuracy

In our first main test, we examine the effect of social skills on analysts' earnings forecast accuracy (*AFE*). Following Clement and Tse (2003), all continuous variables are standardized to range from 0 to 1 at the company-year level.[14] We estimate the following OLS model:

$$AFE_{i,j,t} = \beta_0 + \beta_1 Social\_Skills_i + \beta_2 Alumni\_Ties_{i,j,t} + \beta_3 BSize_{i,t} + \beta_4 NFirm_{i,t} + \beta_5 NInd_{i,t} + \beta_6 Exp_{i,j,t} + \beta_7 Freq_{i,j,t} + \beta_8 Horizon_{i,j,t} + \varepsilon_{i,j,t}, \quad (3)$$

Table 4, column (1), presents the results. The coefficient on *Social_Skills* is negative and significant ($t$-value = 2.16), suggesting that earnings forecasts of analysts with better social skills are more accurate than those of analysts with poorer social skills. In economic terms, the presence of *Social_Skills* is estimated to be associated with a decrease in the standardized *AFE* by 3.2% of the sample mean. The evidence supports our hypothesis that analysts with better social skills perform better. Regarding control variables, we find that an analyst's earnings forecasts are more accurate when the analyst has school ties with covered companies' top executives and directors, covers more companies, and updates forecasts more frequently. Earnings forecasts tend to be less accurate when the analyst works for a larger brokerage firm, covers more industries, and issues forecasts earlier.[15]

## 5.2 | Social skills and stock recommendation profitability and informativeness

Next, we examine the effect of social skills on analysts' stock recommendation profitability ($CAR[-1,90]$), informativeness ($CAR[-1,1]$), and the difference ($CAR[2,90]$), which shows trading opportunities in the post-recommendation window. We estimate the following OLS model:

$$CAR_{i,j,t} = \beta_0 + \beta_1 Social\_Skills_i + \beta_2 Alumni\_Ties_{i,j,t} + \beta_3 BSize_{i,t} + \beta_4 NFirm_{i,t} + \beta_5 NInd_{i,t} + \beta_6 Exp_{i,j,t} + \beta_7 Size_{j,t-1} + \beta_8 MTB_{j,t-1} + Month\,FE + Industry\,FE + \varepsilon_{i,j,t}, \quad (4)$$

where *CAR* denotes $CAR[-1,90]$, $CAR[-1,1]$, or $CAR[2,90]$. We estimate Equation (4) separately for buy and sell stock recommendations, where buy (sell) recommendations include analysts' strong buy and buy (hold, sell, and strong sell) recommendations. Month fixed effects are based on the calendar month of stock recommendations, and industry fixed effects are based on 2-digit SIC codes.

Table 4, columns (2) to (4), report the results for buy stock recommendations. We find that the coefficients on *Social_Skills* are positive and significant for buy stock recommendation profitability (column (2); $t$-value = 1.96) and informativeness (column (3); $t$-value = 3.88). The former result is consistent with sociable analysts being capable of translating information from various information sources into more profitable buy recommendations, whereas the latter

[14] In our main analysis, we rely on the standardized earnings forecast errors to control for company-year effects. Our results are robust to two other approaches, including (1) measuring the earnings forecast error and the determinants of the forecast error after subtracting the corresponding company-year mean (Clement, 1999; Lim, 2001) and (2) using the raw (unstandardized) price-deflated earnings forecast error as well as controlling for company size, growth, performance, and industry and fiscal year fixed effects (untabulated).

[15] Earlier studies (Clement, 1999; Jacob et al., 1999, 2008) document a positive relation between forecast accuracy and broker size, whereas more recent studies (Drake et al., 2020; B. Fang & Hope, 2021; Hope et al., 2021) document a negative relation between forecast accuracy and broker size. In untabulated tests, we find that the relation between forecast accuracy and broker size started turning from positive to negative around 2002–2003, which coincides with the Global Settlement.

**TABLE 4** Analyst social skills and performance.

| Variable | Earnings forecasts (1) *AFE* | Buy recommendations (2) *CAR* [−1,90] | (3) *CAR* [−1,1] | (4) *CAR* [2,90] | Sell recommendations (5) *CAR* [−1,90] | (6) *CAR* [−1,1] | (7) *CAR* [2,90] |
|---|---|---|---|---|---|---|---|
| *Social_Skills* | −0.009** | 0.009* | 0.001*** | 0.007* | −0.005 | 0.004** | −0.007 |
| | (−2.16) | (1.96) | (3.88) | (1.69) | (−1.05) | (2.41) | (−1.20) |
| *Alumni_Ties* | −0.018*** | −0.002 | −0.001 | −0.001 | 0.007 | 0.004* | 0.003 |
| | (−5.66) | (−0.48) | (−0.97) | (−0.22) | (1.41) | (1.65) | (0.90) |
| *BSize* | 0.049*** | 0.004*** | 0.001** | 0.002* | −0.001 | −0.000 | −0.002 |
| | (4.47) | (2.58) | (2.39) | (1.85) | (−0.87) | (−0.76) | (−1.10) |
| *NFirm* | −0.022** | 0.001** | −0.000* | 0.001*** | 0.000 | 0.000 | 0.000 |
| | (−2.53) | (2.57) | (−1.71) | (3.23) | (1.43) | (0.46) | (1.60) |
| *NInd* | 0.011* | −0.001 | −0.000 | −0.001 | 0.001 | 0.001 | −0.000 |
| | (1.83) | (−0.70) | (−1.18) | (−0.56) | (0.51) | (1.52) | (−0.31) |
| *Exp* | 0.004 | 0.001** | 0.001*** | 0.001 | −0.000 | 0.001*** | −0.001* |
| | (0.87) | (2.49) | (3.76) | (1.48) | (−0.10) | (6.00) | (−1.96) |
| *Freq* | −0.034*** | | | | | | |
| | (−4.11) | | | | | | |
| *Horizon* | 0.319*** | | | | | | |
| | (26.74) | | | | | | |
| *Size* | | −0.005*** | −0.005*** | 0.001 | −0.006*** | −0.004*** | −0.003** |
| | | (−4.95) | (−19.49) | (0.57) | (−4.97) | (−8.70) | (−2.57) |
| *MTB* | | −0.000 | −0.000 | −0.000 | 0.001*** | 0.000 | 0.000 |
| | | (−1.55) | (−0.82) | (−1.31) | (2.94) | (0.64) | (1.61) |
| Intercept | 0.196*** | 0.084 | 0.089*** | −0.006 | 0.033 | −0.005 | 0.080*** |
| | (37.16) | (0.91) | (3.69) | (−0.08) | (1.02) | (−0.48) | (3.67) |
| Month & Industry FE | No | Yes | Yes | Yes | Yes | Yes | Yes |
| *N* | 38,875 | 5,062 | 5,062 | 5,062 | 4,795 | 4,795 | 4,795 |
| Adj. $R^2$ | 0.120 | 0.062 | 0.042 | 0.057 | 0.053 | 0.038 | 0.042 |

*Note*: This table presents the results from estimating the OLS regression of Equations (3) and (4). See the Appendix for the variable definitions. For the earnings forecast accuracy test in column (1), all of the continuous variables are scaled to range from zero to one within each company-year (Clement & Tse, 2003). The *t*-statistics (in parentheses) are calculated based on the standard errors clustered at the analyst level.

*, **, and *** represent two-tailed significance levels of 10%, 5%, and 1%, respectively.

result is consistent with these analysts being more effective in communicating and disseminating their buy recommendations to investors. In economic terms, *Social_Skills* is associated with an increase in stock recommendation profitability by 91 basis points and an increase in stock recommendation informativeness by 15 basis points, which are 5.3% and 2.1% of the standard deviation of *CAR*[−1,90] and *CAR*[−1,1], respectively. The significantly positive coefficient on *Social_Skills* for the post-announcement window return (column 4; *t*-value = 1.69), however, suggests that investors do not fully react to buy recommendations of analysts with better social skills during the 3-day announcement window. For the control variables, we find that buy recommendations tend to be more informative and profitable when the issuing analyst works for a larger brokerage firm and has more company-specific experience.

Table 4, columns (5) to (7), provide the results for sell stock recommendations. We find that the coefficient on *Social_Skills* is positive and significant for sell stock recommendation informativeness (column (6); *t*-value = 2.41) but insignificant for sell stock recommendation profitability (column (5)). In economic terms, *Social_Skills* is associated with an increase in stock recommendation informativeness by 35 basis points, which is 7.7% of the standard deviation of $CAR[-1,1]$. These results are consistent with socially skilled analysts being more effective in communicating and disseminating their sell recommendations than are analysts with poorer social skills, even though their sell recommendations are not more profitable.

Overall, these results suggest that analysts with better social skills have greater market influence and issue more profitable buy stock recommendations, consistent with our hypothesis.

## 5.3 | Effect of social skills conditional on companies' information environment

We consider whether the covered companies' information environment moderates the effect of social skills on analyst performance. If social skills facilitate analysts' communication with and information gathering from managers and other information sources, such skills should be more beneficial when the covered companies have less public information available. To test this, we measure company *j*'s information environment by the first principal component, based on the factor analysis of company size, institutional ownership, and annual earnings guidance frequency in fiscal year *t*. Similar to Bushman et al. (2004) and Anderson et al. (2009), we attempt to capture the underlying commonalities of these information environment proxies by employing principal component analysis. We collect the institutional ownership data from Thomson Reuters 13F filings and the management earnings guidance data from I/B/E/S. We use company size to proxy for the richness of a company's information environment (Bowen et al., 2002; Clement et al., 2012), annual earnings guidance frequency to proxy for its commitment to, and provision of, voluntary disclosure (Hirst et al., 2008), and institutional ownership to proxy for its public information production in response to investor demand (Boone & White, 2015). We then classify each company-year into a good or poor information environment using the median value of the first principal component, and augment Equations (3) and (4) by including the interaction term between *Social_Skills* and an indicator variable of lower information environment quality (*Low_Info*).

Table 5 provides the results from estimating augmented Equations (3) and (4). For the test of earnings forecast accuracy, reported in column (1), we find that the main effect of *Social_Skills* is significant (*t*-value = 2.04), but the interaction effect between *Social_Skills* and *Low_Info* is insignificant. For the tests of stock recommendation profitability and informativeness, presented in columns (2) to (7); however, we find that the significant results documented in Table 4 are concentrated in companies with lower information environment quality (i.e., smaller companies, companies with less public earnings guidance, and companies with lower institutional ownership). These results suggest that analysts with better social skills enjoy a significant information advantage in valuing stocks over analysts with poorer social skills, consistent with the view that social skills facilitate analysts' communication with, and information acquisition from, various information sources.

We also examine the first earnings forecasts and stock recommendations issued by analysts in a company-fiscal year and find that the effects of *Social_Skills* for *AFE* and $CAR[-1,1]$ of buy recommendations are larger in magnitude, relative to their Table 4 counterparts. These untabulated findings are consistent with social skills' being more beneficial for analyst performance when less information is available to the public within a given forecast cycle (a company-year).

**TABLE 5** The effect of analyst social skills on performance conditional on information environment.

| Variable | Earnings forecasts (1) *AFE* | Buy recommendations (2) *CAR* [−1,90] | (3) *CAR* [−1,1] | (4) *CAR* [2,90] | Sell recommendations (5) *CAR* [−1,90] | (6) *CAR* [−1,1] | (7) *CAR* [2,90] |
|---|---|---|---|---|---|---|---|
| *Social_Skills* | −0.011** | 0.003 | 0.000 | 0.002 | −0.010 | 0.000 | −0.009 |
| | (−2.04) | (0.68) | (0.70) | (0.68) | (−1.07) | (0.20) | (−1.58) |
| *Low_Info* | 0.034*** | −0.025*** | 0.002** | −0.026*** | 0.018* | 0.005** | 0.013** |
| | (6.77) | (−4.53) | (2.19) | (−5.53) | (1.73) | (2.02) | (2.25) |
| *Social_Skills*×*Low_Info* | 0.004 | 0.013** | 0.003** | 0.011** | 0.009 | 0.006** | 0.004 |
| | (0.71) | (2.40) | (2.44) | (2.16) | (0.56) | (2.52) | (0.71) |
| Intercept & Controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Month & Industry FE | No | Yes | Yes | Yes | Yes | Yes | Yes |
| *N* | 38,875 | 5,062 | 5,062 | 5,062 | 4,795 | 4,795 | 4,795 |
| Adj. $R^2$ | 0.124 | 0.063 | 0.043 | 0.059 | 0.056 | 0.042 | 0.043 |

*Note*: This table presents the results from estimating the augmented Equations (3) and (4) by OLS regression. *Low_Info* is an indicator variable of low information environment, defined based on the median value of the first principal component estimated from the factor analysis of company size, institutional ownership, and annual earnings guidance frequency for company *j* in fiscal year *t*. For the earnings forecast accuracy test in column (1), all of the continuous variables are scaled to range from zero to one within each company-year (Clement & Tse, 2003). Other variables are defined in the Appendix. *t*-statistics (in parentheses) are calculated based on the standard errors clustered at the analyst level.

*, **, and *** represent two-tailed significance levels of 10%, 5%, and 1%, respectively.

## 5.4 | Social skills and All-Star Analyst award

To shed light on whether social skills drive the variations in the top-ranked attributes across analysts, we examine the effect of social skills on the likelihood of an analyst being voted as an All-Star Analyst. The All-Star award is a measure of analysts' perceived performance and is intended to capture multiple aspects of analysts' performance, including but not limited to analyst research output quality (Bonner et al., 2007; W. Chen & Tan, 2013; Huang et al., 2022). In addition to producing higher-quality research, socially skilled analysts can communicate better with clients and be more responsive to clients' needs.[16] These analysts also can provide better services to clients. For example, because analysts with better social skills have better management access, they can help buy-side clients to connect with covered companies' management through activities such as corporate site visits and non-deal roadshows (Groysberg et al., 2011; Maber et al., 2014). Taken together, analysts with better social skills may win more votes for the All-Star award, which is critical to analysts' compensation and career advancement (Brown et al., 2015; Groysberg et al., 2011; Hong & Kubik, 2003; Maber et al., 2014). To test this conjecture, we estimate the following probit model:

$$\begin{aligned} AA\_Award_{i,t} = \beta_0 &+ \beta_1 Social\_Skills_i + \beta_2 Alumni\_Ties_{i,t} + \beta_3 Avg\_AFE_{i,t} \\ &+ \beta_4 |Avg\_CAR[-1,90]|_{i,t} + \beta_5 Avg\_Freq_{i,t} + \beta_6 BSize_{i,t} + \beta_7 NFirm_{i,t} + \beta_8 NInd_{i,t} \\ &+ \beta_9 Avg\_Exp_{i,t} + \beta_{10} AA\_Award_{i,t-1} + \beta_{11} Avg\_Size_{i,t} + \beta_{12} Avg\_MTB_{i,t} + \varepsilon_{i,t}, \end{aligned} \tag{5}$$

[16]For example, in the annual Institutional Investor surveys for the two decades, special service, responsiveness, and management access are among the top-ranked analyst attributes.

where *AA_Award* is analyst *i*'s All-Star Analyst award status in calendar year *t*. Because our main proxy for social skills is based on number of social connections, we control for the analyst's award status in calendar year $t-1$ in the regression to address the concern that the analyst might become more connected *after* being awarded All-Star status.[17] Other variables are defined in the Appendix. *Avg_* is an operator that averages the values across the analyst's covered companies in calendar year *t*.

Panel A of Table 6 presents the descriptive statistics for the variables in Equation (5). Our sample for this analysis is at the analyst-year level. Nine percent of the analysts are awarded All-Star status in year *t*. Furthermore, 34.6% of the analysts are classified as socially skilled, and 32.8% of analysts have school ties with at least one top executive or director of the covered companies.

Panel B of Table 6 provides the results from estimating Equation (5). We find that the coefficient on *Social_Skills* is positive and significant (*z*-value = 3.68). The evidence suggests that analysts with better social skills are more likely to be voted as All-Star than other analysts. In terms of economic significance, the marginal effect at the means for *Social_Skills* is 0.4 percentage point, which is approximately 4.4% of the mean of *AA_Award*. Turning to control variables, we find that an analyst is more likely to receive the All-Star award when the analyst works for a larger brokerage firm, updates forecasts more frequently, covers more industries and companies, and has more company-specific experience.

Overall, the results suggest that analysts with better social skills have better overall performance, not only in terms of research but also in other areas valued by fund managers. The evidence supports our hypothesis and is consistent with social skills as a fundamental factor that drives analyst performance.[18]

# 6 | ADDRESSING ALTERNATIVE EXPLANATIONS

## 6.1 | Analysts without LinkedIn profiles

Our main analyses have excluded analysts without LinkedIn profiles. These analysts might have a stable career and, therefore, do not need the LinkedIn presence. Alternatively, these analysts might be less sociable. We conduct two analyses to examine the group of analysts without a LinkedIn profile to ensure that our main results are not driven by sample bias. First, we include analysts without a LinkedIn profile (i.e., *No_LinkedIn* = 1) and compare their performance with that of analysts with a LinkedIn profile (i.e., *No_LinkedIn* = 0). Second, we include analysts without a LinkedIn profile in the group with weaker social skills (*Social_Skills* = 0) and reestimate Equations (3) to (5). In all additional tests, we include the same control variables and fixed effects as in Equations (3) to (5) but, for brevity, do not tabulate the results.

Panel A of Table 7 shows that analysts without a LinkedIn profile issue less accurate earnings forecasts (column (1)) and less informative buy recommendations (column (3)) than those with LinkedIn profiles. Analysts without a LinkedIn profile are also less likely to be voted as All-Stars

[17] To further alleviate the concern about reverse causation, we focus on a sample of the analysts who did not win the All-Star award in 2015 and examine whether there is a significant increase in social connections for those who won the award in 2016. The untabulated result suggests that new star analysts do not experience a sudden increase in connections and that the size of their social network is generally stable and likely to reflect their social skills.

[18] To address the potential measurement error problem that LinkedIn might include inactive connections or might reflect only an analyst's self-aggressiveness (e.g., adding random people to appear sociable), we use the highest number of endorsements on the analyst's skills reported on LinkedIn (*Max_Endorsements*) as an alternative measure of social skills. The rationale is that the connections who provided endorsement should know the analyst relatively well. When we augment Equations (3) to (5) by replacing *Social_Skills* with *Max_Endorsements*, the untabulated results show that analysts with more endorsements have better earnings forecast accuracy and sell stock recommendation informativeness and are more likely to be voted as All-Stars.

**TABLE 6** Analyst social skills and All-Star Analyst award.

| Panel A: Descriptive statistics | | | | | | |
|---|---|---|---|---|---|---|
| **Variable** | ***N*** | **Mean** | **SD** | **Q1** | **Median** | **Q3** |
| **Dependent variable** | | | | | | |
| *AA_Award* | 4,857 | 0.090 | 0.286 | 0.000 | 0.000 | 0.000 |
| **Independent variables** | | | | | | |
| *Social_Skills* | 4,857 | 0.346 | 0.476 | 0.000 | 0.000 | 1.000 |
| *Alumni_Ties* | 4,857 | 0.328 | 0.470 | 0.000 | 0.000 | 1.000 |
| *Avg_AFE* | 4,857 | 0.436 | 0.144 | 0.355 | 0.438 | 0.517 |
| \|*Avg_CAR*[−1,90]\| | 4,857 | 0.068 | 0.095 | 0.000 | 0.033 | 0.095 |
| *Avg_Exp* | 4,857 | 4.423 | 2.703 | 2.167 | 3.926 | 6.000 |
| *Avg_Freq* | 4,857 | 4.018 | 1.851 | 2.857 | 3.786 | 4.818 |
| *Avg_MTB* | 4,857 | 5.713 | 7.565 | 2.066 | 3.739 | 6.059 |
| *Avg_Size* | 4,857 | 8.917 | 1.478 | 8.036 | 9.062 | 9.927 |
| *BSize* | 4,857 | 3.670 | 1.112 | 2.904 | 3.826 | 4.543 |
| *NFirm* | 4,857 | 13.390 | 7.735 | 7.000 | 13.000 | 18.000 |
| *NInd* | 4,857 | 2.498 | 1.838 | 1.000 | 2.000 | 3.000 |

**Panel B: Regression results**

| **Variable** | **(1)**<br>***AA_Award*** |
|---|---|
| *Social_Skills* | 0.101*** |
| | (3.68) |
| *Alumni_Ties* | 0.097 |
| | (1.61) |
| *Avg_AFE* | −0.150 |
| | (−0.29) |
| \|*Avg_CAR*[−1,90]\| | 0.128 |
| | (0.60) |
| *Avg_Freq* | 0.105*** |
| | (8.40) |
| *BSize* | 0.293*** |
| | (3.83) |
| *NFirm* | 0.043*** |
| | (5.02) |
| *NInd* | 0.064*** |
| | (2.87) |
| *Avg_Exp* | 0.033** |
| | (1.99) |
| *Lag_AA_Award* | 2.684*** |
| | (55.35) |
| *Avg_Size* | 0.154*** |
| | (3.46) |
| *Avg_MTB* | 0.007*** |
| | (4.62) |

(Continues)

**TABLE 6** (Continued)

| Panel B: Regression results | |
|---|---|
| **Variable** | **(1)** ***AA_Award*** |
| Intercept | −6.360*** |
| | (−12.46) |
| *N* | 4,857 |
| Pseudo $R^2$ | 0.690 |

*Note*: Panel A presents the descriptive statistics for the sample used in the tests of analysts' career paths. *Avg_AFE* = Average earnings forecast accuracy, calculated as the mean of the analyst's standardized earnings forecast errors in calendar year *t*. *Avg_CAR* [−1,90] = Average stock recommendation profitability, calculated as the mean of the cumulative market-adjusted returns during the [−1,90] days of the analyst's stock recommendations in calendar year *t*. *Avg_Exp* = Average company-specific experience, defined as the mean of the number of years the analyst has followed the companies in the analyst's portfolio in calendar year *t*. *Avg_Freq* = Average earnings forecast frequency, calculated as the mean of the number of earnings forecasts issued by the analyst for the companies followed in calendar year *t*. *Avg_MTB* = Average market-to-book ratio, calculated as the mean of the market-to-book ratios of the companies the analyst follows in calendar year *t*. *Avg_Size* = Average company size, measured as the mean of the natural logarithm of market value of the companies that the analyst follows in calendar year *t*. See the Appendix for other variable definitions. Panel B presents the results from estimating the probit regression of Equation (5). All of the variables are defined in the Appendix. The *z*-statistics (in parentheses) are calculated based on the standard errors and are clustered at the analyst level.
** and *** represent significance levels of 5% and 1%, respectively.

than those with a LinkedIn profile (column (8)). The results hold even when we compare the analysts without a LinkedIn profile to analysts with weaker social skills (i.e., *Social_Skills* = 0). The evidence is consistent with the conjecture that the analysts without a LinkedIn profile are less sociable or weaker analysts. Panel B of Table 7 shows that our conclusions are robust to classifying analysts without a LinkedIn presence as analysts with weaker social skills.

## 6.2 | Management access

Panel B of Table 3 shows that *Social_Skills* is positively associated with management access during earnings conference calls. Given that prior studies find the relationship between analysts and managers is significantly associated with forecast accuracy (Mayew et al., 2013; Milian et al., 2017), a natural question is whether the effects of social skills are incremental to specific analyst-manager relationships in a form other than *Alumni_Ties*. To answer this question, we additionally control for the number of conference calls attended by an analyst during the company-year in Equations (3) to (5).

The results in panel C of Table 7 are inferentially similar to our main results, suggesting that general social skills are incremental to specific analyst-manager relationships. We find that the effects of conference call participations are significant for *AFE* and all *CAR*s of buy stock recommendations (columns (1)–(4)), suggesting that a better analyst-manager relationship is one of the underlying mechanisms through which social skills contribute to analyst performance.[19] The insignificant effects of conference call participation on *CAR*s of sell stock recommendations (columns (5)–(7)) are consistent with the findings of Cohen et al. (2010) that managers are willing to reveal positive, but not negative, information about their companies to connected analysts. Overall, the results suggest that analysts also use their social skills to obtain significant information from parties outside of management.

[19]In another robustness check, we further control for the average tone of the analyst in the Q&A sessions (*Analyst_Tone*), measured as (the number of positive words—the number of negative words)/the number of total words spoken in the Q&A session, averaged across all conference calls participated in during a company-year. The classification of negative and positive words is based on the Loughran and McDonald (2011) dictionary. Our main results are robust (untabulated).

**TABLE 7** Addressing alternative explanations.

**Panel A: Analysts with versus without LinkedIn profiles**

| Variable | Earnings forecasts (1) *AFE* | Buy recommendations (2) *CAR* [−1,90] | (3) *CAR* [−1,1] | (4) *CAR* [2,90] | Sell recommendations (5) *CAR* [−1,90] | (6) *CAR* [−1,1] | (7) *CAR* [2,90] | Overall performance (8) *AA_Award* |
|---|---|---|---|---|---|---|---|---|
| *No_LinkedIn* | 0.047*** | −0.002 | −0.005* | 0.003 | −0.013 | −0.002 | −0.015 | −0.874*** |
| | (5.83) | (−0.18) | (−1.91) | (0.25) | (−0.99) | (−0.62) | (−1.01) | (−2.68) |
| $N$ | 60,415 | 7,604 | 7,604 | 7,604 | 7,112 | 7,112 | 7,112 | 7,158 |
| Adj./pseudo $R^2$ | 0.130 | 0.085 | 0.046 | 0.076 | 0.064 | 0.037 | 0.052 | 0.706 |

**Panel B: Sensitivity analysis—Including analysts without LinkedIn profiles**

| Variable | Earnings forecasts (1) *AFE* | Buy recommendations (2) *CAR* [−1,90] | (3) *CAR* [−1,1] | (4) *CAR* [2,90] | Sell recommendations (5) *CAR* [−1,90] | (6) *CAR* [−1,1] | (7) *CAR* [2,90] | Overall performance (8) *AA_Award* |
|---|---|---|---|---|---|---|---|---|
| *Social_Skills* | −0.009** | 0.011** | 0.003*** | 0.009* | −0.004 | 0.004* | −0.006 | 0.103* |
| | (−2.45) | (2.11) | (5.19) | (1.69) | (−0.80) | (1.91) | (−0.94) | (1.88) |
| $N$ | 60,415 | 7,604 | 7,604 | 7,604 | 7,112 | 7,112 | 7,112 | 7,158 |
| Adj./pseudo $R^2$ | 0.129 | 0.086 | 0.047 | 0.077 | 0.064 | 0.038 | 0.052 | 0.704 |

**Panel C: Sensitivity analysis—Controlling for conference call participations**

| Variable | Earnings forecasts (1) *AFE* | Buy recommendations (2) *CAR* [−1,90] | (3) *CAR* [−1,1] | (4) *CAR* [2,90] | Sell recommendations (5) *CAR* [−1,90] | (6) *CAR* [−1,1] | (7) *CAR* [2,90] | Overall performance (8) *AA_Award* |
|---|---|---|---|---|---|---|---|---|
| *Social_Skills* | −0.009** | 0.009* | 0.001*** | 0.007 | −0.005 | 0.003** | −0.007 | 0.096*** |
| | (−2.20) | (1.87) | (3.68) | (1.62) | (−1.07) | (2.23) | (−1.17) | (3.65) |
| *NParticipation* | −0.004*** | 0.005*** | 0.001*** | 0.004*** | −0.000 | 0.001 | −0.002 | 0.082 |
| | (−3.14) | (4.14) | (3.23) | (3.14) | (−0.08) | (1.15) | (−1.25) | (1.00) |
| $N$ | 38,875 | 5,062 | 5,062 | 5,062 | 4,795 | 4,795 | 4,795 | 4,857 |
| Adj./pseudo $R^2$ | 0.121 | 0.063 | 0.044 | 0.058 | 0.053 | 0.038 | 0.042 | 0.690 |

**Panel D: Sensitivity analysis—Controlling for physical attractiveness**

| Variable | Earnings forecasts (1) *AFE* | Buy recommendations (2) *CAR* [−1,90] | (3) *CAR* [−1,1] | (4) *CAR* [2,90] | Sell recommendations (5) *CAR* [−1,90] | (6) *CAR* [−1,1] | (7) *CAR* [2,90] | Overall performance (8) *AA_Award* |
|---|---|---|---|---|---|---|---|---|
| *Social_Skills* | −0.008** | 0.010** | 0.002*** | 0.008* | −0.006 | 0.004** | −0.008 | 0.107** |
| | (−2.31) | (2.04) | (3.84) | (1.77) | (−1.24) | (2.45) | (−1.36) | (2.47) |
| *Attractiveness* | −0.011*** | −0.006 | −0.000 | −0.005 | 0.012*** | −0.001 | 0.013*** | −0.057 |
| | (−3.96) | (−1.28) | (−0.27) | (−1.20) | (2.77) | (−0.80) | (2.75) | (−0.47) |
| $N$ | 38,875 | 5,062 | 5,062 | 5,062 | 4,795 | 4,795 | 4,795 | 4,857 |
| Adj./pseudo $R^2$ | 0.120 | 0.062 | 0.041 | 0.057 | 0.053 | 0.038 | 0.042 | 0.690 |

(Continues)

**TABLE 7** (Continued)

**Panel E: Likelihood of issuing stock recommendations immediately after an earnings announcement**

| Variable | (1) *EAD_After_Hour* | (2) *EAD_After_Hour _or_Next_Day* |
|---|---|---|
| *Social_Skills* | 0.014 | 0.011 |
| | (0.18) | (0.40) |
| *N* | 8,964 | 9,804 |
| Pseudo $R^2$ | 0.051 | 0.050 |

**Panel F: Sensitivity analysis—Excluding stock recommendations issued immediately after an earnings announcement**

| | Buy recommendations | | | Sell recommendations | | |
|---|---|---|---|---|---|---|
| Variable | (1) $CAR[-1,90]$ | (2) $CAR[-1,1]$ | (3) $CAR[2,90]$ | (4) $CAR[-1,90]$ | (5) $CAR[-1,1]$ | (6) $CAR[2,90]$ |
| *Social_Skills* | 0.010** | 0.002*** | 0.008* | −0.006 | 0.003*** | −0.007 |
| | (2.21) | (2.78) | (1.83) | (−0.98) | (2.70) | (−1.02) |
| *N* | 4,730 | 4,730 | 4,730 | 4,180 | 4,180 | 4,180 |
| Adj. $R^2$ | 0.067 | 0.044 | 0.061 | 0.060 | 0.041 | 0.042 |

*Note*: Panel A compares the performance of analysts with and without LinkedIn presence. Panel B presents the relations between social skills and analysts' performance, assuming analysts without LinkedIn presence have weaker social skills (*Social_Skills* = 0). Panel C presents the relations between social skills and analysts' performance, controlling for analysts' conference call participations (*NParticipation*). Panel D presents the relations between social skills and analysts' performance, controlling for analysts' physical attractiveness. Panel E presents the relation between social skills and the likelihood of issuing stock recommendations immediately after an earnings announcement. Panel F presents the results of stock recommendation profitability and informativeness based on the sample that excludes stock recommendations with *EAD_After_Hour_or_Next_Day* = 1. In panel E, the control variables are the same as in Equation (4). In all other panels, the control variables are the same as in Equations (3) to (5). The results of intercept and control variables are not tabulated for brevity. All of the variables are defined in the Appendix. The *t*-statistics and *z*-statistics (in parentheses) are calculated based on standard errors clustered at the analyst level.
*, **, and *** represent two-tailed significance levels of 10%, 5%, and 1%, respectively.

## 6.3 | Physical appearance

Prior studies find that physical attractiveness is associated with analyst performance (Cao et al., 2020). Although attractiveness can drive perceived sociability, which is used to validate our measure of social skills in Section 4.1, these two concepts are not the same. Physical attractiveness is the degree to which a person's physical features are considered aesthetically pleasing or beautiful, whereas perceived sociability is the perceived skills to seek out companionship and engage in interpersonal relations. To assure that our results are driven by better social skills rather than physical appearance, we additionally control for analysts' physical appearance (*Attractiveness*) in Equations (3) to (5).

Following C. Li et al. (2020), we construct *Attractiveness* based on an analyst's facial appearance, calculated as the average of the attractiveness ratings (ranging from 1 to 4: *below average* = 1, *average* = 2, *attractive* = 3, *very attractive* = 4), submitted by the MTurk raters for the analyst, and replace the missing values of *Attractiveness* with the value of the first quartile (i.e., 1.83).[20] Panel D of Table 7 shows that our results are robust to controlling for physical attractiveness. We also find that physical attractiveness is positively associated with earnings forecast accuracy (column (1)) and positively associated with the profitability of sell recommendations (column (5)).

[20]In our sample, the correlation between perceived sociability and attractiveness is 0.35. Therefore, the two measures are moderately correlated but do not seem to capture the same concept.

## 6.4 | Piggyback on major corporate news

Prior studies suggest that analysts often update their stock recommendations following the release of corporate news due to the demand from large institutional clients and that such after-hours revisions are associated with greater market reactions (E. Li et al., 2015). As such, our results could be driven by the possibility that sociable analysts choose to piggyback on corporate news to a greater extent than do analysts with poorer social skills. We conduct two tests to investigate this possibility. First, we investigate the likelihood of analysts with better social skills issuing stock recommendations following an earnings announcement. Second, we reestimate Equation (4), excluding the stock recommendations issued on an earnings announcement date and after the announcement time, or on the next trading day after an earnings announcement.

Panel E of Table 7 provides the results of our examination of whether analysts with better social skills are more likely to issue stock recommendations immediately after quarterly or annual earnings announcements of covered companies. We estimate a probit model with the same control variables as in Equation (4). In column (1), the dependent variable is *EAD_After_Hour*, an indicator variable set to one if analyst *i*'s most recent stock recommendation for company *j* in year *t* is issued on the company's earnings announcement date and *after* the announcement time, and zero otherwise; in column (2), *EAD_After_Hour_or_Next_Day* is an indicator variable set to one if the analyst's stock recommendation is issued on the company's earnings announcement date and *after* the announcement time or on the next day after an earnings announcement, and zero otherwise. In both columns, we find no evidence that analysts with better social skills are different from analysts with poorer social skills in terms of the timing of stock recommendation issuance. In panel F of Table 7, we exclude stock recommendations with *EAD_After_Hour_or_Next_Day* = 1 and reexamine stock recommendation profitability and informativeness. The results are inferentially similar to our main results.

# 7 | CONCLUSION

This study is the first large-sample study to examine the effect of social skills on the performance of financial analysts. We find that analysts with better social skills produce more accurate earnings forecasts, and that their stock recommendations elicit stronger market reactions. The effect of social skills on analyst performance is more pronounced for companies with a poorer information environment. We also find that financial analysts with better social skills are more likely to be voted as All-Stars. The evidence collectively suggests that social skills are important in an analyst's overall performance and are valued by institutional investors.

Our study provides a novel measure of an individual's social skills that may be generalized to other professions or industries. In our view, the number of social connections well reflects the social skills of an analyst. We find support for the proxy from prior psychology literature and examine the construct validity through multiple tests. Nevertheless, as in many other empirical studies, justifying the validity of a new measure is challenging. We would, therefore, like to add the caveat that broad social connections may capture other aspects of human characteristics. With such a caveat in mind, our findings suggest the important role of social skills in the financial industry.

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## APPENDIX: VARIABLE DEFINITIONS

| Variable | Definition |
|---|---|
| **Dependent variables** | |
| *AA_Award* | Indicator variable set to one if the analyst is ranked in the top three or as a runner-up by *Institutional Investor* in calendar year *t*, and zero otherwise |
| *AFE* | Standardized earnings forecast error for analyst *i* following company *j* in fiscal year *t* is calculated as $[AFE_{i,j,t} – \min(AFE_{j,t})]/[\max(AFE_{j,t}) – \min(AFE_{j,t})]$, where $\max(AFE_{j,t})$ and $\min(AFE_{j,t})$ denote, respectively, the largest and smallest earnings forecast errors of all of the analysts following company *j* in fiscal year *t*. $AFE_{i,j,t}$ is calculated as the absolute value of the analyst's most recent earnings forecast for company *j* minus company *j*'s actual EPS in fiscal year *t*, scaled by the stock price at the beginning of fiscal year *t* |
| *Answers_Length* | Natural logarithm of the average number of words that all executives reply to the analyst in the Q&A sessions of company *j*'s earnings conference calls in fiscal year *t* |
| *CAR*[−1,90] *CAR*[−1,1] *CAR*[2,90] | Cumulative market-adjusted returns during the [−1,90], [−1,1], or [2,90] days of the analyst's stock recommendation for company *j* in fiscal year *t*. [−1,90] represents the time period from one trading day before to 90 calendar days after the issuance of stock recommendation; [−1,1] represents the time period from one trading day before to one trading day after the issuance of recommendation; [2,90] represents the time period from two trading days after to 90 calendar days after the issuance of stock recommendation. For "hold," "sell," and "strong sell" stock recommendations, we multiply *CAR* by −1 |
| *NParticipation* | Number of company *j*'s earnings conference calls in which the analyst participates during fiscal year *t* |
| *Q&A_Priority* | Analyst priority in the Q&A sessions, calculated as negative one times the average order that the analyst appears in the Q&A sessions of company *j*'s earnings conference calls in fiscal year *t* |
| *Team* | Indicator variable set to one if the analyst who follows company *j* in fiscal year *t* leads an analyst team, and zero otherwise. Specifically, for each earnings forecast in the sample, if there are multiple authors on the associated research report, we treat the forecast as issued by an analyst team and the indicator *Team* equals one; otherwise, the value of *Team* is zero |
| **Key independent variable** | |
| *Social_Skills* | Indicator variable set to one if the analyst has above the median (i.e., 396) number of LinkedIn connections, and zero otherwise |
| **Other variables** | |
| *Alumni_Ties* | Indicator variable set to one if the analyst attended the same university as any of company *j*'s top executives or directors in fiscal year *t*, and zero otherwise |
| *Broker_Demand_for_Social_Skills* | Percentage of financial analyst job postings that require social skills in a broker-year. For brokerage firms without any financial analyst job postings during the year, we set the value to zero |
| *BSize* | Natural logarithm of the number of analysts employed by the brokerage firm in year *t* |
| *Exp* | Number of years in which the analyst has issued at least one earnings forecast for company *j* before fiscal year *t* |
| *Freq* | Number of earnings forecasts issued by the analyst for company *j* in fiscal year *t* |
| *GExp* | Number of years since the analyst first appeared in I/B/E/S |
| *Horizon* | Natural logarithm of the number of days between the analyst's earnings forecast for company *j* and the announcement date of company *j*'s actual EPS in fiscal year *t* |

(Continues)

(Continued)

| Variable | Definition |
|---|---|
| *MBA* | Indicator variable set to one if the analyst has an MBA degree, and zero otherwise |
| *MTB* | Market value of common equity divided by the book value of common equity of company *j* at the end of fiscal year *t* |
| *NAnalyst* | Number of analysts following company *j* in fiscal year *t* |
| *NCall* | Number of earnings conference calls held by company *j* in fiscal year *t* |
| *NFirm* | Number of companies the analyst follows during fiscal year *t* of company *j* |
| *NInd* | Number of 2-digit SIC industries the analyst follows during fiscal year *t* of company *j* |
| *NSector* | Number of segments that company *j* has in fiscal year *t* |
| *Perceived_Sociability* | Analyst's perceived sociability, measured as the average of the sociability ratings (ranging from 1 to 4; *below average* = 1, *average* = 2, *sociable* = 3, *very sociable* = 4) submitted by the Amazon MTurk raters based on the analyst's facial appearance |
| *Recom_Level* | Level of the analyst's first stock recommendation issued for company *j* in fiscal year *t*, where a strong buy, buy, hold, sell, and strong sell recommendation is coded as 5, 4, 3, 2, and 1, respectively |
| *RetVol* | Standard deviation of daily stock returns for company *j* in fiscal year *t* |
| *ROA* | Income before extraordinary items divided by total assets of company *j* at the end of fiscal year *t* |
| *Size* | Company size, which is measured as the natural logarithm of the market value of company *j* at the end of fiscal year *t* |
| *No_LinkedIn* | Indicator variable set to one for analysts whose LinkedIn profiles could not be located, and zero otherwise |
| *Attractiveness* | Measure based on an analyst's facial appearance, calculated as the average of the attractiveness ratings (ranging from 1 to 4; *below average* = 1, *average* = 2, *attractive* = 3, *very attractive* = 4) submitted by the Amazon MTurk raters for the analyst |
| *EAD_After_Hour* | Indicator variable set to one if the analyst's most recent stock recommendation for company *j* in year *t* is issued on the company's earnings announcement date and *after* the announcement time, and zero otherwise |
| *EAD_After_Hour_or_Next_Day* | Indicator variable set to one if the analyst's stock recommendation is issued on the company's earnings announcement date and *after* the announcement time or on the next day of earnings announcement, and zero otherwise |