Beyond Old Boys' Clubs: Financial Analysts' Utilization of Professional Connections

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Abstract

Women often lack the opportunity to enter exclusive social clubs, reaping fewer benefits from their social networks. We investigate, conditioning on having the opportunity to interact with the right people in a professional setting, whether women can better utilize connections for career performance and advancement than men. Using a unique dataset that documents when, where, and with whom a financial analyst interacts at investor conferences, we find that female analysts issue more accurate earnings forecasts than their male counterparts after establishing connections with the firm's executives. Further evidence suggests that female analysts overcome homophilly in interactions with executives and transform conference interactions into long-term relationships, enhancing forecast accuracy for up to three years. In addition, both the capital and labor markets recognize their superior ability to utilize connections. Our findings suggest that women capitalize on professional connections to their advantage, highlighting the benefits of promoting structured networking opportunities for women in professional environments.

JEL Classification: G24, J16, J24

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1 Introduction

Networks are of paramount importance on Wall Street, facilitating information flow for investments (Hochberg, Ljungqvist, and Lu, 2007; Cohen, Frazzini, and Malloy, 2008), corporate policies (Fracassi, 2017), and analyst research (Cohen, Frazzini, and Malloy, 2010). Yet studies on social networks often find women at a disadvantage, reaping fewer benefits for career performance (Fang and Huang, 2017) and advancement (Campbell, 1988; McDonald, 2011; Cullen and Perez-Truglia, 2023). This apparent disadvantage may stem from a lack of opportunity as women are shut away from exclusive social clubs, as the old boy's club allows men to network with other powerful men in ways that are less accessible to women (Michelman, Price, and Zimmerman, 2022; Cullen and Perez-Truglia, 2023). This underscores the importance of promoting structured networking opportunities for women in the workplace. However, it remains unclear how well women can utilize professional connections should they be provided with such opportunity to interact with the right people. In this paper, we aim to answer this question with a unique setting in which we observe when, where, and with whom finance professionals interact. Specifically, we explore actual interactions between financial analysts and corporate executives at investor conferences.

The context of our study revolves around analysts on Wall Street, an industry that is highly competitive and male-dominated. Women are under-represented at around 10% of the population. Despite the fact that the most qualified women self-select into this profession (Kumar, 2010), they still face hurdles imposed by gender stereotypes and biases in advancing their careers.[1] Therefore, it is important to understand whether they can make use of professional connections to narrow this gender gap.

Investor conferences provide a unique setting to study gender differences in the rate of utilization conditional on actual interactions between financial analysts and corporate executives (i.e., keeping the opportunity to interact constant). First, from conference transcripts, we observe the specific company and executives that an analyst interacted with, as well as the timing and frequency

[1] For instance, female analysts benefit less from alumni connections (Fang and Huang, 2017), receive fewer opportunities to ask questions on conference calls (Brown, Francis, Hu, Shohfi, Zhang, and Xin, 2023) and are often stereotyped against in facial impressions (Peng, Teoh, Wang, and Yan, 2022).

of such interactions. Our measure of connections is based on these actual interactions instead of overlapping professional or educational experiences as used in prior literature.[2] Second, investor conferences bring executives, investors, and in-house analysts to the same location and facilitate multi-way information flows (Bushee, Jung, and Miller, 2011; Green, Jame, Markov, and Subasi, 2014a,b; Zhang, 2023). It is important to understand how male and female analysts utilize these interactions, as access to and private communications with management are critical inputs to analyst outputs (Soltes, 2014; Brown, Call, Clement, and Sharp, 2015). The hosting analyst spends substantial time interacting with company executives at conferences, producing more informative reports (Green, Jame, Markov, and Subasi, 2014a). In addition, conference interactions provide an important venue for analysts to establish initial contact with executives, paving ways to build long-term relationships in the future. Third, opportunities to establish connections from an individual's past experiences are often influenced by homophily and gender stereotypes (Shrum, Cheek Jr, and MacD, 1988; Michelman, Price, and Zimmerman, 2022), rendering women at a disadvantage. By contrast, investor conferences represent a form of structured professional networks. They bring together individuals from a variety of industries, organizations, and roles (Bushee, Jung, and Miller, 2011), allowing analysts to interact in a professional capacity and form cross-gender connections. Hence, interactions at investor conferences, to a certain extent, "level the playing field" in access to corporate executives in a male-dominated industry between male and female analysts.

It is ex-ante unclear, conditional on having the opportunity to interact at conferences, whether women are better or worse at utilizing connections for work performance and translating them into career capital in the future. On the one hand, as hosts at investor conferences, female analysts can showcase their expertise and competence to the audience (e.g., investors and corporate executives), thereby challenging gender stereotypes and biases that may prevent them from establishing connections from personal networks. Women are less aggressive and more polite in their communication styles (Lakoff, 1973; Comprix, Lopatta, and Tideman, 2022), which helps them foster a more collaborative environment when interacting with executives; they are more people-orientated

[2]For instance, Cohen, Frazzini, and Malloy (2008, 2010) and Fang and Huang (2017) use attending the same tertiary education institution and Fracassi (2017) use overlapping experiences in employment, education, and other professional activities to measure potential connections within a social network.

(Su, Rounds, and Armstrong, 2009), having a greater tendency to pay attention to and gather interpersonal information (e.g., management style and quality). As female analysts might otherwise lack opportunities to establish connections with key corporate executives from their social networks, they can utilize conference connections as an initial point of contact to build ties that extend beyond the investor conference, transforming one instance of professional connection into long-term management access. On the other hand, it is also possible that female analysts are less able to utilize conference connections. Gender stereotypes work against women even in professional settings (Peng, Teoh, Wang, and Yan, 2022; Brown, Francis, Hu, Shohfi, Zhang, and Xin, 2023). Prior literature suggests that women are less confident (Bengtsson, Persson, and Willenhag, 2005), which could hinder their ability to showcase their expertise and build connections with company executives. Gender differences in temperament could also result in female analysts being more passive (Else-Quest, Hyde, Goldsmith, and Van Hulle, 2006), and thus extracting less information from interactions with executives.

We aim to answer this empirical question with a sample of 694,505 annual earnings forecasts issued by 2,068 analysts (out of which 10.8% are female) from 241 brokers on 1,589 publicly traded firms from I/B/E/S. From 36,076 investor conference transcripts obtained from Refinitiv StreetEvents, we observe instances when specific corporate executives attend the conference hosted by I/B/E/S analysts, thereby forming a connection. We define connections at the firm-analyst-time level based on whether the analyst has met with any of the firm's incumbent top executives at conferences prior to issuing an earnings forecast (on average, 25.5% of the forecasts in our sample have these connections).[3]

First, we verify that professional connections have informational value for financial analysts. On average, analysts forecast accuracy improves by 0.9% if they have previously interacted with a top executive of the firm at an investor conference. Next, we show that female analysts are better at leveraging professional connections to derive informational value than male analysts, with an incremental 4.2% improvement in forecast accuracy after forming connections. Notably, our research design exploits time-varying changes in connections within an analyst-firm pair (i.e., analyst-firm

[3]Top executives are defined as executives included in a firm's Compensation Discussion and Analysis disclosure in the proxy statement and are obtained from ExecuComp.

fixed effects), while taking out any time-varying firm and broker characteristics (i.e., firm-time and broker-time fixed effects). Therefore, the comparison is made between the forecasts issued by the same analyst for the same firm before and after establishing a connection. For instance, assume that two financial analysts – Amy and Adam – cover Alphabet Inc. Suppose that during 2015 (2016), Amy (Adam) established a connection with Alphabet when interacting with one of Alphabet's top executives at a conference. Our findings suggest that Amy's forecast accuracy improvement after establishing connections is around *five times* larger than that of Adam. This design controls for unobserved factors that may influence forecast accuracy and conference attendance at the analyst level (e.g., on average, Amy is more skillful than Adam), the broker-time level (e.g., Amy works for a broker that is spending more resources to organize conferences in the Technology sector than Adam's broker around 2015), the firm-time level (e.g., Alphabet's change in business strategy in 2016 adversely affected the accuracy of analysts forecasts), and at the analyst-firm pair level (e.g., Amy tends to cover larger firms with better information environment than Adam).

Analysts are not randomly assigned as conference hosts. In the male-dominated analyst industry, female analysts might face higher barriers to attaining "host" status, often reaching this level later in their careers after gaining more experience and capability. To address this concern, we first note that while only the more accurate, experienced, and recognized analysts are typically selected to host conferences, this applies to both male and female analysts.[4] In fact, gender appears to have an ambiguous effect on host selections: while female analysts cover more firms when hosting conferences, they also receive hosting opportunities at smaller brokers. These patterns are likely driven by two opposing forces at play: the self-selection of highly capable female analysts to enter and advance in a male-dominated industry (Kumar, 2010) as well as the growing emphasis on diversity and inclusion at public events like investor conferences. Further, it is important to note that we do not find significant pre-trends in forecast accuracy in the years preceding these connections in Figure 2, indicating that there is no significant gender difference in forecast accuracy before forming conference connections with firm executives. Next, we conduct additional analyses to address concerns about potential gender biases in host selection. First, to account for changes

[4] All analysts in our sample have at least one connection with a firm, i.e., having hosted conferences at some point in their careers.

in analyst skills over time as they becomes conference hosts, we expand the analyst fixed effects in our regression models by interacting individual analyst dummies with a binary indicator for whether a forecast is issued after an analyst has attained the host status. These interacted fixed effects control for unobservable gender differences correlated with host selection, alleviating the concern that the observed higher forecast accuracy is driven by female hosts having better skills rather than effectively utilizing conference interactions. Second, we control for the extent to which differences in general analyst ability between female and male hosts drive their ability to utilize conference connections. We do so by including interaction terms between connected forecasts and various observable analyst characteristics (e.g., experience, portfolio size, forecast characteristics) in the regression models. Our results remain robust to these controls. Finally, if the observed improvement in forecast accuracy were solely driven by the higher ability of female hosts, we would expect to see similar gender effects from connections with other firms. In other words, analysts' connections with other firms in an analyst's portfolio would reflect their higher ability to be selected as conference hosts but should not affect how they utilize connections for the focal firm. Consistent with our expectations, we find no gender differences in how hosting other firms influences forecast accuracy for the focal firm.

There are two non-mutually-exclusive explanations for how female analysts leverage conference interactions to improve forecast accuracy. First, female analysts' advantage may stem directly from the interactions at the conference (i.e., the conference channel), where they either obtain more valuable insights about the firm or are better at interpreting what is communicated by executives at the conference. In this case, we expect female analysts' superior forecast accuracy to be short-lived and most pronounced immediately after the conference. Second, female analysts use these conference interactions to build long-term relationships with executives, effectively transforming one-time conference connections into sustained management access in the future (i.e., the relationship channel). We shed light on these two explanations. First, we analyze gender differences in forecast accuracy over time surrounding the conference interactions (see Figure 2). We find that gender differences in the effect of connections begin to manifest in the year of the connection, become more pronounced over time, and taper off by the fourth year. These patterns suggest that female analysts' information advantage extends beyond the conference, likely due to the cultivation of long-term relationships with executives from conference connections. Second, we use participation at earnings conference calls as a proxy for unobservable analyst-executive relationships. Managers have discretion in granting opportunities to favored analysts to ask questions, and participating analysts tend to have superior private information (Mayew, 2008; Mayew, Sharp, and Venkatachalam, 2013), making this an indirect proxy of the otherwise unobservable relationships. We find that connections established at investor conferences increase the chances of analysts asking questions in future earnings conference calls, and when they do, their questions are longer. These results are consistent with our conjecture that female analysts leverage conference connections to improve future management access. Finally, we investigate how female and male analysts communicate and interact with executives at conferences, as the conference channel may be associated with specific analyst behaviors, such as asking more questions, posing longer questions, or hosting private sessions. We find that female analysts ask shorter and less aggressive questions, potentially fostering a collaborative environment conducive to information sharing and relationship building. While we acknowledge the limitation of not observing the full extent of conference interactions, the corroborative evidence in our analyses suggests that female analysts' information advantage is not confined to the conference itself but is amplified through the relationships they build.

Additional analyses reveal the dynamics of interactions at conferences. First, if professional connections at investor conferences help level the playing field by providing female analysts with opportunities to establish ties with executives, we would expect these benefits to be more pronounced for younger female analysts and those without personal connections. Our findings confirm that the incremental value of conference interactions is indeed stronger for less experienced analysts, and analysts lack opportunities to gain access to executives through educational networks. This suggests that networking at investor conferences plays a particularly crucial role for female analysts who are still building their professional foundations. Second, we investigate whether female analysts gain useful information through connections formed with key executives responsible for financial reporting – the CFO (Mian, 2001; Jiang, Petroni, and Wang, 2010). We find that while all analysts benefit more from connections with the CFO, female analysts establish stronger ties and have greater improvements in forecast accuracy than their male counterparts. Finally, we examine whether female analysts are able to overcome homophily in the professional connections built at investor conferences. We find that female analysts' advantage exists in both in-group connections (i.e., with a female executive) and out-of-group connections (i.e., with a male executive). These results are consistent with interactions with executives at conferences allowing female analysts to build cross-gender connections. By demonstrating their expertise and establishing ties based on their professional accomplishments during these interactions, female analysts can overcome some of the gender stereotypes that may inhibit their access to information in social settings.

After finding evidence that female analysts are better at obtaining useful information from their professional connections formed at investor conferences, we investigate whether the capital market and labor market recognize this strength of female analysts. In the capital market, we document stronger market reactions to forecasts issued by connected female analysts. In addition, female analysts are 2.8 times more likely to eventually join the firms that they have connections with than male analysts, suggesting that they are able to transform professional connections into outside career opportunities. While connections increase the unconditional likelihood of being voted as an "All star" analyst, there is no statistically significant gender difference - both connected male and female analysts are more likely to achieve "All star" recognition. In contrast to gender stereotypes and discrimination documented in the previous literature (e.g., Fang and Huang, 2017 and Peng, Teoh, Wang, and Yan, 2022), networks built through professional interactions benefit female analysts more or equally compared to male analysts in the labor market.

Our paper is the first to investigate women's ability to utilize professional connections for career performance and advancements among financial analysts. The literature recognizes the value of social interactions at work. For instance, MBA connections have long-lasting spillover effects on decision-making later in life, influencing corporate and entrepreneurial decisions (Lerner and Malmendier, 2013; Shue, 2013). Social networks have an impact on productivity, placement, and earnings in the labor market (Simon and Warner, 1992; Bandiera, Barankay, and Rasul, 2009, 2010). Women's lack of access to exclusive social clubs, or the old boy's club, contributes to the gender gap in promotions and pay (Michelman, Price, and Zimmerman, 2022; Cullen and Perez-Truglia, 2023).

Women benefit less from social ties in advancing their careers (Fang and Huang, 2017). At the same time, becoming part of the boys' network increases a woman's labor market opportunities (Agarwal, Qian, Reeb, and Sing, 2016). Our findings suggest that the observed disadvantage women have in utilizing social networks does not stem from the fact that they lack the skills to utilize connections. Rather, it is more likely that they lack such opportunities from their personal networks. Our findings highlight the importance of promoting professional and structured networking opportunities for women, which could help to bridge the gender gap in social connections.

Second, our study extends the literature on gender gaps in a competitive environment in general, and among financial analysts in particular. It is well recognized that gender stereotypes, social norms, and household burdens often put women at a disadvantage in the workforce (e.g., Bertrand, Goldin, and Katz, 2010; Bertrand, Kamenica, and Pan, 2015). In the financial analyst industry, existing studies have identified a range of factors, including innate traits, social constraints, and skills that disadvantage female analysts (e.g., Fang and Huang, 2017; Li, Lin, Lu, and Veenstra, 2020; Comprix, Lopatta, and Tideman, 2022; Peng, Teoh, Wang, and Yan, 2022; Du, 2023). Yet despite these apparent disadvantages, professional women do not deliver inferior performance when working in sell-side research (e.g., Green, Jegadeesh, and Tang, 2009; Kumar, 2010; Fang and Huang, 2017; Peng, Teoh, Wang, and Yan, 2022), mutual funds (Niessen-Ruenzi and Ruenzi, 2019), hedge funds (Aggarwal and Boyson, 2016), or as top company executives (e.g., Huang and Kisgen, 2013; Khan and Vieito, 2013; Aggarwal and Boyson, 2016; Ewens and Townsend, 2020). Our paper identifies an important gender-specific factor that is largely overlooked in the prior literature, one that likely allows women to bridge the gender gap — the use of connections formed in professional contexts. We show that women benefit more than men from leveraging professional networks at investor conferences to enhance their work performance.

Finally, our findings add to the understanding of the nature of information flow at investor conferences. We provide evidence on how individual analysts benefit from private access to management at investor conferences, both in terms of immediate career performance and long-term career outcomes. Prior literature shows that institutional investors (Bushee, Jung, and Miller, 2011), hosting brokerage firms (Green, Jame, Markov, and Subasi, 2014a), and corporate managers (Zhang, 2023) benefit from acquiring information at investor conferences. Our study adds to the literature by showing that the hosting analyst is able to leverage professional connections formed at conferences and transform them into better performance and career advancement.

2 Literature Review and Institutional Background

2.1 Network Value and Inequality

Social networks, often formed informally through shared experiences, can have important implications in the business world. Personal connections influence placement and earnings in the labor market. For example, references reduce employers' uncertainty about worker productivity and improve job matching (Simon and Warner, 1992). Workers prefer working with someone they are socially connected to (Bandiera, Barankay, and Rasul, 2009, 2010). Social interactions often have long-lasting impacts later in life, as shared MBA education would influence one's decision to become an entrepreneur and corporate decisions as top executives of firms (Lerner and Malmendier, 2013; Shue, 2013). In the financial market, networks facilitate information flow (Hochberg, Ljungqvist, and Lu, 2007; Cornelli and Goldreich, 2001; Ljungqvist, Marston, and Wilhelm Jr, 2006). Professionals working in competitive industries often benefit from personal networks formed from overlapping experiences. Mutual fund managers place larger bets on firms if they share common educational experiences with the firm's directors and officers and perform significantly better on these holdings than non-connected holdings (Cohen, Frazzini, and Malloy, 2008). Financial analysts produce higher-quality research for companies with which they share education ties (Cohen, Frazzini, and Malloy, 2010; Fang and Huang, 2017). Firms perform better when their executives are more connected through common experiences (employment, education, and other experiences) with other executives (Fracassi, 2017).

Yet the access to and the ability to benefit from networks are far from equal across genders. For instance, male analysts benefit two to three times more (in terms of forecast accuracy) from common education experience with corporate executives than their female counterparts (Fang and

Huang, 2017). People in white male networks receive twice as many jobs leads as people in female or minority networks (McDonald, 2011). Women receive fewer job leads when hiring is based on referrals (Erkens, Wang, and Young, 2022).

Women's apparent disadvantage in utilizing networks from common experiences could stem from a lack of opportunity. Similarity breeds connection (Lewis, Gonzalez, and Kaufman, 2012). Informal networks formed from one's social activities are often homogeneous with regard to many sociodemographic, behavioral, and intrapersonal characteristics (McPherson, Smith-Lovin, and Cook, 2001). As a result, women have been shut away from social clubs and exclusive ties, and these ties form the basis of information networks later in people's careers. For example, through smoking breaks, male employees have the opportunity to schmooze, network, and interact with more powerful men in ways that are less accessible to women, resulting in faster promotions (Cullen and Perez-Truglia, 2023). Exclusive social groups formed among undergraduates attending Harvard University largely shape upward mobility after graduation, yet many social clubs still do not accept female members today (Michelman, Price, and Zimmerman, 2022). Consequently, opportunities for women to engage in social activities that run counter to social norms can be valuable for career advancement. Agarwal, Qian, Reeb, and Sing (2016) show that participation of women in golf—a predominately male social activity—significantly increases their likelihood of serving on a board of directors in male-dominated industries.

As women are often inhibited by gender stereotypes and discrimination in forming and utilizing informal networks, our study examines the value of providing women with formal, structured network opportunities. Structured networks give women the opportunity to meet with people who are important to their careers. Interactions in a professional setting allow women to showcase their expertise and competence and challenge gender stereotypes. Female analysts, who may face limited opportunities to establish connections with key corporate executives through traditional social networks, can leverage investor conferences as a strategic entry point for building relationships that extend beyond the event itself. Gender differences in personality characteristics have implications in the labor market (Flinn, Todd, and Zhang, 2024); differences in communication styles and personal traits can help female analysts extract valuable insights and cultivate stronger connections with executives during such conferences. First, prior literature suggests that women tend to adopt less aggressive and more polite forms of language (Lakoff, 1973; Comprix, Lopatta, and Tideman, 2022). This approach may foster a perception of friendliness and openness in interactions, creating a more favorable environment for executives to share information or establish rapport. Second, individuals vary in their focus on physical versus social environments, with women demonstrating a greater orientation toward people (Su, Rounds, and Armstrong, 2009; Su and Rounds, 2015). This heightened people-oriented focus could allow female analysts to gather nuanced interpersonal information, such as management quality and leadership style, that is particularly relevant to their analyses and reports.

However, women might be less able to utilize professional connections. Women tend to be less confident than men (Bengtsson, Persson, and Willenhag, 2005), which could manifest in how women interact with other professionals (Kirkwood, 2009). Moreover, due to gender differences in temperament based on psychology literature (e.g., Else-Quest, Hyde, Goldsmith, and Van Hulle, 2006), women might be more sensitive and more passive than men when interacting with people in a professional setting, thus extracting less benefit from professional networks. Gender stereotypes could persist in professional interactions (Bordalo, Coffman, Gennaioli, and Shleifer, 2019; Peng, Teoh, Wang, and Yan, 2022), and women may conform to their gender identity. Therefore, whether and how well women can utilize professional connections remain an open empirical question.

Using a unique dataset that documents the occurrence of actual interactions between financial analysts and corporate executives, we examine gender differences in utilizing professional connections. A unique advantage in our setting is that we observe the occurrence of actual interactions between financial analysts and corporate executives. In contrast, most prior studies develop proxies for personal networks based on shared experiences, such as attending the same schools and having overlapping activities (Cohen, Frazzini, and Malloy, 2008, 2010; Fang and Huang, 2017; Shue, 2013; Lerner and Malmendier, 2013). These common experiences form the potential set of networks but do not take into account whether and how actual connections are formed from these shared experiences. We ask the question, conditioning on these professional interactions taking place, how do men and women differ in deriving value from such connections for career performance and advancement?

2.2 Analyst-Manager Interactions at Conferences

Private communication with management serves as one of the most important inputs to analysts' research, ranked higher than primary research, earnings announcements, and public company filings (Brown, Call, Clement, and Sharp, 2015). Analysts value and spend considerable time acquiring management access, as such communications often offer them the context to interpret public firm disclosures and insights to understand a firm's operations (Soltes, 2014), therefore leading to more accurate research output (Cohen, Frazzini, and Malloy, 2010; Fang and Huang, 2017). Given these benefits, many brokerage houses expend significant resources to organize investor conferences, bringing together corporate executives, investors, and in-house analysts to the same location and facilitate multi-way information flows (Bushee, Jung, and Miller, 2011; Green, Jame, Markov, and Subasi, 2014b; Zhang, 2023). While Regulation Fair Disclosure (Reg FD) restricts the management from selectively disclosing material information, it does not preclude limited-access conferences. At conferences, management has some latitude in discussing aspects of the firm that may help to fill up the audience's information "mosaic" without violating Reg FD. Prior studies show that analysts and institutional investors obtain useful information to update their prior beliefs about the firm after conference interactions with the management (Bushee, Jung, and Miller, 2011; Green, Jame, Markov, and Subasi, 2014a; Bushee, Jung, and Miller, 2017).

Broker-hosted investor conferences provide an excellent opportunity for affiliated analysts to interact with senior corporate managers.[5] Conferences usually start with corporate managers making prepared remarks on their firm's strategy, followed by public Q&As and, if available, private breakout sessions and one-on-one meetings. The hosting analyst plays a key role in organizing these sessions, interacting meaningfully with corporate executives throughout the conference, including moderating firm presentations, moderating public Q&A sessions, collecting and consolidating questions from investors, and facilitating private breakout sessions. As a result, conference interactions provide a salient channel for analysts to establish contact and form professional connections with corporate executives. Such professional connections are highly valuable for the financial analysts'

[5]Because of the competitive nature of the brokerage industry, it is very rare for analysts from a competing broker to attend a conference hosted by another broker.

career performance and advancement, including 1) improving job performance by filling up their information mosaic to improve research outputs and 2) developing long-term career capital by maintaining connections formed with managers and broadening the depth of management access (Soltes, 2014).

We argue that female analysts may be able to take advantage of these professional connections built at investor conferences for several reasons. First, as hosts, female analysts can showcase their expertise and competence to the audience (e.g., investors and corporate managers) at investor conferences, thereby challenging gender stereotypes and biases that may exist within their personal networks (Bertrand, Kamenica, and Pan, 2015; Bordalo, Coffman, Gennaioli, and Shleifer, 2019). By demonstrating their capabilities and building connections based on their professional accomplishments, women can overcome some of the gender stereotypes that inhibit their information access. Second, while personal networks tend to exhibit greater homophily, investor conferences bring together individuals from a variety of industries, organizations, and roles, offering financial analysts an opportunity to build professional networks that span beyond their educational backgrounds and personal network (Bushee, Jung, and Miller, 2011). It, therefore, provides more opportunities for female analysts to form cross-gender connections and bridge gender gaps, which provides access to a broader range of resources and information that may not be available within their existing networks. Finally, it is well recognized in the sociology literature that women are more people-oriented - they pay more attention to people around them and develop stronger links with people (Su, Rounds, and Armstrong, 2009; Graziano, Habashi, and Woodcock, 2011; Su and Rounds, 2015). Investor conferences provide networking platforms and opportunities for interaction in a professional environment, ensuring equal access to corporate executives for both male and female analysts. This allows female analysts to more effectively leverage their people-oriented skills.

2.3 Gender Differences and Performances

A large volume of literature has examined how and why women are under-represented in the financial and corporate sectors. Explanations include innate characteristics, social norms as well as gender stereotypes that work against professional women. First, women are more likely to shy away from competition and risk. Experimental evidence suggests that women are less likely to take up competition than men (Niederle and Vesterlund, 2007; Croson and Gneezy, 2009). Archival evidence shows that male retail investors take more risky trades than female investors (Barber and Odean, 2001).

Beyond these innate differences, professional women face more constraints imposed by social norms and household burdens in advancing their careers. Bertrand, Goldin, and Katz (2010) shows that women face more career interruptions because of motherhood, which contributes to the divergence of earnings from their male MBA graduating classmates. Gender identity norms may discourage women from advancing in their careers, which leads to lower earnings than their husbands (Bertrand, Kamenica, and Pan, 2015). Women's productivity is more affected when childcare responsibilities arise (Du, 2023).

In particular, an emerging stream of literature has examined how gender differences, stereotypes, and social norms have adversely affected women working on Wall Street. Wall Street analysts represent a particularly powerful setting because 1) self-selection into a male-dominated and highly demanding work environment likely results in a relatively homogeneous group of individuals in terms of education and competitiveness, and 2) the gender, performance outcomes, and career advancements of analysts are observable. For example, Fang and Huang (2017) shows that despite graduating with the same level of alumni ties with corporate boards, women benefit less from social connections in the accuracy of their forecasts (job performance) and in the likelihood of achieving "All star" status (career advancements). During earnings conference calls, an important source of information for analysts' forecasts, female analysts appear on calls less frequently, speak less, and ask less aggressive questions (Comprix, Lopatta, and Tideman, 2022; Brown, Francis, Hu, Shohfi, Zhang, and Xin, 2023). Female analysts who are perceived to be dominant tend to be judged negatively, while their male counterparts are judged positively (Peng, Teoh, Wang, and Yan, 2022).

Yet, despite these documented hurdles, professional women in corporate and finance do not deliver inferior performance. In the finance industry, existent evidence suggests that there are no gender differences in performance among mutual fund managers or hedge fund managers. Niessen-Ruenzi and Ruenzi (2019) find no differences in fund performance between female- or male-managed mutual funds. Aggarwal and Boyson (2016) show that hedge funds managed by all females perform no differently than funds managed by all males and have similar risk profiles. Similarly, prior evidence does not suggest that female analysts produce inferior research outputs than their male counterparts (Green, Jegadeesh, and Tang, 2009; Kumar, 2010; Fang and Huang, 2017; Peng, Teoh, Wang, and Yan, 2022). Finally, among top company executives, while female executives take less risk, there is no evidence suggesting that their firms have worse performance (Khan and Vieito, 2013; Ewens and Townsend, 2020). On the contrary, firms managed by female CEOs make fewer but more value-increasing acquisitions (Huang and Kisgen, 2013), are associated with better performance and smaller risk (Khan and Vieito, 2013), and produce more accurate earnings forecasts (Francoeur, Li, Singer, and Zhang, 2022). We identify an important gender-specific factor that is largely overlooked in the prior literature, and that likely allows women to bridge the gender gap — the use of connections formed in professional contexts. We analyze whether women are *better* at capitalizing on professional networks at investor conferences for career performance and advancement.

3 Sample construction and variable definitions

3.1 Data and sample

We gather broker-hosted investor conference transcripts from Refinitiv StreetEvents for the period January 2004 to December 2022. In order to examine how analyst-executive connections affect observable analyst outputs, we require the hosting broker to cover the attending firm in I/B/E/S, which results in 49,586 transcripts. Each transcript records the date and name of the conference, the name of the company and each executive that attended the conference, the name of the hosting broker, as well as the name of the hosting analyst, if present. From the information contained in these transcripts, we are able to identify the date on which a specific analyst interacts with a certain executive during conference presentations. Using fuzzy name matching, we link the hosting analysts to I/B/E/S and attending company executives to ExecuComp. We are able to identify a connection in 36,076 of the transcripts. Section I in the Internet Appendix provides snippets of conference transcripts that we extract information on participants. It also contains the distribution of transcripts over our sample period (Table IA1). The number of transcripts (transcripts with connections) increases gradually in the early period of the sample and stabilizes at around 3,000 (2,000) per year after 2011.

We obtain analysts' annual earnings forecasts with release dates between January 1, 2004 and December 31, 2022 from the I/B/E/S database. We manually collect analysts' full names and identify their gender based on LinkedIn profiles, official websites of the brokerages, and media coverage following Du (2023). In order to determine whether an analyst has any connections with executives of the firm prior to issuing forecasts for that firm, we perform two steps. First, we merge the forecast sample with ExecuComp based on the firm identifier GVKEY to obtain the identity of top executives working for the firm in the fiscal year. Second, using the timestamp of connections obtained from conference transcripts, we indicate whether the issuing analyst has interacted with any of these executives at conferences and, therefore, has established a connection prior to issuing the forecast. Firm characteristics are obtained from Center for Research in Security Prices (CRSP) and Compustat.

To have a sample of comparable analysts, we restrict the sample to analysts who have at least one connection during the sample period, such that all analysts in the sample are above a certain seniority and caliber to be able to host firms at conferences. In addition, we restrict the forecasts for firms with at least one "connected" executive (i.e., executives who have interacted with at least one analyst at conferences). This is to mitigate concerns that smaller firms that are not invited to conferences also have more opaque information environments that affect the accuracy of analyst forecasts. We drop stocks with a price below $1 to avoid the influence of penny stocks (DeHaan, Shevlin, and Thornock, 2015). We also exclude forecasts with missing variables (see Table 1 for sample construction details). The final sample consists of 694,505 observations at the analyst-firm-forecast release date level, which includes 2,068 unique analysts from 241 unique brokers, covering 1,589 unique firms.

Figure 1 plots the number of male and female analysts that established a connection with at least one executive at investor conferences in each year. We observe an increase in the proportion of analysts who establish connections by hosting investor conferences over time among both genders. Less than 4% of analysts in the I/B/E/S universe built up connections with executives at investor conferences at the start of the sample in 2004, while the proportion increased to around 18% in 2022. Notably, the level and trends of the percentage of analysts with conference interactions are similar between male and female analysts.

Panel A of Table 2 contains the summary statistics of variables for our sample. 10.8% of the analysts are female analysts in the sample, which is consistent with the analyst female representation in previous studies (Kumar, 2010; Fang and Huang, 2017; Du, 2023). On average, analysts cover 20 firms and have 5.8 years of firm-specific experience. As we focus on gender differences of utilization conditional on having a conference interaction, it is important to understand whether there are systematic gender differences in the characteristics analysts need to establish connections. Panel B of Table 2 divides the main sample (at the forecasts level) into four different subsamples: female ($Female = 1$) or male analysts ($Female = 0$) and with ($Connection = 1$) or without connections ($Connection = 0$). We test for differences in the main variables across these four groups, clustering standard errors at the analyst level to account for potential intra-analyst dependencies. First, comparing analysts before and after they have established connections, we observe that connected analysts are more experienced, issue more accurate forecasts, and cover larger firms, consistent with the expectation that better and more senior analysts are more likely to host conferences and, therefore, establish connections. This is true for both male and female analysts. Second, comparing gender differences, we observe that female analysts, both with and without connections, cover fewer firms and issue forecasts with smaller horizons compared to their male counterparts. Most importantly, we do not observe a significant gender disparity (second difference) in the differences between connected and non-connected analysts (first difference). In other words, the findings suggest that the process of becoming connected does not require different characteristics for male and female analysts.

3.2 Variable definition

A. Connection

To measure whether analysts have connections with executives of a firm under coverage, we define $Connection_{i,j,t}$ as a dummy variable equal to one if analyst i has established connections by interacting with at least one incumbent executive of firm j at conferences prior to the forecast release date t and zero otherwise. The connection is defined at the analyst-executive level. If an executive moves to a different firm after the initial meeting with the analyst at conferences, the connection is carried forward to the new firm. In the sample, 25.5% of analysts have connections with at least one executive of the firm they cover based on the summary statistics in Table 2.

B. Forecast accuracy

We use the demeaned absolute forecast error as in Clement (1999) to measure analysts' performance on earnings forecasts:

$$Forecast\,error_{i,j,t} = \frac{AFE_{i,j,t} - \overline{AFE_{j,t}}}{\overline{AFE_{j,t}}}, \tag{1}$$

where $AFE_{i,j,t}$ is the absolute forecast error (the absolute difference between the analyst forecast and the firm's actual earnings per share) of analyst i for firm j on the forecast release date t, and $\overline{AFE_{j,t}}$ is the average absolute forecast error of all analyst forecasts on firm j in the I/B/E/S universe for the same fiscal year end. Scaling by $\overline{AFE_{j,t}}$ controls for variations in forecast errors that are common to all I/B/E/S analysts. [6] $Forecast\,error_{i,j,t}$, therefore, is a percentage measure of analyst is forecast error relative to the average forecast error of all I/B/E/S analyst, following prior literature (Fang and Huang, 2017; Peng, Teoh, Wang, and Yan, 2022).

[6]The results are robust to using the raw measure of absolute forecast error (Table IA2). We use the relative measure in the baseline analyses to reduce heteroskedasticity (see, e.g., Clement (1999) and Malloy (2005)). Additionally, we adopt the forecast accuracy measure from Fang and Huang (2017), which is closely related to our setting, to ensure comparability.

4 Gender difference in analysts' utilizing executive connections built at investor conferences

4.1 Baseline result on connections

To examine the gender difference in the effect of connections on analysts' performance, we run a panel regression with the following model:

$$\begin{aligned} Forecast\,error_{i,j,t} =& \alpha + \beta_1 Connection_{i,j,t} \times Female_j + \beta_2 Connection_{i,j,t} + \beta_3 Female_j \\ &+ Controls + Fixed\,effects + \varepsilon_{i,j,t}, \end{aligned} \tag{2}$$

where $Connection_{i,j,t}$ indicates whether analyst i has connected with any executive in firm j as of the forecast release date t; $Female_j$ is a dummy variable equal to one if the analyst is a female and zero otherwise. *Controls* is a vector of control variables, including measures of the analysts' capacity and experience (i.e., the number of firms covered by the analyst and the analyst's firm-specific experience), forecast horizon, and forecast frequency, as well as time-varying firm characteristics including firm size, ROA, book to market ratio and R&D expenses. We cluster standard errors by analyst throughout the analyses.

As reported in Table 3, we include an array of fixed effect structures to mitigate concerns over unobserved correlated variables. Column (1) reports the baseline specification. First, we include analyst fixed effects to rule out inherent time-invariant differences in abilities, preferences, and other characteristics that may differ between male and female analysts and affect their forecast accuracy (Kumar, 2010; Fang and Huang, 2017; Du, 2023; Peng, Teoh, Wang, and Yan, 2022). Second, it is possible that female and male analysts cover different types of firms. Therefore, we include firm fixed effects to control for time-invariant firm characteristics such as organizational structure, industry, and location. These characteristics may affect both a firm's tendency to attend conferences and its information environment, which influences the forecast accuracy among analysts at conference-hosting brokers. Third, brokerage firms play an important role in organizing investor conferences (Bushee, Jung, and Miller, 2011; Green, Jame, Markov, and Subasi, 2014a), and thus, are likely to affect whether their analysts can host investor conferences and whether executives attend these conferences. Companies attend investor conferences to communicate with institutional investors, broaden investor reach, and learn from investors (Green, Jame, Markov, and Subasi, 2014b; Zhang, 2023). While management exercises discretion in choosing which conference to attend, the selection should occur at the entity level instead of at the analyst level. In other words, management's decision to attend a conference should be based on the prestige and influence of the broker instead of the identity of the hosting analyst. Therefore, to rule out the influence of brokerage firms, we add broker $\times$ time fixed effects in the regressions. In Column (2), we replace firm fixed effects with firm $\times$time fixed effects, which absorbs all time-varying firm characteristics. This specification essentially restricts the comparison to forecasts issued for the same firm for the same fiscal year end and compares how connections affect female and male analysts' accuracy differently. Column (3) reports our most restrictive fixed effect structure in which we replace analyst and firm fixed effects with analyst $\times$ firm fixed effects. This structure exploits the rich time-series variations in analyst-firm connections, which is a unique feature of our data. It examines the changes in forecast accuracy before and after an analyst establishes connections with a certain firm and examines the different rates at which female and male analysts are able to utilize connections to improve forecast accuracy. Because it focuses on changes within an analyst-firm pair estimation, it effectively rules out concerns over omitted variables at the analyst level (e.g., more capable female analysts are self-selected into a male-dominated industry), at the firm level (e.g., more conferences are organized for firms in certain industries), and at the analyst-firm level (e.g., female analysts gravitate towards firms in certain industries with better information environment).[7]

We first find that connecting with an executive of a firm is associated with 0.6% or 0.9% lower forecast errors among male analysts. More importantly, the coefficient estimates of the interaction terms between *Connection* and *Female* are negative and statistically significant at the 5% or 1%

[7] In untabulated analysis, we replace broker-time fixed effects with the much more demanding analyst-time fixed effects. Analyst-time dummies absorb all unobserved time-varying analyst characteristics, including analyst skills at the time of hosting a conference. The direction of our coefficient estimate remains unchanged, although it is marginally insignificant. The combination of firm-time and analyst-time fixed effects severely restricts the variation that is used to estimate the effect of connections. In the robustness analysis reported in Table IA3 of the Internet Appendix, we further control for the interaction terms between various observed analyst characteristics (e.g., skills, experiences, and characteristics of the firms they cover) and *Connection*. The concern is that differences in abilities around the time a female or male analyst becomes connected drive the differences in utilizing conference connections. Our results remain unchanged.

level in all model specifications. The results indicate that female analysts' connections with firms' executives are associated with a larger improvement in forecast accuracy. The economic magnitude of the gender difference amounts to around 4.2% in Column (3) after controlling for firm $\times$ time, analyst $\times$ firm, and broker $\times$ time fixed effects. It means that the effect of professional connections on forecast accuracy is more than five times larger for female analysts than that for male analysts ((0.042+0.009)/0.009=5.7), which is economically salient.[8]

The coefficients on the control variables are consistent with prior literature (e.g., Clement (1999)). For example, forecasts made by analysts having more firm-specific experience and covering more firms are more accurate. In addition, forecast accuracy decreases with forecast horizon, the time gap between the earnings announcement date and the forecast release date.[9]

To examine the effect of connections over time, we plot the coefficient estimates of the interaction term between *Female* and yearly indicators of *Connection*, starting from 4 years before to 4 years after the investor conference in Figure 2. We use the regression model that includes control variables as well as firm $\times$ time and analyst $\times$ firm fixed effects (as in Column (3) of Table 3). Prior to the conference interaction, we observe no significant gender difference in forecast accuracy between connected and unconnected analysts, consistent with a lack of pre-trend and supporting the parallel trend assumption. In comparison, female analysts start to exhibit significantly lower forecast errors compared to male analysts in the first year after interacting with executives at conferences, and the effect persists for up to three years. This long-term nature of the gender effect suggests that these interactions likely foster sustained relationships between female analysts and executives, rather than simply providing short-term informational advantages from a single conference.

We further investigate whether the frequency of connections (i.e., through repeated meetings with executives from the same firm at conferences) or the range of connections (interacting with different executives within a firm) improves analyst forecast accuracy. More specifically, we explore

[8]For reference, Fang and Huang (2017) shows that inferred connections based on shared education experience reduce forecast error by two to three times larger for male analysts than for female analysts. While these magnitudes are not directly comparable because of the different fixed effects structures employed, it provides comfort that the gender difference we document is economically significant but not too large to be implausible.

[9]Table IA4 in the Internet Appendix reports the results using standardized control variables, offering a useful perspective for comparing the relative economic magnitudes of these variables.

the time-series properties of analyst-executive connections and run regressions of forecast error on *No. of meetings* and *No. of executives*. *No. of meetings* is the total number of times the analyst has interacted with executives of the firm at conferences. The intuition is that repeated interactions are likely to deepen connections. *No. of executives* is the number of unique executives that an analyst has interacted with within a firm. This measure captures the breadth of connections that an analyst has established and likely reflects her ability to extract useful information from multiple sources. The model specifications are the same as those in Table 3. Table IA6 in the Internet Appendix contains the regression results for *No. of meetings* (Panel A) and *No. of executives* (Panel B). We find that once a female analyst establishes connections with a firm, she benefits from both increasing the frequency and depth of interaction. Specifically, for a female analyst who has connections with an executive of the firm, her forecast error decreases by around 1% if she has one additional meeting with the firm's executives and by around 3% if she interacts with an additional executive of the firm. By contrast, *No. of meetings* and *No. of executives* do not have any effect on connected male analysts' forecasts in the baseline case.

4.2 Alternative explanations

The primary concern of our baseline analysis is that it may be harder for women to become conference hosts, and females who do reach this position are likely to be of a higher caliber. The implication is that the female host analysts captured in our sample are exceptionally capable, excelling in both analytical skills and networking. As a result, their ability to utilize professional connections could be (at least partially) driven by the fact that they are better analysts in general, regardless of their gender. To address this concern, we first note that there are no observable gender differences between analysts who are connected with executives in their covered firms and those who are not, as reported in Table 2. While connected analysts are more senior and more accurate, this holds true for both female and male analysts.

To gain further insight into the selection process among analysts to host investor conferences, we estimate models of *Host analyst* as a function of the interaction between *Female* and various analyst characteristics. *Host analyst* is defined at the analyst-year level, which is a dummy variable equal to one if the analyst hosts a conference in a year, and zero otherwise. Panel A of Table 4 presents the regression results. On average, analysts who are more likely to host an investor conference in a given year tend to be more accurate, cover more firms, have greater experience, work at larger brokerage firms, and have previously been recognized as All-Star analysts. However, we do not find that female analysts need to be more capable than their male counterparts to host a conference. While female analysts do cover more firms than male analysts when hosting an investor conference, they receive opportunities to host even at smaller brokerage firms. Female analysts also tend to be less accurate when becoming hosts, but this gender difference disappears once analyst fixed effects are included in the determinant model. Since the determinant model shows correlations rather than causal relationships, several explanations are plausible. One possibility is that firms promote diversity at public events like investor conferences, making it easier for female analysts to be chosen as hosts. Alternatively, female analysts might take a more proactive approach in seeking opportunities to serve as hosts at these professional events since they might not otherwise have the same opportunity to socialize with company executives using their personal networks.

Even though we do not find clear evidence of gender-related selection bias (among observable analyst characteristics) in being connected or becoming hosts at investor conferences, we conduct additional tests to alleviate potential concerns over unobservable analyst attributes.[10] First, we augment our baseline models in Table 3 by including analyst × *After_host* fixed effects, which hold constant unobservable analyst characteristics that may correlate with whether a female or a male analyst becomes a conference host. *After_host* is a dummy variable equal to one if analysts have held at least one investor conference at the time of forecast issuance and zero otherwise. As shown in Panel B of Table 4, our results remain robust to this specification.

Second, if our main findings were driven solely by the fact that connected female analysts have higher ability, we would expect a similar improvement in the forecast accuracy of the focal firm when analysts are connected to other firms in their coverage portfolios. To test this, we construct a dummy variable, *Connection_other firm*, which is equal to one if the analyst is connected to any

[10]Table IA3 of the Internet Appendix further controls for interaction terms between the array of analyst characteristics that we use as control variables (e.g., analyst skills, experiences, characteristics of the firms they cover) and *Connection*. Our main findings remain robust after controlling for how observed differences in skills and abilities between female and male analysts might influence the way they benefit from connections.

firm other than the one associated with the forecast in the year of the forecast issuance, and zero if the analyst is not connected in the year. We then rerun the regressions in Table 3, replacing *Connection* with *Connection_other firm*. Panel C of 4 shows that female analysts connected to executives of other firms in their portfolios do not improve forecast accuracy for the focal firm more than their male counterparts. This finding suggests that our baseline results are not solely driven by the selection bias related to female hosts being more capable than male hosts.

Another explanation is that female analysts may issue more optimistic forecasts than male analysts to curry favor with executives in order to gain information access (Milian, Smith, and Alfonso, 2017; Brown, Francis, Hu, Shohfi, Zhang, and Xin, 2023; De Amicis, Falconieri, and Tastan, 2021). Prior literature shows that managers discriminate among analysts, granting more private access to those who issue more favorable reports about their firm (Chen and Matsumoto, 2006; Francis and Philbrick, 1993; Francis, Chen, Willis, and Philbrick, 2004). As a result, the results we document can be driven by the managers' tendency to grant more access to optimistic analysts (regardless of gender) rather than by female analysts' ability to establish stronger professional ties. To mitigate this concern, we empirically test the effect of connections on forecast optimism in Section III of the Internet Appendix. We find that female analysts are not more optimistic about firms that they are connected with than their male counterparts. In addition, we see no gender difference in forecast optimism around establishing connections in a dynamic model as shown in Figure IA1. These results are inconsistent with the alternative explanations that female analysts are more likely to curry favors with the management to gain access.

5 Mechanism

5.1 How do connections benefit host analysts?

There are two possible, non-mutually-exclusive explanations for how female analysts utilize conference interactions to enhance forecast accuracy. First, their advantage is specific to the interactions at the conference, either because they obtain more insight about the firm or are better at interpreting what is communicated by executives at the conference. In this case, the information advantage for female analysts would likely be short-lived, peaking immediately after the conference. Second, female analysts could use conference interactions to establish long-term relationships with executives, turning one-time interactions into ongoing access to management. We explore these two potential explanations.

Figure 2 shows that female analysts exhibit superior forecast accuracy for up to three years after the conference. The long-term nature of the improvement suggests that the benefits accruing to female analysts likely go beyond the information exchanged from a single event. In other words, it is possible that female analysts are better at transforming one-time meetings with executives at investor conferences into repeated interactions in the future. However, direct evidence of these private interactions between analysts and executives is difficult, if not impossible, to observe. To circumvent this empirical challenge, we use subsequent participation on conference calls as a proxy for the extent of management access for an analyst. Participation in conference calls is an important source of information for analysts (Brown, Call, Clement, and Sharp, 2015). Executives have the discretion to discriminate among analysts and grant more participation to those with better relationships (Mayew, 2008; Brown, Call, Clement, and Sharp, 2019). Further, analysts who ask questions during earnings conference calls are regarded as possessing superior private information compared to those who do not participate (Mayew, Sharp, and Venkatachalam, 2013). We examine gender differences in the effect of these connections on both the likelihood of participating in earnings calls and, for those who participate, the length of the questions they ask. Using earnings call transcripts from Capital IQ, We create a dummy variable (*Participate*) indicating whether the analyst asks questions during an earnings call, assuming that analysts who have issued a forecast for a firm in the previous year of the call are those likely interested in asking questions. For participating analysts, we count the number of words in their questions and take the logarithm (*Ln_word counts*). We then run regressions of *Participate* and *Ln_word counts* on the interaction between *Connection* and *Female*, controlling for analyst and firm characteristics, as well as firm, broker, and conference fixed effects.

Table 5 reports the regression results. The positive and significant coefficients for *Connection* indicate that connections made at investor conferences increase the likelihood of analysts asking questions during future earnings calls, and when they do, the questions tend to be longer. More importantly, the positively significant interaction terms between *Female* and *Connection* suggest that this effect is stronger for female analysts. These results indicate that female analysts likely enjoy greater improvements in management access after establishing conference connections, consistent with them transforming conference interactions into long-term relationship capital.

It is also possible that female hosts differ from male hosts in their hosting styles when interacting with executives at investor conferences, which could influence the value derived by analysts. To explore this possibility, we investigate gender differences in observable characteristics of how female and male analysts conduct the public Q&A sessions of the conference. Specifically, we focus on five metrics: 1) the aggressiveness of host analysts' questions, following Comprix, Lopatta, and Tideman (2022) (*Aggressiveness*); 2) the number of questions asked (*No. of questions*); 3) the average length of questions (*No. of words per questions*); 4) the organization of private sessions at the conference (*Private*); 5) the sentiment of hosts' questions (*Sentiment*). We regress these characteristics on the *Female* indicator, controlling for broker × time and firm × time fixed effects to account for any time-varying characteristics of brokers and firms. Additional control variables at the analyst and forecast levels are also included.

Table 6 presents the results of these analyses. We find no significant gender differences in most characteristics, except for aggressiveness and the average length of questions. Female host analysts tend to be less aggressive and ask shorter questions at investor conferences compared to their male counterparts. These traits may foster a more collaborative and welcoming atmosphere at investor conferences, either promoting information sharing or contributing to the development of long-term relationships with executives. We would like to caveat that our analysis is based on a limited set of observable and measurable characteristics of how analysts ask questions and interact with executives during public meetings at conferences. While these findings do not fully disentangle the effects of conference-specific interactions from relationship-building dynamics, the non-significant gender differences in key conference characteristics, such as the organization of private sessions or the number and sentiment of questions asked, suggest that our baseline results are unlikely to be solely driven by information restricted to investor conferences.

5.2 Cross-sectional tests based on analyst characteristics

We perform cross-sectional tests of our baseline results based on two key analyst characteristics. First, we anticipate that the gender difference in utilizing connections will be more pronounced among less experienced analysts, as women with fewer years in the field may rely more heavily on relationships established at investor conferences. However, connections might also complement experiences, becoming more valuable as female analysts acquire skills and expertise over time. We divide our sample based on whether the analyst's experience is above or below the median and run regressions within each subsample. Panel A of Table 7 demonstrates that the gender difference in the effect of connections on forecast accuracy is only evident in the sub-sample of less experienced analysts.

Second, given that professional connections may serve as a substitute for personal networks developed from one's past experiences, we expect our baseline findings to be more pronounced among analysts without alternative connections to executives. Following Cohen, Frazzini, and Malloy (2008) and Fang and Huang (2017), we use school ties with executives as a measure of analysts' social network, and run regressions within the subsamples of analyst-firm pairs with and without school ties to executives. As shown in Panel B of Table 7, the gender difference in the effect of connections on forecast accuracy is observed only in the subsample of analysts without school ties to executives. These cross-sectional findings suggest that female analysts may derive greater benefits from professional networks when they lack alternative forms of social capital, such as experience or school ties.

5.3 Connections with CFOs

In this section, we consider connections with chief financial officers (CFOs), as prior literature identifies the CFO as the key executives responsible for preparing, communicating, and forecasting financial information, and as a result, more likely to possess financial information that is useful for financial analysts (Mian, 2001; Jiang, Petroni, and Wang, 2010; Armstrong, Guay, and Weber, 2010; Li, Sun, and Ettredge, 2010). If our proposed mechanism – professional connections formed at conferences transmit information that helps analysts to make more accurate forecasts – is at play, we will expect a stronger effect when analysts connect with the CFO. We classify connections into two categories, namely connections with the incumbent CFO of the firm and connections with other executives of the firm, and create two indicator variables *CFO connection* and *Non-CFO connection*, respectively. We modify Equation 2 by regressing *Forecast error* on these indicator variables and their interaction terms with *Female*, controlling for the same set of fixed effects and control variables as in Table 3. This specification allows us to disentangle the effects of 1) connections with CFO, 2) connections with non-CFO top executives, and 3) no connections on forecast accuracy among male and female analysts.

Table 8 reports the regression results. The coefficient estimates on *CFO connection* and *non-CFO connection* are consistently negative and significant in most estimates, suggesting that in the baseline, both CFO and non-CFO connections are associated with smaller forecast errors. There is no evidence that male analysts obtain more information from CFO connections, as the F-statistics comparing the two coefficient estimates are insignificant. The coefficient estimates of *CFO connection* $\times$ *Female* are negative and statistically significant in all regressions and amount to 2.6%-5.3% depending on the model specifications, while those of *non-CFO connection* $\times$ *Female* are statistically insignificant. Moreover, the coefficient estimates of *CFO connection* $\times$ *Female* are around two to three times larger in magnitude than those of *non-CFO connection* $\times$ *Female*, and the differences are statistically significant in two out of three models based on F-statistics. In other words, the gender difference in the effect of connections on forecast accuracy is largely driven by connections with CFOs, through which financial information is more likely to be communicated. The findings indicate that female analysts' larger improvement in forecast accuracy is likely driven by utilizing the professional connections built at investor conferences to obtain information that is helpful in improving research outputs.

5.4 Within (cross)-gender connections

Moreover, we conjecture that conference interactions allow them to overcome homophily biases that might exist in personal relationships. The hosting analyst can form cross-gender connections by showcasing their professional expertise and competence to a diversified audience. In this case, we would expect analysts to benefit from interacting with executives of both genders. To test this hypothesis, we distinguish between within-gender connections (male analyst-male executive and female analyst-female executive) and cross-gender connections (male analyst-female executive and female analyst-male executive). We modify Equation 2 and replace *Connection* with two separate indicators on connections with male executives (*Male connection*) and connections with female executives (*Female connection*); we separately interact them with *Female*, an indicator on whether the analyst is female.

Table 9 reports the regression results. In the baseline case, both coefficient estimates of *Male connection* and *Female connection* are significantly negative. Moreover, the effect of female executive connection is around two to three times larger (F-statistics are significant under 10% in two out of three specifications). This suggests that interactions with female executives are more likely to improve analysts' forecast accuracy than those with male executives. This is consistent with prior literature that female executives exert more effort in preparing financial information for external users (Francoeur, Li, Singer, and Zhang, 2022) and are more willing to communicate (Rosener, 2011). As a result, connections with female executives allow analysts to obtain more information that is useful in generating forecasts. Next, the coefficient estimates on the interaction terms, *Female Connection* $\times$ *Female* and *Male Connection* $\times$ *Female*, are significantly negative, suggesting that female analysts issue more accurate forecasts, compared to male analysts, after establishing connections with both male and female executives. Notably, female analysts do not benefit more from connections with female executives - the corresponding F-statistics show that the coefficient estimates of *Female connection* $\times$ *Female* do not significantly differ from those of *Male connection* $\times$ *Female*. Since female analysts are better at utilizing both in-group connections (i.e., with female executives) and out-of-group connections (i.e., with male executives), it is not consistent with the alternative explanation that our results are driven by female analysts interacting more with female executives. Moreover, these results suggest that professional connections established at conferences exhibit little homophily, which is in direct contrast to analysts' educational networks (Fang and Huang, 2017). As a result, professional connections formed from conference interactions help to overcome the hurdle for professional women to benefit from network connections.

6 Additional analysis

6.1 Market reactions around forecast revisions

Our results so far suggest that female analysts are better at capitalizing on their professional connections formed at investor conferences. If the capital market participants are aware of this ability, they would respond more strongly to the forecast revisions made by connected female analysts around the forecast release time than to connected male analysts, controlling for forecast accuracy and other factors that influence market reactions. To investigate the market perception of female analysts' ability to utilize professional connections, we calculate the stock price reaction in the two-day event window [0,1] around the release date of an analyst forecast. We compute the two-day buy-and-hold cumulative abnormal return (*CAR [0,1]*) as:

$$CAR[0,1]_{j,t} = \prod_{t=0}^{1}(1 + R_{jt}) - \prod_{t=0}^{1}(1 + R_{jt}^{DGTW}) \tag{3}$$

where $R_{j,t}$ is the raw return of stock j on day t, and $R_{j,t}^{DGTW}$ is the return on day t of a benchmark portfolio with the same size, book-to-market, and momentum characteristics as the stock, following Daniel, Grinblatt, Titman, and Wermers (1997).

Following the model specifications in Green, Jame, Markov, and Subasi (2014a), we run regressions of *CAR[0,1]* on the interaction term between *Connection* and *Female*, controlling for known determinants of market reaction including forecast accuracy, broker size, the number of firms covered, firm-specific experience, whether the forecast is in the short window pre- or post- earnings forecasts, whether there is a concurrent recommendation, the absolute revision, firm size, B/M, ROA, and R&D. We include analyst, firm, time or analyst × firm and time fixed effects. Imposing a stringent set of analyst $\times$ firm fixed effects controls for the selection of coverage firms by analysts of a different gender. As a result, we can focus on the *changes* in market reactions within an analyst-firm pair surrounding forecast revisions before and after the analyst establishes connections with firm executives.

The results are presented in Table 10. Columns (1) and (2) contain the full sample of all forecast revisions, and *CAR[0,1]* is multiplied by -1 for downgrades. We find that controlling for forecast accuracy and other key determinants of market reaction around analyst forecast revisions, the market reaction of a given analyst on a given firm is 0.2% stronger when a female analyst starts to establish connections with the firm executives, compared to that for male analysts. Columns (3) and (4) ((5) and (6)) contain the regression results for the sample of upgrading (downgrading) forecast revisions. We find consistent higher market reactions to forecasts issued by connected female analysts across the two sub-samples, with *CAR[0,1]* being 0.168% higher (0.225% lower) if female analysts with connections upgrade (downgrade) their earnings forecasts on a certain firm. The findings indicate that the market participants recognize female analysts' ability to capitalize on their professional networks established at investor conferences.

6.2 Labor market outcomes

We next examine whether analysts' connections with executives influence their career outcomes and whether female analysts are able to transform these connections into human capital. We first investigate analysts' outside career opportunities, specifically at firms under their coverage, as job-hopping to these firms is the most direct way to capitalize on professional connections formed with these executives. We obtain the career paths of analysts from the Capital IQ People Intelligence Database and define a dummy variable, *Move to covered firms*, which is equal to one if analysts move to a firm under their coverage portfolio at a later stage of their careers (i.e., as an exit opportunity from the analyst industry).[11] From the 2,068 I/B/E/S analysts in our main sample, we form a panel at the analyst-year level with 19,188 observations. In a given year, we define an

[11]The Capital IQ People Intelligence Database contains the sequence of positions and firms an analyst works at. Hence, we are able to identify whether an analyst works in a covered firm after being an equity analyst.

analyst as connected if he or she had a previous conference interaction with at least one executive from the coverage firms (*Connected analyst*). We run linear probability regressions of the dependent variable *Move to covered firms* on the independent variables *Connected analyst*, *Female*, and their interaction terms, controlling for broker size, the number of firms covered by the analyst in the year, overall experience of the analyst, and the average forecast errors of forecasts issued by the analyst in the year. We also add broker $\times$ time and analyst fixed effects to rule out the possibility that working in a prominent brokerage house and being more capable increases an analyst's likelihood of connecting with executives and moving to covered firms at the same time.

Panel A of Table 11 contains the regression results. Connected male analysts are 1.8% more likely to join covered firms than unconnected male analysts, but the effect disappears if we control for analyst fixed effects in Column (3). Consistent with women being better at capitalizing on professional connections, we find female analysts are 2.8 times ((0.032+0.018)/0.018) more likely to move to covered firms than male analysts if they have connections with the executives. The gender difference is statistically significant at 5% or 10% level in all model specifications.

The second measure for analysts' career outcomes we investigate is whether an analyst is being voted as Institutional Investor "All star" analysts. Being "All star" is related to higher compensation (e.g., Emery and Li, 2009), and is widely used as a measure of analysts' favorable career outcomes in previous literature. We run linear probability regressions of the dependent variable *All star* on the independent variables *Connected analyst*, *Female*, and their interaction terms in the same model specifications as above and present the results in Panel B of Table 11.

The results show that both connected male and female analysts are more likely to be star analysts. There is no significant gender difference - the coefficient estimates of the interaction term between *Connected analyst* and *Female* are positive across all specifications but statistically insignificant. The findings indicate that professional connections built at investor conferences benefit males and females equally in terms of achieving external recognition, overcoming gender stereotypes and discrimination that are frequently documented in the previous literature. For example, Peng, Teoh, Wang, and Yan (2022) find that while appearing as dominant increases male analysts' chance of being "All star", it substantially reduces the chances for female analysts, and Fang and Huang

(2017) show that educational connections allow less accurate male analysts to be voted as "All star", but the effect is reversed in women.

7 Conclusion

This paper is the first to investigate women's ability to utilize connections, conditional on having access to professional networks, in the sample of financial analysts. Female analysts issue more accurate forecasts when they have built connections with executives, especially CFOs, of the firms at investor conferences compared to their male counterparts. We find evidence that female analysts transform interactions at investor conferences into long-term relationships and management access; they also overcome homophily in professional connections built up at investor conferences. Female analysts' ability to utilize professional connections is recognized in both the capital market and the labor market. Their forecasts generate greater market reactions after being connected, and female analysts are more likely to move to a connected firm later in their careers than male analysts, transforming professional connections to human capital.

The findings indicate that when given the chance to network in professional contexts, women in competitive industries leverage connections to improve work performance, which has important policy implications. In light of the increasing awareness of gender inequality issues, companies and organizations spend considerable resources to host dedicated sessions focusing on promoting network opportunities among professional women. Based on our findings, these initiatives go beyond "woke-washing" as they provide women exposure to a broader range of resources and support, helping them overcome challenges in entering male-dominated professional networks. We also acknowledge that while these initiatives effectively create opportunities for women to build professional connections, achieving a truly equitable professional environment requires broader structural reforms. Dismantling the old boys' club will necessitate sustained efforts to reshape workplace cultures, broaden access to informal networks, and mitigate the biases that perpetuate gender disparities. Exploring these broader approaches remains an important avenue for future research.

Appendix

I Variable description

This table contains a description of all variables used in our empirical analyses. Data sources are as follows:

1. IBES: I/B/E/S database
2. CRSP: CRSP stock price data
3. Compustat: Compustat quarterly financial statement data
4. StreetEvents: Refinitiv StreetEvents Event Calendar and Transcript
5. II: Institutional Investor magazine
6. CIQ: Capital IQ People Intelligence
7. LinkedIn: LinkedIn profiles
8. BoardEx: BoardEx database

Variable name	Description	Data source
Connection$_{i,j,t}$	Dummy variable equal to one if the analyst has established connections with at least one of the executives of the firm through investor conferences and zero otherwise.	IBES, StreetEvents
Forecast error$_{i,j,t}$	The absolute forecast error for analyst i's forecast of firm j less the mean absolute forecast error (across all analysts for firm j in the same fiscal year), scaled by the mean absolute forecast error in the IBES universe.	IBES
Female$_i$	Dummy variable equal to one if the analyst is female and zero otherwise.	IBES
Avg. forecast error$_{i,t}$	The average forecast error of analyst i's forecasts in a year.	IBES
All star$_{i,t}$	Dummy variable equal to one if the analyst is elected as an "All Star" analyst in a year and zero otherwise.	II
No. of firms covered$_{i,t}$	The number of firms covered by an analyst in a year.	IBES
Firm-specific experience$_{i,j,t}$	The number of years analyst i has covered firm j in a year.	IBES

Variable name	Description	Data source
Forecast horizon$_{i,j,t}$	The difference in the calendar dates of the firm's earnings announcement date and the analyst forecast release date.	IBES
Forecast frequency$_{i,j,t}$	The number of forecasts issued by analyst i on firm j in a year.	IBES
Firm size$_{j,t}$	Log of total assets.	Compustat
B/M$_{j,t}$	Book-to-market ratio.	Compustat
R&D$_{j,t}$	R&D expenses.	Compustat
ROA$_{j,t}$Return on assets.	Compustat	
Host in a year$_{i,t}$	Dummy variable equal to one if an analyst hosts an investor conference in a year, and zero otherwise.	IBES, StreetEvents
Avg. forecast error$_{i,t}$	Average forecast error of the forecasts issued by an analyst in a year.	IBES
Avg. experience$_{i,t}$	Average firm-specific experience of all firms covered by an analyst in a year.	IBES
After_host$_{i,t}$	Dummy variable equal to one if analysts have held at least one investor conference at the time of forecast issuance, and zero otherwise.	IBES, StreetEvents
Connection_other firm$_{i,j,t}$	Dummy variable equal to one if the analyst is connected to any firm other than the one associated with the forecast in the year of the forecast issuance, and zero if the analyst is not connected in the year.	IBES, StreetEvents
Participate$_{i,j,t}$	Dummy variable equal to one if an analyst asks a question on an earnings conference call, zero otherwise.	IBES, Capital IQ
Ln_word counts $_{i,j,t}$	The logarithm of the number of words in the questions asked by an analyst during a conference cal.	IBES, Capital IQ
Connected analyst$_{i,t}$	Dummy variable equal to one if an analyst is connected with at least one executive and zero otherwise.	IBES, StreetEvents

Variable name	Description	Data source
Aggressiveness	The sum of the four individual aggressiveness measures: directness, follow-up, negative questions, and preface, following Comprix, Lopatta, and Tideman (2022).	IBES, StreetEvents
No. of questions$_{i,j,t}$	The number of questions asked by the host analyst at the investor conference.	IBES, StreetEvents
No. of words per question$_{i,j,t}$	The average word count of questions asked by the host analyst at the investor conference	IBES, StreetEvents
Private session$_{i,j,t}$	Dummy variable equal to one if the conference has private sessions including one-on-one meetings and breakout sessions. Private meetings are identified by searching through transcripts for mentions of "one-on-one," "breakout," or an indication towards the end of the transcript for "moving to another room" (and all common variants) (Bushee, Jung, and Miller, 2011; Zhang, 2023).	IBES, StreetEvents
Sentiment	The average question sentiment scores. Sentiment scores are calculated as the number of positive words minus the number of negative words, scaled by the total number of words in a sentence. Sentiment word lists are based on the Loughran-McDonald Master Dictionary (Loughran and McDonald, 2011).	IBES, StreetEvents
Analyst experience$_{i,t}$	The number of years analyst i has covered any firm in the IBES sample.	IBES
School ties$_{i,j,t}$	Whether an analyst attended the same university as the executive of the covering firm.	IBES, LinkedIn, BoardEx
CFO connection$_{i,j,t}$	Dummy variable equal to one if the analyst has connections with the incumbent CFO of a firm and zero otherwise.	IBES, StreetEvents
Non-CFO connection$_{i,j,t}$	Dummy variable equal to one if the analyst has connections with other executives of a firm and zero otherwise.	IBES, StreetEvents

Variable name	Description	Data source
Female connection$_{i,j,t}$	Dummy variable equal to one if the analyst has connection with a female executive of a firm and zero otherwise.	IBES, StreetEvents
Male connection$_{i,j,t}$	Dummy variable equal to one if the analyst has connection with a male executive of a firm and zero otherwise.	IBES, StreetEvents
No. of meets$_{i,j,t}$	The accumulative number of meetings the analyst have with the executives of a firm.	IBES, StreetEvents
No. of executives$_{i,j,t}$	The number of executives of a firm the analyst has connection with.	IBES, StreetEvents
Broker size$_{i,t}$	The number of analysts of a brokerage firm in a year.	IBES
Pre earning$_{i,j,t}$	Dummy variable equal to one if the forecast is in the [-14,0] windown before the firm's earnings announcement.	IBES
Post earning$_{i,j,t}$	Dummy variable equal to one if the forecast is in the [0,14] windown after the firm's earnings announcement.	IBES
Concurrent recommendation$_{i,j,t}$	Dummy variable equal to one if the analyst j issues a recommendation for firm j in the window [-3,3] around the earnings forecast.	IBES
Abs. revision$_{i,j,t}$	The absolute value of the difference between analyst i's current earnings forecast value on firm j and previous earnings forecast value on firm j scaled by the previous earnings forecast value.	IBES
Upgrade$_{i,j,t}$	Dummy variable equal to one if analyst i's current earnings forecast value on firm j is larger than the previous earnings forecast value on firm j.	IBES
Move to covered firms$_{i,t}$	Dummy variable equal to one if an analyst works at a firm under her coverage after being an equity analyst and zero otherwise.	IBES, CIQ
All star$_{i,t}$	Dummy variable equal to one if an analyst is elected as "All star" analyst and zero otherwise.	II

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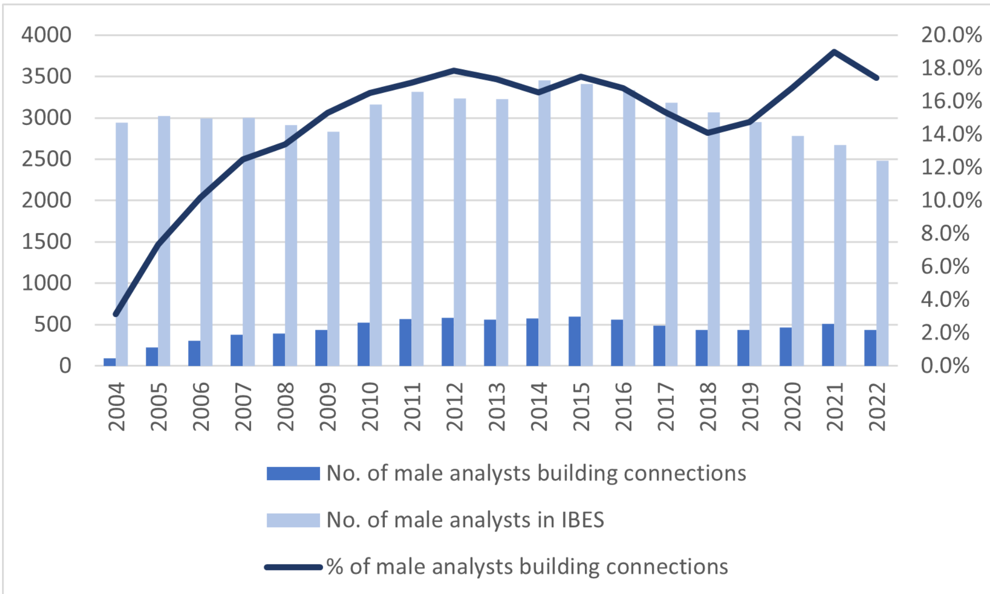
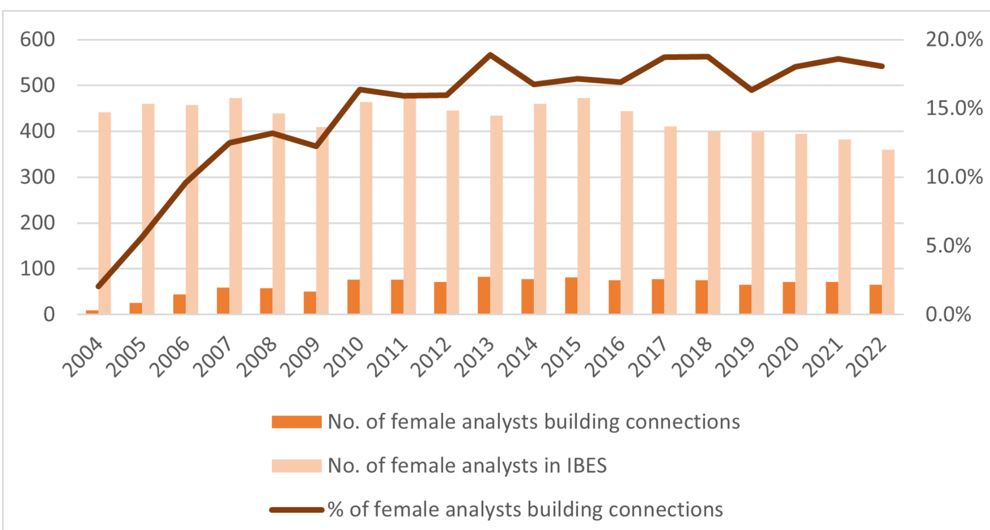
Figure 1: Proportion of analysts building connections through conferences over time

This figure plots the proportion of male (female) analysts that built up connections with at least one executive each year in the sample period 2004-2022 in Panel A (Panel B). The bars indicate the number of male (female) analysts that built up connections with at least one executive each year and the number of analysts in the I/B/E/S sample each year in Panel A (Panel B).



Panel A: Male analysts building connections through conferences



Panel B: Female analysts building connections through conferences

Figure 2: Dynamic gender effect of establishing connections on forecast accuracy

This figure plots the coefficient estimates of the interaction term between *Connection* and *Female* in years after gaining connections at investor conferences. The model specification is the same as Column (3) in Table 3. 10% confidence intervals are plotted with dashed lines.

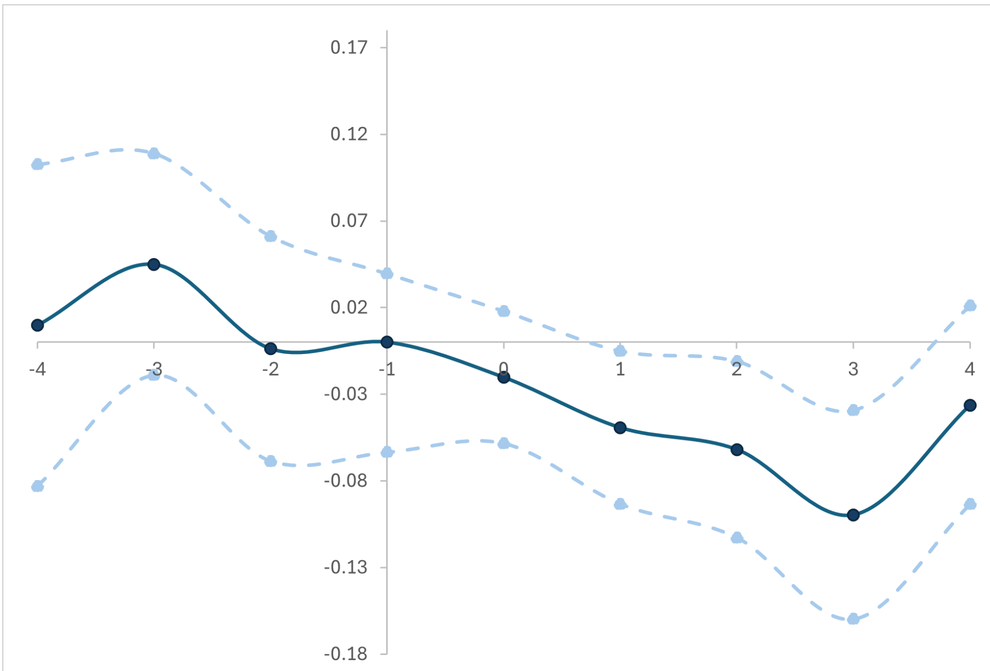


Table 1: Sample construction

This table presents the sample construction procedure for the analyst earnings forecast accuracy analyses.

Steps	No. of obs.	No. of analysts	No. of brokers	No. of firms
I/B/E/S analyst earnings forecasts 2004-2022	3,160,155	10,468	843	10,468
Restrict to firms with executive information from ExecuComp	1,597,880	7,596	628	2,545
Restrict to analysts with at least one executive connection	934,741	2,115	261	2,479
Restrict to executives with at least one analyst connection	745,464	2,115	259	1,688
Restrict to the sample without missing variables	694,557	2,068	251	1,598
Restrict to the sample without singletons in analyst, firm, and broker-time	694,505	2,068	241	1,589

Table 2: Summary statistics

This table contains the summary statistics of the main variables used in the analyses. Panel A contains the number of observations (Obs), mean, standard deviation (Std. Dev.), 25, 50 and 75 percentile of the variables. Panel B compares the mean of the variables in the sub-samples in male and female analysts with and without connections. *t*-statistics are provided in parentheses. Standard errors are clustered by analyst. All variables are defined in the Appendix. I.

Panel A: Summary statistics in the analysis sample						
Variable	Obs	Mean	Std. Dev.	P25	P50	P75
Forecast level variables						
Connection	694505	0.255	0.436	0	0	1
Female	694505	0.108	0.311	0	0	0
Forecast error	694505	-0.029	0.748	-0.627	-0.159	0.394
No. of firms covered	694505	20.032	7.844	15	19	24
Firm-specific experience	694505	5.765	5.641	2	4	8
Forecast horizon	694505	208.713	105.127	111	201	293
Forecast frequency	694505	6.235	3.08	4	6	8
Firm size	694505	8.935	1.744	7.72	8.869	10.137
ROA	694505	0.013	0.037	0.004	0.014	0.027
B/M	694505	0.425	0.417	0.194	0.338	0.557
R&D	694505	0.104	0.877	0	0.023	0.106
Host experience	694505	3.546	4.959	0	3	7
CAR [0,1] (%)	557809	1.129	4.938	-1.138	0.538	2.838
Analyst-year level variables						
Host in a year	58096	0.177	0.381	0	0	0
Move to covered firms	19188	0.066	0.248	0	0	0
All star	17997	0.139	0.345	0	0	0
Earnings conference call variables						
Participate	428701	0.074	0.262	0	0	0
Ln_word counts	31796	5.052	0.54	4.727	5.081	5.403

Table 2: Summary statistics (continued)

Panel B: Differences in male and female analysts with and without connections

	Forecast error	No. of firms covered	Firm-specific experience	Forecast horizon	Forecast frequency	Firm size	ROA	B/M	R&D
(1) Male without connections	-0.024	20.010	5.227	209.495	6.134	8.876	0.012	0.437	0.106
(2) Male with connections	-0.046	20.679	7.443	207.405	6.442	9.114	0.013	0.403	0.102
(3) Female without connections	-0.015	18.633	4.953	207.192	6.225	8.867	0.015	0.400	0.080
(4) Female with connections	-0.043	19.344	7.272	205.098	6.937	9.093	0.016	0.386	0.131
(5) Connection diff Male	-0.022***	0.669***	2.216***	-2.091***	0.307***	0.238***	0.002***	-0.035***	-0.005
=(2)-(1)	(-6.22)	(2.59)	(16.61)	(-4.38)	(2.98)	(5.70)	(3.84)	(-3.99)	(-0.79)
(6) Connection diff Female	-0.028***	0.712	2.319***	-2.095**	0.713***	0.227*	0.001	-0.014	0.051
=(4)-(3)	(-3.54)	(1.52)	(6.16)	(-1.98)	(2.88)	(1.88)	(0.72)	(-0.74)	(1.63)
(7) Gender diff without connections	0.009	-1.377*	-0.275	-2.303**	0.090	-0.009	0.003***	-0.037**	-0.026*
=(3)-(1)	(1.19)	(-2.25)	(-0.83)	(-2.51)	(0.55)	(-0.09)	(2.92)	(-1.98)	(1.88)
(8) Gender diff with connections	0.004	-1.334*	-0.172	-2.307*	0.496	-0.020	0.002*	-0.017	0.029
=(4)-(2)	(0.45)	(-1.94)	(-0.35)	(-1.82)	(1.50)	(-0.13)	(1.81)	(-0.74)	(0.75)
(9) Diff in Diff	-0.005	0.043	0.103	-0.004	0.405	-0.011	-0.001	0.020	0.055*
=(6)-(5) or (8)-(7)	(-0.63)	(0.08)	(0.26)	(0.00)	(1.51)	(-0.09)	(-0.77)	(0.97)	(1.75)

Table 3: Gender difference in the effect of executive connections on forecast accuracy

This table contains the regression results of Forecast error on the interaction term between *Female* and *Connection*. The dependent variable *Forecast error* is defined as the absolute forecast error for analyst i's forecast of firm j less the mean absolute forecast error (across all analysts for firm j in the same fiscal year), scaled by the mean absolute forecast error. *Connection* is a dummy variable equal to one if the analyst has established connections with at least one of the executives of the firm through investor conferences and zero otherwise. *Female* is a dummy variable equal to one if the analyst is a female and zero otherwise. Standard errors are clustered by analyst. t-statistics are provided in parentheses. $***$, $**$, and $*$ represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	Forecast error		
	(1)	(2)	(3)
Connection × Female	-0.019**	-0.022**	-0.042***
	(-2.05)	(-2.36)	(-2.72)
Connection	-0.009***	-0.006*	-0.009**
	(-2.77)	(-1.71)	(-2.04)
No. of firms covered	-0.001*	-0.000	-0.001**
	(-1.88)	(-1.03)	(-2.00)
Firm-specific experience	-0.001*	-0.001	
	(-1.67)	(-1.51)	
Forecast horizon	0.004***	0.004***	0.004***
	(157.98)	(159.07)	(158.02)
Forecast frequency	0.010***	0.010***	0.011***
	(13.45)	(12.84)	(12.30)
Firm size	-0.005		
	(-1.43)		
ROA	0.105***		
	(2.77)		
B/M	-0.016***		
	(-3.58)		
R&D	0.001		
	(0.77)		
Analyst fixed effects	Yes	Yes	No
Broker×Time fixed effects	Yes	Yes	Yes
Firm fixed effects	Yes	No	No
Firm×Time fixed effects	No	Yes	Yes
Analyst×Firm fixed effects	No	No	Yes
Observations	694505	694207	693325
Adjusted R^2	0.258	0.267	0.292

Table 4: Addressing the gender difference in becoming hosts and gaining connections at investor conferences

This table contains analyses addressing the concern that the gender difference in becoming investor conference hosts and gaining connections at investor conferences drives our baseline results. Panel A contains the regression results of *Host analyst* on interaction terms between *Female* and analyst characteristics including their average forecast error and the number of firms covered at the analyst-year level. *Host analyst* is a dummy variable equal to one if an analyst hosts an investor conference in a year, and zero otherwise. Panel B contains the baseline results in Table 3 controlling for analyst×after_host fixed effects. *After_host* is a dummy variable equal to one if analysts have held at least one investor conference at the time of forecast issuance, and zero otherwise. Panel C contains regression results of Forecast error on the interaction term between *Female* and *Connection_other firm*. *Connection_other firm* is a dummy variable equal to one if the analyst is connected to any firm other than the one associated with the forecast in the year of the forecast issuance, and zero if the analyst is not connected in the year. Standard errors are clustered by analyst. t-statistics are provided in parentheses. $***$, $**$, and $*$ represent statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Determinants of being a host analyst			
	Host analyst		
	(1)	(2)	(3)
Female	-0.011		
	(-0.89)		
Avg. forecast error	-0.029***	-0.024***	-0.027***
	(-13.31)	(-13.58)	(-13.41)
Female × Avg. forecast error	0.011**	0.005	-0.001
	(2.36)	(1.13)	(-0.28)
No. of firms covered	0.012***	0.010***	0.011***
	(23.52)	(20.62)	(27.34)
Female × No. of firms covered	0.003**	0.003***	0.002**
	(2.35)	(2.76)	(2.11)
Avg. experience	0.002**	0.003***	0.002**
	(2.46)	(3.62)	(2.36)
Female × Avg. experience	0.001	0.000	-0.000
	(0.28)	(0.17)	(-0.16)
Broker size	0.001***	0.001***	
	(21.74)	(14.23)	
Female × Broker size	-0.000**	-0.000**	-0.000***
	(-2.27)	(-2.04)	(-2.75)
All star	0.170***	0.046***	0.031***
	(10.27)	(3.71)	(2.60)
Female × All star	0.058	-0.015	-0.014
	(1.34)	(-0.42)	(-0.44)
Time fixed effects	No	Yes	Yes
Analyst fixed effects	No	Yes	Yes
Broker× time fixed effects	No	No	Yes
Observations	69961	69302	67339
Adjusted R^2	0.177	0.468	0.516

Table 4: Addressing the gender difference in becoming hosts and obtaining connections at investor conferences (continued)

Panel B: Controlling for analyst-after_host FE			
	(1)	(2)	(3)
Connection × Female	-0.016*	-0.017**	-0.034**
	(-1.86)	(-2.01)	(-2.23)
Connection	-0.008**	-0.005	-0.008*
	(-2.43)	(-1.49)	(-1.66)
Controls	Yes	Yes	Yes
Analyst×After_host fixed effects	Yes	Yes	Yes
Broker×Time fixed effects	Yes	Yes	Yes
Firm fixed effects	Yes	No	No
Firm×Time fixed effects	No	Yes	Yes
Analyst×Firm fixed effects	No	No	Yes
Observations	694461	694161	693285
Adjusted R^2	0.260	0.269	0.292
Panel C: Connections with other firms			
	(1)	(2)	(3)
Connection_other firm × Female	0.008	0.007	0.018
	(0.68)	(0.62)	(1.40)
Connection_other firm	0.001	0.001	0.001
	(0.26)	(0.24)	(0.17)
Controls	Yes	Yes	Yes
Analyst fixed effects	Yes	Yes	No
Broker×Time fixed effects	Yes	Yes	Yes
Firm fixed effects	Yes	No	No
Firm×Time fixed effects	No	Yes	Yes
Analyst×Firm fixed effects	No	No	Yes
Observations	517698	517338	516085
Adjusted R^2	0.258	0.270	0.298

Table 5: Earnings conference call participation and connections

This table contains the regression results of Participate (Ln_word counts) on the interaction term between *Female* and *Connection*. The dependent variable *Participate* is a dummy variable equal to one if an analyst asks a question on an earnings conference call, zero otherwise. *Ln_word counts* is the logarithm of the number of words in the questions asked by an analyst during a conference call. If an analyst asks multiple questions, the word count is averaged before taking the logarithm. *Connection* is a dummy variable equal to one if the analyst has established connections with at least one of the executives of the firm through investor conferences and zero otherwise. *Female* is a dummy variable equal to one if the analyst is a female and zero otherwise. Standard errors are clustered by analyst. *t*-statistics are provided in parentheses. ∗∗∗, ∗∗, and ∗ represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	Participate			Ln_word counts		
	(1)	(2)	(3)	(4)	(5)	(6)
Connection × Female	0.012**	0.009**	0.010**	0.058*	0.063**	0.087**
	(2.50)	(2.14)	(2.32)	(1.75)	(1.97)	(2.03)
Connection	0.016***	0.013***	0.014***	0.042***	0.035***	0.031*
	(9.81)	(8.79)	(8.77)	(3.69)	(3.51)	(1.92)
No. of firms covered	-0.000	-0.000	-0.000	0.002	0.002	0.001
	(-0.18)	(-0.62)	(-1.06)	(1.60)	(1.60)	(1.03)
Firm-specific experience	0.000***	0.001***	0.000***	0.004***	0.004***	0.003**
	(3.15)	(4.22)	(2.74)	(2.99)	(3.42)	(2.16)
Firm size	-0.008***	-0.007***	0.061***	-0.047***	-0.054***	-0.060
	(-4.59)	(-4.39)	(9.14)	(-4.23)	(-4.81)	(-0.64)
ROA	0.016	0.017	-0.018	0.183*	0.170	0.755
	(0.92)	(0.95)	(-0.52)	(1.72)	(1.61)	(1.29)
B/M	0.002	0.003	-0.013**	0.027*	0.026*	-0.048
	(0.94)	(1.13)	(-2.21)	(1.85)	(1.78)	(-0.49)
Firm fixed effects	Yes	Yes	No	Yes	Yes	No
Broker fixed effects	No	Yes	Yes	No	Yes	Yes
Conference fixed effects	No	No	Yes	No	No	Yes
Observations	428701	428699	426708	31796	31783	13197
Adjusted R^2	0.029	0.033	0.052	0.245	0.271	0.271

Table 6: Gender differences in behavior at investor conferences

This table contains the regression results of investor conference characteristics on *Female*. *Aggressiveness* is the sum of aggressiveness measures directness, follow-up, negative questions, and preface following Comprix, Lopatta, and Tideman (2022). *No. of questions* is the log form of the number of questions asked by the host analyst at the investor conference. *No. of words per question* is the log form of the average word count of questions asked by the host analyst at the investor conference. Standard errors are clustered by analyst. *Private session* is a dummy variable equal to one if the conference has private sessions including one-on-one meetings and breakout sessions. *Sentiment* is the average question sentiment scores. Control variables include *No. of firms covered*, *Firm-specific experience*, *Forecast frequency*, *Forecast horizon* (the average of the forecasts in the conference year), and *Avg. forecast error* t-statistics are provided in parentheses. $***$, $**$, and $*$ represent statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Summary statistics for characteristics of investor conferences

Variable	N	Mean	SD	P25	Median	P75
Aggressiveness	16017	1.337	0.253	1.182	1.333	1.500
No. of questions	16017	2.525	0.784	2.197	2.708	3.045
No. of words per question	16017	4.004	0.424	3.780	4.034	4.271
Sentiment	16017	-0.002	0.020	-0.005	0	0.005
Private session	16017	0.135	0.342	0	0	0

Panel B: Gender difference in characteristics of investor conferences

Dependent variable	Aggressiveness	No. of questions	No. of words per question	Private session	Sentiment
	(1)	(2)	(3)	(4)	(5)
Female	-0.035***	0.040	-0.109***	0.000	0.014
	(-2.65)	(1.39)	(-4.56)	(0.24)	(0.98)
Controls	Yes	Yes	Yes	Yes	Yes
Broker × time fixed effects	Yes	Yes	Yes	Yes	Yes
Firm × time fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	16017	16017	16017	16017	16017
Adjusted R^2	0.143	0.481	0.250	0.220	0.269

Table 7: Cross-sectional tests based on analyst experience and school ties

This table contains the regression results of *Forecast error* on the interaction term between *Female* and *Connection* in the subsamples partitioned based on analyst experience (Panel A) and analyst school ties (Panel B). The dependent variable *Forecast error* is defined as the absolute forecast error for analyst i's forecast of firm j less the mean absolute forecast error (across all analysts for firm j in the same fiscal year), scaled by the mean absolute forecast error. *Connection* is a dummy variable equal to one if the analyst has established connections with at least one of the executives of the firm through investor conferences and zero otherwise. *Female* is a dummy variable equal to one if the analyst is a female and zero otherwise. Standard errors are clustered by analyst. t-statistics are provided in parentheses. $***$, $**$, and $*$ represent statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Cross-sectional tests based on analyst experience

	Forecast error					
Analyst experience	High	Low	High	Low	High	Low
	(1)	(2)	(3)	(4)	(5)	(6)
Connection × Female	0.005	-0.025**	0.003	-0.033***	-0.002	-0.056***
	(0.40)	(-2.23)	(0.20)	(-2.75)	(-0.13)	(-2.77)
Connection	-0.008	-0.013**	-0.002	-0.015***	0.000	-0.025***
	(-1.61)	(-2.58)	(-0.40)	(-2.73)	(0.02)	(-3.42)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Analyst fixed effects	Yes	Yes	Yes	Yes	No	No
Broker×Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	No	No	No	No
Firm×Time fixed effects	No	No	Yes	Yes	Yes	Yes
Analyst×Firm fixed effects	No	No	No	No	Yes	Yes
Observations	332595	361881	332112	361434	331669	360796
Adjusted R^2	0.266	0.257	0.283	0.273	0.302	0.299

Panel B: Cross-sectional tests based on analyst school ties

	Forecast error					
School ties	Yes	No	Yes	No	Yes	No
	(1)	(2)	(3)	(4)	(5)	(6)
Connection × Female	0.094	-0.017*	0.100	-0.018*	-0.000	-0.053***
	(1.25)	(-1.79)	(0.57)	(-1.85)	(-0.00)	(-3.19)
Connection	-0.022	-0.010***	-0.029	-0.008**	-0.053	-0.010**
	(-0.56)	(-2.81)	(-0.50)	(-2.14)	(-0.83)	(-2.09)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Analyst fixed effects	Yes	Yes	Yes	Yes	No	No
Broker×Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	No	No	No	No
Firm×Time fixed effects	No	No	Yes	Yes	Yes	Yes
Analyst×Firm fixed effects	No	No	No	No	Yes	Yes
Observations	13857	638796	13692	638522	13687	637692
Adjusted R^2	0.280	0.258	0.330	0.267	0.317	0.293

Table 8: Gender difference in the effect of CFO connections on forecast accuracy

This table contains the regression results of Forecast error on the interaction terms between *Female* and *CFO connection* as well as *Female* and *Non-CFO connection*. The dependent variable *Forecast error* is defined as the absolute forecast error for analyst i's forecast of firm j less the mean absolute forecast error (across all analysts for firm j in the same fiscal year), scaled by the mean absolute forecast error. *CFO connection* (*Non-CFO connection*) is a dummy variable equal to one if the analyst has connections with the incumbent CFO (other executives) of a firm and zero otherwise. *Female* is a dummy variable equal to one if the analyst is a female and zero otherwise. Standard errors are clustered by analyst. *t*-statistics are provided in parentheses. $***$, $**$, and $*$ represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	Forecast error		
	(1)	(2)	(3)
CFO connection × Female (β_{CFO_Female})	-0.026**	-0.032***	-0.053***
	(-2.51)	(-3.09)	(-3.22)
Non-CFO connection × Female ($\beta_{Non-CFO\_Female}$)	-0.009	-0.007	-0.028
	(-0.71)	(-0.58)	(-1.55)
CFO connection (β_{CFO_Male})	-0.010**	-0.008*	-0.007
	(-2.49)	(-1.79)	(-1.28)
Non-CFO connection ($\beta_{Non-CFO\_Male}$)	-0.009*	-0.004	-0.012**
	(-1.87)	(-0.88)	(-2.12)
Control variables	Yes	Yes	Yes
Analyst fixed effects	Yes	Yes	No
Broker×Time fixed effects	Yes	Yes	Yes
Firm fixed effects	Yes	No	No
Firm×Time fixed effects	No	Yes	Yes
Analyst×Firm fixed effects	No	No	Yes
Observations	694505	694207	693325
Adjusted R^2	0.258	0.267	0.292
F-test for coefficient equality	*p*-value	*p*-value	*p*-value
$\beta_{CFO\_Female}=\beta_{Non-CFO\_Female}$	0.187	0.049**	0.091*
$\beta_{CFO\_Male}=\beta_{Non-CFO\_Male}$	0.773	0.501	0.383

Table 9: Within (cross)-gender connections on forecast accuracy

This table contains the regression results of Forecast error on the interaction term between *Female* and *Female connection* as well as *Female* and *Male connection*. The dependent variable *Forecast error* is defined as the absolute forecast error for analyst i's forecast of firm j less the mean absolute forecast error (across all analysts for firm j in the same fiscal year), scaled by the mean absolute forecast error. *Female connection* (*Male connection*) is a dummy variable equal to one if the analyst has connections with a female (male) executive of a firm and zero otherwise. *Female* is a dummy variable equal to one if the analyst is a female and zero otherwise. Standard errors are clustered by analyst. t-statistics are provided in parentheses. $***$, $**$, and $*$ represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	Forecast error		
	(1)	(2)	(3)
Female connection × Female ($\beta_{FemaleE\_FemaleA}$)	-0.040**	-0.050***	-0.072**
	(-1.98)	(-2.59)	(-2.16)
Male connection × Female ($\beta_{MaleE\_FemaleA}$)	-0.015	-0.017*	-0.037**
	(-1.63)	(-1.85)	(-2.40)
Female connection ($\beta_{FemaleE\_MaleA}$)	-0.029***	-0.021**	-0.024**
	(-3.59)	(-2.48)	(-2.07)
Male connection (β_{MaleE_MaleA})	-0.008**	-0.005	-0.008*
	(-2.14)	(-1.24)	(-1.71)
Control variables	Yes	Yes	Yes
Analyst fixed effects	Yes	Yes	No
Broker×Time fixed effects	Yes	Yes	Yes
Firm fixed effects	Yes	No	No
Firm×Time fixed effects	No	Yes	Yes
Analyst×Firm fixed effects	No	No	Yes
Observations	694505	694207	693325
Adjusted R^2	0.258	0.267	0.292
F-test for coefficient equality	p-value	p-value	p-value
$\beta_{FemaleE\_FemaleA}=\beta_{MaleE\_FemaleA}$	0.177	0.066*	0.245
$\beta_{FemaleE\_MaleA}=\beta_{MaleE\_MaleA}$	0.011**	0.066*	0.166

Table 10: Market reactions around the forecast revisions and connections with executives

This table contains the regression results of CAR in the window of [0,1] after forecast revisions on the interaction term between *Female* and *Connection*. The dependent variable *CAR [0,1]* is the cumulative abnormal return in the window [0,1] after forecast revisions. In Columns (1) and (2), *CAR [0,1]* is multiplied by -1 if the revision is a downgrade. *Connection* is a dummy variable equal to one if the analyst has established connections with at least one of the executives of the firm through investor conferences and zero otherwise. *Female* is a dummy variable equal to one if the analyst is a female and zero otherwise. Control variables include *Broker size*, *No. of firms covered*, *Firm-specific experience*, *Forecast error*, *Pre earning*, *Post earning*, *Concurrent recommendation*, *Absolute revision*, *Firm size*, *B/M*, *ROA*, and *R&D*. Standard errors are clustered by analyst. t-statistics are provided in parentheses. $***$, $**$, and $*$ represent statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable:	CAR [0,1]					
	Full sample		Upgrade		Downgrade	
	(1)	(2)	(3)	(4)	(5)	(6)
Connection × Female	0.132***	0.200***	0.107*	0.168*	-0.165**	-0.225**
	(2.58)	(2.58)	(1.72)	(1.73)	(-2.18)	(-2.02)
Connection	0.021	-0.023	-0.000	-0.072**	-0.046*	-0.044
	(1.17)	(-0.86)	(-0.01)	(-2.02)	(-1.69)	(-1.03)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Analyst fixed effects	Yes	No	Yes	No	Yes	No
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	No	Yes	No	Yes	No
Analyst×Firm fixed effects	No	Yes	No	Yes	No	Yes
Observations	557809	556992	318708	317214	238856	236806
Adjusted R^2	0.072	0.074	0.096	0.091	0.120	0.118

Table 11: Analyst career outcomes and professional connections

This table contains linear probability regressions of *Move to covered firms* (*All star*) on the interaction term between *Connected analyst* and *Female* in the sample at the analyst-year level. The dependent variables are *Move to covered firms*, a dummy variable equal to one if an analyst works at a firm under her coverage after being an equity analyst and zero otherwise, in Panel A, and *All star*, a dummy variable equal to one if an analyst is elected as "All star" analyst and zero otherwise, in Panel B. *Connected analyst* is a dummy variable equal to one if an analyst is connected with at least one executive and zero otherwise. *Female* is a dummy variable equal to one if the analyst is a female and zero otherwise. Control variables include *Broker size*, *No. of firms covered*, *Overall experience*, *Avg. forecast error*. Standard errors are clustered by analyst. t-statistics are provided in parentheses. $***$, $**$, and $*$ represent statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Move to covered firms and connections			
Dependent variable:		Move to covered firms	
	(1)	(2)	(3)
Connected analyst × Female	0.036**	0.032*	0.042**
	(2.01)	(1.70)	(2.24)
Connected analyst	0.018***	0.018***	-0.001
	(3.19)	(2.88)	(-0.20)
Female	-0.015	-0.010	
	(-1.32)	(-0.84)	
Control variables	Yes	Yes	Yes
Time fixed effects	Yes	No	No
Broker×Time fixed effects	No	Yes	Yes
Analyst fixed effects	No	No	Yes
Observations	19188	18682	18652
Adjusted R^2	0.086	0.091	0.357
Panel B: All star analysts and connections			
Dependent variable:		All star	
	(1)	(2)	(3)
Connected analyst × Female	0.012	0.029	0.009
	(0.44)	(1.27)	(0.41)
Connected analyst	0.077***	0.036***	0.036***
	(6.70)	(3.62)	(4.04)
Female	0.010	-0.008	
	(0.43)	(-0.37)	
Control variables	Yes	Yes	Yes
Time fixed effects	Yes	No	No
Broker×Time fixed effects	No	Yes	Yes
Analyst fixed effects	No	No	Yes
Observations	17997	17517	17408
Adjusted R^2	0.144	0.316	0.515

Internet Appendix for

Beyond Old Boys' Clubs: Financial analysts' Utilization of Professional Connections

December, 2024

I Details on Investor Conference Transcripts Sample

We gather broker-hosted investor conference transcripts from Refinitiv StreetEvents for the period January 2004 to December 2022. In order to examine how analyst-executive connections affect observable analyst outputs, we require the hosting broker to cover the attending firm in I/B/E/S, which results in 49,586 transcripts.

The title sections of conference transcripts contain the name and title of corporate executives that represent the company to present at the conference (under "Corporate Participants") as well as the name and title of the affiliated analysts hosting the conference (under "Conference Call Participants"). We provide two examples below.

I.1 Example 1

JANUARY 08, 2019 / 4:00PM GMT, Boston Scientific Corp at JPMorgan Global Healthcare Conference

CORPORATE PARTICIPANTS

Daniel J. Brennan *Boston Scientific Corporation - Executive VP & CFO*
Ian T. Meredith *Boston Scientific Corporation - Executive VP & Global Chief Medical Officer*
Michael F. Mahoney *Boston Scientific Corporation - Chairman, President & CEO*
Susan Vissers Lisa *Boston Scientific Corporation - VP of IR*

CONFERENCE CALL PARTICIPANTS

Robert Justin Marcus *JP Morgan Chase & Co, Research Division - Analyst*

I.2 Example 2

JANUARY 09, 2019 / 3:30PM GMT, AMAG Pharmaceuticals Inc at JPMorgan Global Healthcare Conference

CORPORATE PARTICIPANTS

Edward H. Myles *AMAG Pharmaceuticals, Inc. - Executive VP & CFO*
Julie Krop *AMAG Pharmaceuticals, Inc. - Executive VP of Development & Chief Medical Officer*
Nicholas Grund *AMAG Pharmaceuticals, Inc. - Executive VP & Chief Commercial Officer*
William K. Heiden *AMAG Pharmaceuticals, Inc. - CEO, President & Director*

CONFERENCE CALL PARTICIPANTS

Jessica Macomber Fye *JP Morgan Chase & Co, Research Division - Analyst*

Table IA1 presents descriptive statistics on the sample of transcripts.

Table IA1: Composition of Conference Transcripts

This table presents the total number of transcripts and the number of transcripts in which we identify a connection between an analyst and a company executive.

Year	All Transcripts	Transcripts with Connections
2004	684	183
2005	988	448
2006	1,320	686
2007	1,812	975
2008	1,809	1,082
2009	2,143	1,286
2010	2,585	1,685
2011	3,074	2,093
2012	3,184	2,228
2013	3,254	2,311
2014	3,386	2,496
2015	3,592	2,709
2016	3,362	2,543
2017	3,064	2,359
2018	2,574	2,081
2019	2,551	2,091
2020	3,157	2,760
2021	3,708	3,250
2022	3,339	2,810

II Robustness checks

This section contains the robustness checks of our baseline results.

Table IA2: Raw measure of forecast error

This table contains the regression results of Forecast error on the interaction term between *Female* and *Connection*. The dependent variable *Forecast error_absolute* is defined as the absolute forecast error for analyst i's forecast of firm j scaled by the stock price one year before the forecast announcement date. *Connection* is a dummy variable equal to one if the analyst has established connections with at least one of the executives of the firm through investor conferences and zero otherwise. *Female* is a dummy variable equal to one if the analyst is a female and zero otherwise. Standard errors are clustered by analyst. t-statistics are provided in parentheses. $***$, $**$, and $*$ represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	Forecast error_absolute		
	(1)	(2)	(3)
Connection × Female	-0.039	-0.036*	-0.048*
	(-0.58)	(-1.84)	(-1.66)
Connection	-0.022	0.003	0.004
	(-1.09)	(0.39)	(0.31)
No. of firms covered	-0.002	-0.000	-0.001
	(-0.65)	(-0.46)	(-1.08)
Firm-specific experience	0.004**	-0.001	
	(2.39)	(-1.22)	
Forecast horizon	0.004***	0.004***	0.004***
	(43.42)	(44.75)	(44.21)
Forecast frequency	0.035***	0.006***	0.009***
	(6.23)	(3.21)	(4.69)
Firm size	-0.075**		
	(-2.22)		
ROA	-5.266***		
	(-8.51)		
B/M	0.324***		
	(3.77)		
R&D	-0.070***		
	(-4.36)		
Analyst fixed effects	Yes	Yes	No
Broker×Time fixed effects	Yes	Yes	Yes
Firm fixed effects	Yes	No	No
Firm×Time fixed effects	No	Yes	Yes
Analyst×Firm fixed effects	No	No	Yes
Observations	685448	685139	684256
Adjusted R^2	0.613	0.822	0.826

Table IA3: Gender difference in the effect of executive connections on forecast accuracy - regression models with interaction controls

This table contains regression results of Forecast error on the interaction term between *Female* and *Connection*. The model specifications are similar to those in Table 3, except that we also include the interaction terms between the control variables in Table 3 and *Connection*. Standard errors are clustered by analyst. t-statistics are provided in parentheses. $***$, $**$, and $*$ represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	Forecast error		
	(1)	(2)	(3)
Connection × Female	-0.018**	-0.021**	-0.041***
	(-1.97)	(-2.29)	(-2.59)
Connection	-0.013	0.020	0.005
	(-0.67)	(0.98)	(0.17)
Control variables	Yes	Yes	Yes
Control variables×Connection	Yes	Yes	Yes
Analyst fixed effects	Yes	Yes	No
Broker×Time fixed effects	Yes	Yes	Yes
Firm fixed effects	Yes	No	No
Firm×Time fixed effects	No	Yes	Yes
Analyst×Firm fixed effects	No	No	Yes
Observations	694505	694207	693325
Adjusted R^2	0.258	0.267	0.292

Table IA4: Gender difference in the effect of executive connections on forecast accuracy - Standardized independent variables

This table contains the regression results of Forecast error on the interaction term between *Female* and *Connection*. The dependent variable *Forecast error* is defined as the absolute forecast error for analyst i's forecast of firm j less the mean absolute forecast error (across all analysts for firm j in the same fiscal year), scaled by the mean absolute forecast error. *Connection* is a dummy variable equal to one if the analyst has established connections with at least one of the executives of the firm through investor conferences and zero otherwise. *Female* is a dummy variable equal to one if the analyst is a female and zero otherwise. All continous control variables are standardized. Standard errors are clustered by analyst. t-statistics are provided in parentheses. $***$, $**$, and $*$ represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	Forecast error		
	(1)	(2)	(3)
Connection × Female	-0.019**	-0.022**	-0.042***
	(-2.05)	(-2.36)	(-2.72)
Connection	-0.009***	-0.006*	-0.009**
	(-2.77)	(-1.71)	(-2.04)
No. of firms covered	-0.005*	-0.003	-0.006**
	(-1.88)	(-1.03)	(-2.00)
Firm-specific experience	-0.003*	-0.003	
	(-1.67)	(-1.51)	
Forecast horizon	0.380***	0.393***	0.394***
	(157.98)	(159.07)	(158.02)
Forecast frequency	0.030***	0.031***	0.033***
	(13.45)	(12.84)	(12.30)
Firm size	-0.009		
	(-1.43)		
ROA	0.004***		
	(2.77)		
B/M	-0.007***		
	(-3.58)		
R&D	0.001		
	(0.77)		
Analyst fixed effects	Yes	Yes	No
Broker×Time fixed effects	Yes	Yes	Yes
Firm fixed effects	Yes	No	No
Firm×Time fixed effects	No	Yes	Yes
Analyst×Firm fixed effects	No	No	Yes
Observations	694505	694207	693325
Adjusted R^2	0.258	0.267	0.292

Table IA5: Robustness checks with various combinations of fixed effects

This table contains the robustness tests of Table 3 with various combinations of fixed effects. The dependent variable, independent variables and control variables are the same as those in Table 3. t-statistics are provided in parentheses. $***$, $**$, and $*$ represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	Forecast error								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Connection × Female	-0.009	-0.006	-0.006	-0.016*	-0.017*	-0.020**	-0.016*	-0.019**	-0.022**
	(-1.02)	(-0.62)	(-0.69)	(-1.66)	(-1.78)	(-2.14)	(-1.67)	(-2.05)	(-2.36)
Connection	-0.016***	-0.011***	-0.008**	-0.014***	-0.012***	-0.012***	-0.012***	-0.009***	-0.006*
	(-4.49)	(-2.86)	(-2.20)	(-4.27)	(-3.55)	(-3.50)	(-3.46)	(-2.77)	(-1.71)
Female	0.015**	0.008	0.008						
	(2.00)	(0.97)	(1.09)						
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	No	Yes	Yes	No	No	No	Yes	Yes	No
Time fixed effects	No	No	Yes	No	Yes	No	Yes	No	No
Analyst fixed effects	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Broker×Time fixed effects	No	No	No	No	No	Yes	No	Yes	Yes
Firm×Time fixed effects	No	No	No	No	No	No	No	No	Yes
Observations	694557	694548	694547	694557	694556	694515	694547	694505	694207
Adjusted R^2	0.236	0.240	0.242	0.250	0.251	0.252	0.254	0.258	0.267

Table IA6: Does the frequency and range of connections within a firm matter?

This table contains the regression results of Forecast error on the interaction term between *Female* and *No. of meets* or *No. of executives* in the sample of analysts who have connections with at least one executive of the firm. The dependent variable *Forecast error* is defined as the absolute forecast error for analyst i's forecast of firm j less the mean absolute forecast error (across all analysts for firm j in the same fiscal year), scaled by the mean absolute forecast error. *No. of meets* is the accumulative number of meetings the analyst have with the executives of a firm. *No. of executives* is the number of executives of a firm the analyst has connections with. Standard errors are clustered by analyst. t-statistics are provided in parentheses. $***$, $**$, and $*$ represent statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Measure of connection frequency - Number of meets			
	Forecast error		
	(1)	(2)	(3)
Female × No. of meetings	-0.007**	-0.008***	-0.011**
	(-2.22)	(-2.69)	(-2.12)
No. of meetings	0.001	0.001	0.002
	(0.60)	(0.86)	(1.06)
Control variables	Yes	Yes	Yes
Analyst fixed effects	Yes	Yes	No
Broker×Time fixed effects	Yes	Yes	Yes
Firm fixed effects	Yes	No	No
Firm×Time fixed effects	No	Yes	Yes
Analyst×Firm fixed effects	No	No	Yes
Observations	176682	176195	175909
Adjusted R^2	0.274	0.292	0.309
Panel B: Measure of connection range - Number of executives			
	Forecast error		
	(1)	(2)	(3)
Female × No. of executives	-0.027***	-0.029***	-0.033**
	(-3.08)	(-2.97)	(-2.23)
No. of executives	0.004	0.001	0.008
	(0.98)	(0.28)	(1.39)
Control variables	Yes	Yes	Yes
Analyst fixed effects	Yes	Yes	No
Broker×Time fixed effects	Yes	Yes	Yes
Firm fixed effects	Yes	No	No
Firm×Time fixed effects	No	Yes	Yes
Analyst×Firm fixed effects	No	No	Yes
Observations	176682	176195	175909
Adjusted R^2	0.274	0.292	0.309

III Executive connections and forecast optimism

A possible alternative explanation for our baseline results is that female analysts may issue more optimistic forecasts than male analysts to curry favor with executives in order to gain management access (Milian, Smith, and Alfonso, 2017; Brown, Francis, Hu, Shohfi, Zhang, and Xin, 2023; De Amicis, Falconieri, and Tastan, 2021). As a result, the results we document can be driven by the managers' tendency to grant more access to an optimistic analyst (regardless of gender) instead of by female analysts' ability to establish stronger professional ties. To mitigate this concern, we empirically test the effect of connections on forecast optimism; we follow Cowen, Groysberg, and Healy (2006) to define the relative forecast optimism in analysts' earnings forecasts:

$$Forecast\,optimism_{i,j,t} = \frac{Forecast_{i,j,t}^{t-k} - \overline{Forecast_{j,t}^{t-k}}}{STDEV(Forecast_{j,t}^{t-k})}, \tag{4}$$

where $Forecast_{i,j,t}^{t-k}$ is analyst i's earnings forecast for firm j made at time t-k, and $\overline{Forecast_{j,t}^{t-k}}$ is the average earnings forecast for firm j made within the same time horizon. The relative optimism is estimated for three different horizons: forecasts made less than 91 days prior to a firm's earnings announcement date, forecasts made more than 90 days and less than 181 days before the earnings announcement, and forecasts made more than 180 days before the earnings announcement. We run regressions with the same model specifications as in Table 3 with the dependent variable *Forecast optimism*.

Table IA7 contains the regression results. Consistent with prior findings, connections with incumbent executives are associated with more optimistic forecasts (Chen and Matsumoto, 2006). The coefficient estimates of *Connection* are positive and statistically significant in all model specifications. However, the coefficient estimates of the interaction terms between *Connection* and *Female* are statistically insignificant, indicating that female analysts are not more optimistic about firms that they are connected with than male analysts. These results are inconsistent with the alternative explanations that female analysts are more likely to curry favors with executives to gain access to management.

Table IA7: Gender difference in the effect of executive connections on forecast optimism

This table contains the regression results of Forecast optimism on the interaction term between *Female* and *Connection*. The dependent variable *Forecast optimism* is the relative forecast optimism measure constructed following Cowen, Groysberg, and Healy (2006). *Connection* is a dummy variable equal to one if the analyst has established connections with at least one of the executives of the firm through investor conferences and zero otherwise. *Female* is a dummy variable equal to one if the analyst is a female and zero otherwise. Standard errors are clustered by analyst. t-statistics are provided in parentheses. $***$, $**$, and $*$ represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	Forecast optimism		
	(1)	(2)	(3)
Connection × Female	-0.016	-0.016	0.007
	(-1.04)	(-1.05)	(0.30)
Connection	0.024***	0.027***	0.016**
	(4.83)	(5.06)	(2.34)
No. of firms covered	-0.001	-0.001	-0.000
	(-1.00)	(-1.18)	(-0.32)
Firm-specific experience	-0.000	-0.000	
	(-0.14)	(-0.14)	
Forecast horizon	-0.000***	-0.000***	-0.000***
	(-12.17)	(-12.05)	(-12.01)
Forecast frequency	-0.005***	-0.006***	-0.006***
	(-5.38)	(-5.78)	(-6.44)
Firm size	-0.002		
	(-0.30)		
ROA	-0.004		
	(-0.07)		
B/M	-0.014*		
	(-1.89)		
R&D	0.001		
	(0.39)		
Analyst fixed effects	Yes	Yes	No
Broker×Time fixed effects	Yes	Yes	Yes
Firm fixed effects	Yes	No	No
Firm×Time fixed effects	No	Yes	Yes
Analyst×Firm fixed effects	No	No	Yes
Observations	692990	692767	691880
Adjusted R^2	0.034	0.030	0.072

Figure IA1: Dynamic gender effect of establishing connections on forecast optimism

This figure plots the coefficient estimates of the interaction term between *Connection* and *Female* in years after gaining connections at investor conferences. The model specification is the same as Column (3) in Table IA7. 10% confidence intervals are plotted with dashed lines.

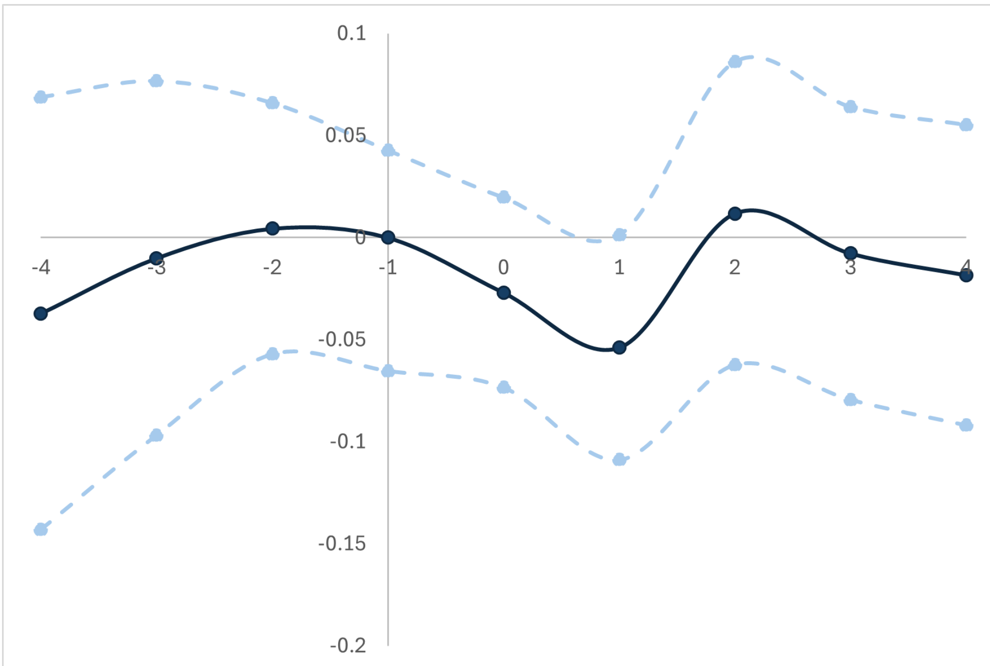


Table R1: Gender difference in the effect of executive connections on forecast accuracy - Analyst×Time fixed effects

This table contains the regression results of Forecast error on the interaction term between *Female* and *Connection*. The dependent variable *Forecast error* is defined as the absolute forecast error for analyst i's forecast of firm j less the mean absolute forecast error (across all analysts for firm j in the same fiscal year), scaled by the mean absolute forecast error. *Connection* is a dummy variable equal to one if the analyst has established connections with at least one of the executives of the firm through investor conferences and zero otherwise. *Female* is a dummy variable equal to one if the analyst is a female and zero otherwise. Standard errors are clustered by analyst. t-statistics are provided in parentheses. $***$, $**$, and $*$ represent statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Original sample				
	Forecast error			
	(1)	(2)	(3)	(4)
Connection × Female	-0.012	-0.008	-0.010	-0.010
	(-1.41)	(-0.98)	(-1.17)	(-0.78)
Connection	-0.014***	-0.013***	-0.008**	-0.010**
	(-3.87)	(-3.70)	(-2.08)	(-2.06)
No. of firms covered	-0.003***	-0.003***	-0.000	-0.000
	(-3.57)	(-3.93)	(-0.07)	(-0.18)
Firm-specific experience	-0.001***	-0.001	-0.001	
	(-3.28)	(-1.62)	(-1.48)	
Forecast horizon	0.004***	0.004***	0.004***	0.004***
	(164.22)	(164.78)	(159.22)	(158.69)
Forecast frequency	0.015***	0.014***	0.014***	0.016***
	(18.53)	(17.14)	(16.79)	(16.22)
Firm size	-0.002*	-0.010***		
	(-1.66)	(-2.90)		
ROA	0.125***	0.084**		
	(3.57)	(2.18)		
B/M	-0.010***	-0.012***		
	(-2.75)	(-2.59)		
R&D	0.000	0.001		
	(0.14)	(0.75)		
Analys×Time fixed effects	Yes	Yes	Yes	Yes
Firm fixed effects	No	Yes	No	No
Firm×Time fixed effects	No	No	Yes	Yes
Analyst×Firm fixed effects	No	No	No	Yes
Observations	694276	694267	693962	693093
Adjusted R^2	0.269	0.272	0.284	0.306

Panel B: Sample including firms that do not have connections

	Forecast error			
	(1)	(2)	(3)	(4)
Connection × Female	-0.010	-0.004	-0.004	-0.008
	(-1.31)	(-0.59)	(-0.58)	(-0.62)
Connection	-0.010***	-0.012***	-0.008**	-0.010**
	(-2.92)	(-3.68)	(-2.31)	(-2.14)
No. of firms covered	-0.003***	-0.003***	-0.000	-0.000
	(-4.52)	(-4.65)	(-0.24)	(-0.39)
Firm-specific experience	-0.001***	-0.001***	-0.001**	
	(-4.21)	(-2.78)	(-2.26)	
Forecast horizon	0.003***	0.004***	0.004***	0.004***
	(175.13)	(176.06)	(169.90)	(169.60)
Forecast frequency	0.015***	0.014***	0.014***	0.016***
	(20.29)	(19.09)	(17.86)	(17.87)
Firm size	-0.001	-0.009***		
	(-1.19)	(-2.82)		
ROA	0.128***	0.097***		
	(4.34)	(3.10)		
B/M	-0.010***	-0.011***		
	(-3.09)	(-2.77)		
R&D	0.000	0.002		
	(0.17)	(1.15)		
Analys×Time fixed effects	Yes	Yes	Yes	Yes
Firm fixed effects	No	Yes	No	No
Firm×Time fixed effects	No	No	Yes	Yes
Analyst×Firm fixed effects	No	No	No	Yes
Observations	863093	863077	862534	861365
Adjusted R^2	0.264	0.268	0.279	0.301

Table R2: Investor conferences hosted by male versus female analysts

This table contains the regression results of ... on *Female* . t-statistics are provided in parentheses. $***$, $**$, and $*$ represent statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable:		Engagement score	
	(1)	(2)	(3)
Female	-0.012***	-0.012***	-0.012***
	(-3.26)	(-3.43)	(-3.15)
Controls	Yes	Yes	Yes
Broker fixed effects	Yes	No	No
Firm fixed effects	Yes	Yes	Yes
Time fixed effects	Yes	No	No
Broker × time fixed effects	No	Yes	Yes
Firm × time fixed effects	No	No	Yes
Observations	18504	18374	15396
Adjusted R^2	0.126	0.139	0.177
Dependent variable:		CAR[0,1]	
	(1)	(2)	(3)
Female	0.001***	0.001***	0.001*
	(2.83)	(2.88)	(1.87)
Controls	Yes	Yes	Yes
Broker fixed effects	Yes	No	No
Firm fixed effects	Yes	Yes	Yes
Time fixed effects	Yes	No	No
Broker × time fixed effects	No	Yes	Yes
Firm × time fixed effects	No	No	Yes
Observations	15899	15773	13164
Adjusted R^2	0.155	0.169	0.215

Table R3: Raw measure of forecast error (winsorized at [0.5, 0.95])

This table contains the regression results of Forecast error on the interaction term between *Female* and *Connection*. The dependent variable *Forecast error_absolute* is defined as the absolute forecast error for analyst i's forecast of firm j scaled by the stock price one year before the forecast announcement date. *Connection* is a dummy variable equal to one if the analyst has established connections with at least one of the executives of the firm through investor conferences and zero otherwise. *Female* is a dummy variable equal to one if the analyst is a female and zero otherwise. Standard errors are clustered by analyst. *t*-statistics are provided in parentheses. $***$, $**$, and $*$ represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	Forecast error_absolute		
	(1)	(2)	(3)
Connection × Female	0.001	-0.018**	-0.027**
	(0.04)	(-2.37)	(-2.06)
Connection	-0.030***	-0.001	-0.006
	(-4.36)	(-0.31)	(-1.36)
No. of firms covered	-0.001	-0.000	-0.001**
	(-1.34)	(-1.10)	(-2.15)
Firm-specific experience	0.002***	-0.001**	
	(3.13)	(-2.01)	
Forecast horizon	0.003***	0.003***	0.003***
	(71.81)	(71.16)	(70.52)
Forecast frequency	0.026***	0.005***	0.006***
	(13.85)	(7.18)	(7.67)
Firm size	-0.109***		
	(-10.78)		
ROA	-1.545***		
	(-10.08)		
B/M	0.223***		
	(10.22)		
R&D	-0.013***		
	(-2.66)		
Analyst fixed effects	Yes	Yes	No
Broker×Time fixed effects	Yes	Yes	Yes
Firm fixed effects	Yes	No	No
Firm×Time fixed effects	No	Yes	Yes
Analyst×Firm fixed effects	No	No	Yes
Observations	685448	685139	684256
Adjusted R^2	0.495	0.728	0.734