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Gender and connections among Wall Street analysts

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Gender and Connections among Wall Street Analysts

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We examine how alumni ties with corporate boards differentially affect male and female analysts' job performance and career outcomes. Connection improves men's job performance—forecasting accuracy and recommendation impact—significantly more than women's . Controlling for performance, connection further contributes to men's, but not women's, likelihood of being voted by institutional investors as "star" analysts, a marker of career success. These asymmetric effects are stronger in more opaque firms and among younger analysts, but is absent from a placebo test. Our evidence indicates that men reap higher benefits from social networks than women in both job performance and subjective evaluation.

Key words: analyst research; gender; connections; social network

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"I love my job [as an analyst]. The market does not care whether I am a man or a woman, only whether I am right or wrong."

--Kate Reddy, Sarah Jessica Parker's character in the comedy "*I don't know how she does it*".

Introduction

Gender equality ignites impassioned debates. In the past few decades, women have advanced significantly in the labor market and education. Not only are they now the majority of the American workforce,[1] they also out-number men among college graduates (Goldin, Katz, and Kuziemko, 2006) and account for half the class in medical and law schools. Despite these broad changes, however, the perplexing pattern remains that women are thinly represented at the top of the business world: Despite the push by many companies to enhance gender diversity especially at the top, the ranks of women among senior corporate officers and company boards remain in the single digits and low teens.[2] It thus appears that women's empowerment in education and labor market has not resulted in the breaking of the proverbial "glass ceiling" in business.

This paper explores the idea that the persistent gender gap at the top of the business world could at least partially be attributed to the differential way in which men and women benefit from—and are even evaluated according to—their connections in the business community.

The context of our study is Wall Street analysts; we study the interplay between gender, connections, job performance and career outcomes in this population. Wall Street is a fascinating setting to study these issues for at least three reasons. First, Wall Street traditionally has the reputation of being male-dominated. But many Wall Street firms have been actively trying to promote gender diversity. Empirically separating the reality versus the myths of Wall Street's

[1] Economist, Dec 30, 2009.

[2] According to recent Bloomberg reports, in 2012 the proportion of female CFOs in S&P 500 firms reached a record high of 10.8%; the proportion of female CEOs was 4%, also a record high.

“gender inequality” is a worthy endeavor. Second, information is of paramount value on Wall Street, and as has been documented by Cohen, Frazzini, and Malloy (2008 and 2010), connections ~~in~~ the form of alumni ties facilitates the transmission of information, enabling connected analysts to make more impactful stock recommendations and mutual fund managers to make more profitable trades. Our paper builds on the work of Cohen, Frazzini and Malloy and asks whether women and men are able to extract information from their networks to enhance their job performance to the same extent. We use the same alumni connections measures used by Cohen, Frazzini and Malloy (2008, 2010).

Finally, the analyst labor market is fiercely competitive and the stakes are high: winners make millions and losers lose their jobs. Yet how analysts are evaluated is vague and largely subjective. One of the most important indicators of an analyst’s career success is his/her being voted by institutional investors (mutual fund and hedge fund managers) as an “All American” analysts (AAs). The voting is organized by the influential *Institutional Investor* magazine every year through an opinion poll among thousands of fund managers. The result of this poll is prominently featured in the October issues of the magazine each year. Winners of the AA titles are celebrated by their own employers and coveted by rival banks. As a result, the AA title is one of the key determinants of analyst compensation: A 2007 compensation survey among analysts indicates that AAs on average command three times the pay of other analysts in the same bank. As an opinion poll, the determinants of AA election are largely subjective. For example, the *Institutional Investor* asks fund managers to evaluate analysts on a dozen or so dimensions, the top of the list include: Industry knowledge, communication, responsiveness, and written reports. In contrast, actual forecast accuracy appears near the bottom of the list.[3] Several papers find that

[3] See various October issues of the *Institutional Investor* magazine for details of the AA election criteria.

the link between the AA title and future job performance is weak or transient, leading some authors to conclude that the AA election is a "popularity contest" (Emery and Li, 2009) .

Thus for analysts, while earnings forecast accuracy and recommendation impact are objective measures of performance, their career outcomes also depend on subjective evaluation—voting by institutional money managers. How does connection affect both job performance and subjective evaluation? How do the effects differ between men and women? These are the questions we examine in this paper.

One challenge in any study of gender effects is of course self-selection and endogeneity. Men and women may enter the analyst labor market at the different rates. Their innate quality and social networks may be different. They may cover different types of stocks. We address endogeneity in a number of ways. First, focusing on the highly competitive analyst profession helps alleviates selection bias. While gender differences in risk aversion and competitiveness is large in the general population, studies have found that the differences are much smaller once knowledge is controlled for (Dwyer et al. (2002)). Kumar (2010) argues that only the most competitive women become a financial analyst. In our own analysis, we find that the education background and degrees of connection are similar among men and women. In fact a higher fraction of female analysts have ivy-league education than male analysts. Second, in addition to control for a number of industry and firm effects, our core identification is based on with-in analyst variation of social connection. A typical analyst covers 7-8 stocks; among these, the analyst on average has an alumni connection with one or two companies' senior officers or board members. Since alumni ties are determined long ago, this within-analyst variation in connection is exogenous, allowing us to compare, for the same analyst, the performance differential due to connection, and then compare this differential across gender types. Furthermore, to control for heterogeneity across firms (e.g., some firms are more difficult to evaluate than others), we rank all analysts covering the same firm in terms of their relative performance. In sum, our approach allows us to examine how connections help analysts improve their performance relative to other analysts covering the same firm, and examine how this effect differs by gender.

Our finding suggests that connection improves men's job performance—forecast accuracy and recommendation impact—more than women's . While connections improve forecast accuracy across the board, the marginal effect among men is significantly larger. For example, while connections lead to a 3% improvement in accuracy rankings in general, among men, there is a further improvement of about 1.8%. The differential impact of connections is even more pronounced in recommendation impact. While connections improve male analysts' recommendation impact (2-day cumulative abnormal return) by about 1.2%, the effect is absent for female analysts. Thus, our evidence indicates that the effect documented in Cohen, Frazzini, and Malloy (2010) whereby analysts obtain useful information through connections is driven by male analysts. Furthermore, we find that connection's differential impact is stronger for firms that are informationally opaque and have poor disclosure quality. These results suggest that connection as a channel for information transmission is more effective among male analysts than female analysts.

Second, we find that *controlling for job performance*, connections still directly contributes to male analysts' odds of being elected an AA. This effect is absence among female analysts, for whom education and past forecast accuracy are the main determinants. This suggests that investors subjectively value connections per se among male analysts but not among female analysts. While we cannot completely rule out the possibility that connections are more correlated with unobserved skill among men, the conclusion still holds that the asymmetry in the results indicate that male analysts are able to reap more career benefits from connections than female analysts. Finally, we find that connections' differential impact on job performance is particularly pronounced among young analysts. Thus men and women's differential ability to capitalize on social connections may explain gender gaps in long-term career trajectories.

In a fascinating paper examining the professional musicians' job market, Goldin and Rouse (2000) finds evidence for sex-biased hiring. Our conclusion is different. In our sample, we do not find sex-biased elections of star analysts. Female analysts represent about 12% of all analysts and account for about 14% of AA analysts. Thus they are not under-represented in numbers among elected star analysts. The gender gap in our paper is more subtle: there is an asymmetry in the factors that drive male and female analysts success; men overall reap more benefits from connections than women both in terms of job performance and in terms of subjective evaluation by others. We believe these findings help explain the persistent gender gap at the top of the business world. Successfully climbing the corporate ladder requires both better job performance and favorable subjective evaluations by others. If men are better able to capitalize on connections for both objectives, this difference would perpetuate the observed gender gap at the top of the business world.

The rest of the paper is organized as follows. Section I reviews the literature. Section II discusses our data. Section III presents the main empirical findings. Section IV presents hypothesis testing and robustness checks. Section V concludes.

I. Gender, Connections, and Performance Evaluation

A number of papers have shown that women and men differ in their attitude towards risk and competition: Women are more risk averse and are more likely to shun competition. Barber and Odean (2001) find that among retail investors, men are more risk-willing in their trading behavior than women. Huang and Kisgen (2012) and Levy, Li, and Zhang (2011) both document that women executives and board members are less acquisitive than men. Using a well-calibrated experiment, Niederle and Vesterlund (2007) show that even though men and women exhibit the same level of skill towards a task, men are twice as likely as women to embrace competition by entering a tournament for the same task. If reaching the top of the business world involves taking risks and competing in a series of tournaments, men and women's differential risk appetite and preference for competition helps to explain why so few women reach the top.

Beyond the gender differences in innate characteristics, women's endogenous career choices and social constraints further contribute to the gender disparity among the business elite. Women's careers are more likely to be interrupted by child bearing and family considerations. Bertrand, Goldin, and Katz (2010) show that female MBAs' earnings lag males' significantly a decade after graduation, despite being nearly identical at the outset of their careers. And this gap is largely explained by differences in career interruptions and weekly hours, both of which are in turn due to motherhood.

In our setting, since we focus on Wall Street analysts—one of the most demanding and selective professions—gender difference in risk -preferences and career choices are unlikely to fully explain our results. Both men and women in this profession have chosen a highly competitive career. Kumar (2010) argue that self-selection means that only the most competitive women would enter this career. Dwyer et al. (2002) show that gender difference in risk aversion is much smaller among more knowledgeable investors.

Our paper is related to the literature that examines socialization as a source of gender difference in the work place. Athey, Avery, and Zemsky (2000) theorize that if senior employees are more likely to mentor junior employees of the same "type" (e.g., gender or ethnicity), then minority employees (such as females) will receive less mentoring. Using a small sample of field data, Ibarra (1992) demonstrates that while network positions of men and women exhibit no difference once background characteristics are controlled for, men appear better able to use network ties to improve their positions in organizations. Our empirical findings echo these conclusions: we find that generally men and women are equally connected and skilled; but while connections contributes to better job performance and career outcomes for men, it does to a much less extent for women.

II. Data and Descriptive Statistics

Detailed data on analysts' fiscal year-end earnings-per-share (EPS) forecasts and buy/sell stock recommendations are obtained from the I/B/E/S database for the years 1993-2009. The accuracy of the earnings forecasts and the price impact of their recommendations are used as analysts' performance measures. Analysts' AA status is manually collected from the October issues of the *Institutional Investor* magazine each year.

To identify analyst gender, we obtain full names of AA analysts from the *Institutional Investor* magazine. When the name alone is ambiguous, we check the accompanying articles in *Institutional Investors* magazine that describe the analysts. For non-AA analysts, we obtained and cross-check gender classification from Kumar (2010), which uses information from the analysts registries in Nelson's directory of investment research.

To measure analysts' connections with company officers and directors, we follow Cohen, Frazzini, and Malloy (2008 and 2010) and construct alumni ties between analysts and corporate insiders. Specifically, we obtain analysts' education information from Cohen, Frazzini, and

Malloy (2010), and officer and directors' education information from BoardEx. We construct three variants of the connection variable. The first measure identifies an analyst as "connected" to a company he/she covers if the analyst and one of the officers/directors of the company attended the same university (*Connect1*). The second measure requires that the analyst and officer/director attended the same school (e.g., business school) within the university (*Connect2*).[4] In a further refinement, the third definition requires that the analyst and the officer/board member attended the same school with overlapping periods (*Connect3*). Each subsequent definition reduces the number of analyst-firm pairs that are considered connected. In particular, since analysts are generally younger than corporate officers and board members, *Connect3* significantly reduces the number of connections in our sample.

Table 1 reports the number of analysts in our sample and the gender distribution. On average we are able to obtain education and connection information for over 650 (580 male and 78 female) analysts each year, representing about 25% of the overall IBES analyst population. Among these, the 78 females represent about 12%. The percentage of female analyst rose and fell over the sample period however. Also reported in Table 1 is the number of AA analysts and the gender distribution in this sub-sample. On average around 73 analyst each year in our sample win the AA title, representing slightly less than 10% of the analyst pool. This percentage is consistent with those reported in earlier work (e.g., Fang and Yasuda (2009), (2014)). Among AA analysts, females account for about 14% on average, slightly higher than the female pretense in the overall analyst sample (11%).

Figure 1 depicts the evolution of female percentage over time. The percentage of female analysts rose from 10% in 1993 to 14% in 1997, before gradually falling back to about 11% by 2009. There is also a rise and fall in female percentage among star analysts: it rose from 7% in

[4] We considered 6 degrees: MBA, general Masters, PhD, medical degree, law degree, and undergraduate degree.

1993 to 22% in 2001, before falling back to 14% by 2009. The graph shows that since 1999, the percentage of female analysts among AAs has consistently exceeded the percentage of female analysts in the overall sample. Thus, judging from this percentage at least, there is no gender bias in the overall star election outcome.

Table 2 reports statistics on analysts' connections. Panel A compares connections by gender. Using the *Connect1* measure, each male analyst is connected to 2.21 stocks that he covers on average while each female analyst is connected to 2.33 stocks, slightly higher than the male figure, but the difference is not statistically significant over any period of time. Conclusions based on the *Connect2* measure is the same: male and female analysts are equally connected on average. Due to the more stringent requirement for the Connect2 measure, not surprisingly the number of connections is smaller across both genders: 1.24 for male and 1.33 for female. Turning to *Connect3* ~~th~~e measure that requires overlapping school ties, we first note that these connections are much more rare for analysts. Male analysts are connected to only 0.13 stocks on average and female are connected to 0.08 stocks on average. The rarity of overlapping connections is because analysts are generally much younger than corporate officers/directors. This is particularly true for female analysts as we show in the next set of statistics that female analysts are generally younger than their male counterparts. The gender difference in *Connect3* is significant in the pooled test across the years, but insignificant for most of the individual years, which is the time unit of our analysis below.

Table 3 reports statistics on analysts demographic and work patterns. Here, male and female analysts look significantly different on a number of dimensions. Female analysts appear to have stronger education credentials than their male counterparts. A higher fraction of them (30%) have attended an Ivy League college compare to men (24%). More of them have MBAs

(48%) than men (42%) or other post-graduate degrees (62% versus 60%). To examine educational difference more closely, Figure 2a plots the percentage of male/female analysts with Ivy League degrees over time. The graph shows that generally the proportion of analysts with Ivy League degrees have fallen over time. But the positive gender gap whereby a higher fraction of female analysts have Ivy League degrees is a consistent pattern throughout the sample period, and the gap is particularly large in the earlier years. Figure 2b plots the corresponding percentages among the AA analysts sample. First we note that Ivy-League degrees are significantly more common among star analysts (around 60% and 35% for female and male analysts, respectively. Second, we continue to see the clear gender gap that a much higher fraction of female analysts have Ivy League degrees.

Table 3 also shows that female analysts tend to work for larger brokers employing more analysts than male analysts. They are less experienced, with an average experience of 4.71 years compare to male analysts' 5.14 years. They also have a slightly lower work load, on average covering 3.46 industry segments and 15.26 stocks compare to male analysts' 3.92 industries and 18.15 stocks. The fact that female analysts have a lower work load is not surprising, given that the typical analysts are also in the prime years of child-rearing. This pattern is consistent with the evidence in Bertrand, Goldin, and Katz (2010). Since work intensity does affect research quality, in our subsequent analysis we are careful to control for these differences.

Summarizing the basic statistics presented above, we find that generally there is no gender gap in analysts' connectedness. There is also no gender gap in the overall odds for male and female analysts to be elected to star analysts. Female analysts appear to have stronger education backgrounds than male analysts. But they tend to be less experienced and have a slightly lower work load. The similarity between male and female analysts' connectedness and female analysts' stronger education attainment alleviate the concern that the patterns we report below are due to systematic differences in connections and qualifications. They are also consistent with Kumar (2010) that only the most competitive and qualified women enter the analyst work force.

III. Main Findings

To measure analyst forecast accuracy, we follow existing literature (Clement and Tse, 2005; Kumar, 2010) and compute a standardized forecast accuracy measure as follows:

$$(1) \qquad Standardized\_Accuracy_{\mathrm{i,\,j,\,t}} = \frac{\text{Raw Accuracy}_{\mathrm{i,\,j,\,t}} - \min(\text{Raw Accuracy}_{\mathrm{j,t}})}{\max(\text{Raw Accuracy}_{\mathrm{j,t}}) - \min(\text{Raw Accuracy}_{\mathrm{j,t}})}$$

where Raw Accuracy$_{i,\,j,\,t}$ is the percentage forecast error (the absolute difference between the analyst's forecast and the actual reported earnings per share, scaled by price) on the forecast made by analyst *i* for firm *j* in year *t*, and min(.) and max(.) are the minimum and maximum of the Raw Accuracy measures exhibited by all analysts covering the same firm *j* in the same period *t*, respectively.[5] This standardization converts the simple percentage error measure into a ranking: All analysts covering the same firm in the same year are ranked *relative* to one another. Thus it removes the heterogeneity in forecast errors across firm-year combinations, and the resulting measure is comparable across analysts and firms.[6] To calculate the measure, we require that the firm is covered by at least 5 analysts in a given year.

[5] We repeated our analysis using a different scaling method, and found qualitatively the same results. The alternative scaling converts measures to z-scores by subtracting the variable's mean and dividing it by it standard deviation.

[6] Unstandardized percentage forecast error may not be comparable across firms and analysts covering them because while 5% forecast error may be quite good for a complex and volatile technology company, it may be large for a stable and simple utility business. The standardization also reflects investors' perspective, comparing analysts covering the same firm, rather than across firms.

To measure the impact of analysts' stock recommendations, we follow a large body of prior literature and focus on the stocks' 2-day cumulative abnormal returns[7] immediately after the recommendation change, using the daily Daniel, Grinblatt, Titman, and Wermers (1997) (DGTW) characteristics-based benchmarks. Specifically:

(2) $$CAR[0,1] = \sum_{\tau=0}^{1} \left(r_{i,\tau} - B_{i,\tau} \right),$$

where [0,1] is the 2-day window from the date of the recommendation release to 1-day after, $r_{i,\tau}$ is the return for stock i on date τ, $B_{i,\tau}$ is stock i's DGTW-benchmarked return on date τ. Subtracting the contemporaneous benchmark return from the stock return removes expected stock movements associated with stocks' size, book-to-market ratio, and momentum, leaving only firm-specific abnormal returns that reflect market's reactions to analyst recommendation changes.[8]

A. Connections and Forecast Accuracy

Table 4 presents regressions results on forecast accuracy. Panel A, B, and C report results using *Connect1*, *Connect2*, and *Connect3* as measures of analyst-firm connection, respectively. Each panel examines four models. Model (1) is the baseline regression, with the male and connection variable entering the regressions separately but no interaction effects. Models (2)-(4) add in the interaction term between male and connection, a key variable of interest. They differ in the fixed effects included in the regressions. Standard errors are corrected for heteroscedasticity and are clustered at analyst level.

[7] In an earlier version we examined other horizons such as the 30 days after the recommendation date and find qualitatively similar results. In this version we focus on the 2-day window since it is more difficult to attribute further returns to recommendation as the horizon increases. The 2-day window captures the more relevant price impact due to analyst recommendations (Fang and Yasuda (2014)).

[8] The DGTW benchmarks are available via http://www.smith.umd.edu/faculty/rwermers/ftpsite/Dgtw/coverpage.htm. Details of the DGTW benchmark construction is discussed in Daniel, Grinblatt, Titman, and Wermers (1997).

Focusing on Panel 1, Model (1) indicates that male analysts have better ranking in relative accuracy, and connections are associated with better accuracy (the dependent variable is standardized forecast error; the smaller the error, the better). Male analysts are associated with a 1% better ranking than female analysts (the coefficient on the Male indicator), a small magnitude that is statistically significant. Connections are associated with a 4.5% better ranking (the coefficient on *Connect1*), a much larger magnitude that is highly significant. Model (2) adds in the interaction terms between male and connection. The interaction term is significantly negative, indicating that for male analysts, connection further contributes to better accuracy. The coefficient estimate indicates that for male analysts, connection further improves accuracy ranking by 1.8%, 60% of the overall effect due to connection (3%). It is also interesting to note that once the interaction term is introduced, the magnitude on the male indicator alone becomes much smaller, at 0.6%, marginally significant at the 10% level.

Models (3) and (4) control for different fixed effects and yield the same conclusions. It is important to note that the connection variables are constructed at the analyst-firm-year level. Thus, the same analyst would have different *Connect1* measures for different stocks he/she covers. In other words, the connection variable is not picking up cross-sectional variations among analysts, but identifies the difference due to connection, even within the analyst. In Model (3), analystyear fixed effects are controlled, absorbing variations across analyst-year combinations, leaving the connection variable truly picking up the effect due to connection, *within the same analyst-year*. In this specification, the coefficient on the male and connection interaction is virtually unchanged, at -1.9%. Finally in Model (4), when we control for firm-year fixed effects, the interaction terms remains negative and highly significant, at -1.1%. Overall, these estimates indicate that the "value" of connection for male analysts is about 30% to 60% higher than the overall effect, a large economic magnitude.

Control variables in the regressions generally have the expected sign. For example, star analysts and more experienced analysts have better accuracy (albeit insignificant in some specifications) but number of firms and industries covered (work intensity) worsens accuracy.

Panels B and C repeat the analysis using *Connect2* and *Connect3* and yield similar conclusions. Panel B shows that *Connect2* is generally associated with a 2% improvement in accuracy ranking, and for male analysts, it is associated with a further 1.3%-2% improvement. Panel C shows that overlapping connection is more valuable and is associated with an accuracy ranking improvement ranging from 5% to 11%. For male analysts, overlapping connections result in further accuracy ranking improvements of 5%-6%.

Summarizing the results in Table 4, we find that connections are associated with a 2%-6% improvement in accuracy rankings. For male analysts, connections are associated with a further 1.3%-5% improvement in accuracy rankings. The finding that connections are valuable and improves job performance for analysts is not new and consistent with Cohen, Frazzini, and Malloy (2010). Our new insight is that the "value" of connections seems substantially higher (about 60%) for male analysts than female analysts.

B. Connections and Recommendation Impact

Tables 5 and 6 study the impact of connections on buy and sell stock recommendations respectively. The organization of both tables are similar to Table 4. In Panels A, B, and C, we report results using *Connect1*, *Connect2*, and *Connect3*, respectively. Each panel consists of four models, same as the four specifications in Table 4.

Model (1) in Table 5 shows that connections are associated with stronger price impact on buy recommendations. The magnitude ranges from 0.9% (Panel A, *Connect1*) to 1.2% (Panel C, *Connect3*). These estimates are not only highly significant statistically, but also large in economic terms. It is also interesting to note that the effect is larger for overlapping connections, as we would expect. We also find that male analysts generally have higher price impact on buy recommendations; the magnitude is a consistent 0.4% across the three connection measures. In Model (2), which adds in the male and connection interaction term, the overall effect on the connection variables become completely insignificant (and even turning negative in some cases), but the male and connection interaction terms are highly significant, with coefficients ranging from 1.2% (*Connect1*, Panel A), to 1.7% (*Connect3*, Panel C). These results indicate that while connections are valuable and enhance analysts' price impact ~~as~~ reported in Cohen, Frazzini, and Malloy, this effect is completely driven by male analysts and not present in female analysts.

Once again it is important to point out that the coefficient estimates are consistent across models and connection variables. The effect is present with similar magnitudes even in Model (3) which controls for analyst-year fixed effects, and as such, the coefficients identify *within* analyst variations due to connections.

Combining the evidence here with Table 4, we reach a consistent conclusion that connections benefit male analysts more than they do female analysts as a job-performance enhancer. Cohen, Frazzini, and Malloy (2010) argue that social networks help improve analysts job performance because they facilitate information transmission. Our evidence suggest that connection as an information transmission channel is more effective for male analysts than female analysts.

Table 6 repeats the analysis for sell recommendations. Contrary to the buy recommendation results in Table 5, there is no effect associated with either connections or gender. The weaker results for sell recommendations is consistent with a number of prior studies (e.g., Cohen, Frazzini, and Malloy (2010) which examine analyst connections and Fang and Yasuda (2014) which examines star status).[9]

Overall, the analysis of earnings forecast and stock recommendations leads to the clear conclusion that connections matter; but more importantly, male analysts are better able to use connections to improve their job performance than female analysts.

C. Connections and AA Election

In this section we explore the impact of connections on the odds of being elected by institutional investors as an AA analyst. The evidence in the last two sub-sections shows that connections have a differential impact on job performance: Male analysts appear better able to translate connections into more accurate forecasts and impactful recommendations. To the extent that investors care about these performance metrics, connection alone should not further affect an analyst's odds of being elected. This is our null hypothesis. If connections per se affect an analyst's election probability above and beyond performance measures, it would indicate either that connections are correlated with unobserved analysts traits that are valued by investors, or that investors subjectively value connections as an attribute.

Table 7 reports probit regression results examining AA election outcomes. Equations (1) and (2) examine elections among male analysts and equations (3) and (4) examine elections

[9] A number of factors can explain the asymmetry between buy and sell recommendations. First, analysts' main clients are investors such as mutual funds. The majority of this buy-side clientele have some restrictions on short-selling, making negative views less of a research focus by analysts. Second, firms (and insiders) are more wary of disclosing material negative information, and the associated litigation risk. The litigation risk is less severe for positive views. Thus negative private information is less likely to be passed on by social connections than positive opinions.

among female analysts. We examine two outcome variables: One is being elected as an AA, whether or not the analyst was an AA in the previous year or not. The other is being promoted to AA status, conditioned on not being an AA in the previous year.

Table 7 Panel A indicates that different factors matter in the election of male and female star analysts. For male analysts, connections contribute significantly to being elected or promoted as an AA. The economic magnitude is such that being connected has about 1.5% higher probability of being elected as AA or being promoted to AA. Number of stocks covered also contributes positively to the AA election. The number of industries covered has a negative impact, possibly because as analysts cover more sectors, their insights into a specific sector becomes less valuable, or as their focus widens, quality of research is negatively affected. Interestingly, forecast accuracy and recommendation impact do not affect AA outcomes in any significant way, even though the signs are as expected. In sharp contrast, the results for female analysts show that Ivy League degrees significantly increases the odds of being elected as AA by 5%.. Ivy League degree could be proxying for unobserved competence/skill. As with male analysts, covering more stocks is also rewarded for female analysts. Forecast accuracy is important as well: Inaccurate forecasts in the past reduce the chance of being elected. However, the connection variable per se is not significant in affecting the odds of being elected a star in the female population, unlike in the male analysts sample. Panel B and C show that our findings are robust using Connect2 and Connect3.

The evidence in Table 7 suggests that different factors matter for male and female analysts' odds of being elected an AA, the ultimate career success symbol among analysts. Connections increase male analysts' odds of being elected, but they do not affect female analysts odds. In contrast, for female analysts, education (which could be a proxy for skill) and past performance (accuracy) matters. We are not able to distinguish whether connections are correlated with unobservable analyst characteristics that are valued by investors, or whether investors perceive analysts' connections as a valuable attribute in itself. In either case, however, the asymmetric result in the male and female sample indicates that male analysts benefits more directly from connections than female analysts do.

IV. Additional Analyses

In this section, we present additional analyses that help us test hypotheses regarding why connection matters differentially for male and female analysts.

A. Quality of information

As we argued before, one explanation for the differential effect of connections is that male analysts are better able to capitalize on their social networks and obtain useful information. If this is the case, connections' differential effects should be are more pronounced in firms whose disclosure is poor and information is more opaque. To test this hypothesis, we examine four information proxies. The first is a financial reporting quality measure based on Dechow and Dechiv (2002). It is the standard deviation of unexplained accruals; a larger variability of unexplained accruals indicates lower financial reporting quality. We multiply the measure by negative 1 so that a high measure indicates high reporting quality. The second measure is 10-K disclosure quality, which is based on textual analysis of 10-Ks. It is from Li (2008). In addition, we use stock volatility and asset tangibility as measure of the firms' information environment. The value of private information is higher for volatile and opaque firms that are harder to understand and predict.

Using each measure, we sort stocks into high and low information quality, and re-estimate the regressions in Tables 4 and 6 in the sub-samples, and then compare the key coefficients. Table 8 Panel A reports results on earnings forecast accuracy (similar to Table 4); Panel B reports results on recommendation impact (similar to Table 6). For brevity, we report result using *Connect1*. Using other measures yields similar results. Panel A shows that as in Table 4, connection improves forecast accuracy across the board. There is generally no gender difference in accuracy: the male coefficient is mostly insignificant. The interaction term between male and connections is always negative and significant, but its magnitude and statistical significance is higher among firms with low information quality and high opaqueness. Formal tests of coefficient equality across equations indicate that the differences in coefficients between the high- and low-information quality samples are significant. The evidence is consistent with the notion that male analysts are better able to use connections for useful information.

Results in Panel B reinforce this conclusion. Consistent with Table 6, neither connection itself nor the male indicator is significant in explaining recommendation impact. The only effect of connections loads on the interaction term between the two. Importantly across firms sorted by information quality, the coefficient is at least twice as large among opaque firms with low information quality than in firms with high information quality.

Overall the findings of this section provide strong support that information channel plays a key role in explaining the differential effect of connection on job performance between genders.

B. Young vs. old analysts

If male and female analysts have differential abilities to capitalize on networks, we expect this effect to be particularly pronounced among young analysts, who have not yet built up sufficient human capital of their own and for whom connections may matter materially.

To test this hypothesis, we split the analyst sample into young and old analysts based on the median experience of 5 years and repeat the baseline regression in the two sub-samples. Table 9 reports the results based on all three connection measures. Results in this table show that connections are important for both old and young analysts. Their coefficients are generally larger in the old analyst sample, suggesting the long lasting value of connections. However the interaction term between gender and connection are generally not significant in the older analyst sample but large and significant in the young analyst sample. Connections help young male analysts improve forecast accuracy from 2.6% (*Connect1*) to 7.8% (*Connect3*), highly significant and economically large. Thus the evidence suggests that as we hypothesized, connections differential impact on job performance is even stronger among young analysts than old analysts. This is important as young analysts' differential ability to capitalize on connections could lead to long term differences in career trajectories.

C. Placebo test: A different star-selection

We have shown that connections matter differentially for male and female analysts in the subjective evaluation of analysts by institutional investors. The AA voting analysis shows that connections per se is valued for male analysts above and beyond job performance, but is it not for female analysts.

Does this mean that investors use different criteria when evaluating male and female analysts? After all, connections may matter for male analysts because they are more correlated with unobservable skill for men than for women. But note that this explanation still suggests that men are better able to use connections than women in unobservable ways. However, to differentiate between these two possibilities, we turn to a different star-ranking, from the *Wall Street Journal*. Since 1992, the *Journal* publishes its own annual "Best on the Street" list of top analysts. Unlike the *Institutional Investor* AA list which is based on investor voting, *Wall Street Journal*'s ranking is algorithm-based and computerized. A research company named FactSet Research Systems collects, verifies the underlying data on stock recommendations made by analysts, and computes an aggregate numerical score for each analyst's performance made through the past 12 months, taking into account analysts' buy/hold/sell calls. While the exact algorithm is not disclosed, the *Wall Street Journal*'s description of the process emphasizes its "objectivity, accuracy, and fairness". If connection's differential effect on AA elections reflect a bias in investors subjective evaluation of analysts, then we should not observe this same asymmetry in Wall Street Journals' computerized ranking.

We obtained *Wall Street Journal* "Best on the Street" rankings for the period 1999- 2009, and re-estimate the probit regression using this star-analyst list. Table 10 reports the results. Contrary to the AA election results in Table 7, we see that the factors affecting the outcome is largely symmetric in the male and female sub-samples. In particular, past forecast errors reduce the odds of being top-ranked for both male and female analysts, while number of stocks covered by rewarded in both samples. It is interesting to note that the WSJ ranking is less persistent than the AA election: Last WSJ top ranking does not explain current ranking, but past AA ranking has a huge impact on current ranking (Table 7).

Thus, results in this table provide at least suggestive evidence that the asymmetry in the AA election outcome reflects the differential way in which investors subjectively evaluate male and female analysts.

D. Same-sex Connections

It has often been argued (anecdotally at least) that the observed gender difference in high places in business reflects a "basis problem": If only there are more female officers and directors, the female executive network will further promote more female presence, closing the gender gap. In our context, this hypothesis suggests that the differential impact of connections for male and female analysts is partially due to the paucity of female executives; female analysts' connections are weaker as they would benefit more from same-sex connections.

To test this hypothesis, we replace the connection variable with three gender-classified connectons: Male-Male; Male-Female, and Female-Female. The male-female connection is where the analyst is a male and he is connected to a female executive. Results are reported in Table 11. Consistent with the basis hypothesis, we see that the Female-Female connection does translate into significantly better job performance: a 2.5% improvement on the relative accuracy ranking (compared to the 2% overall improvement found in Table 4). However the evidence shows that the Male-Male connection translates into an even larger, 4.7% improvement. Furthermore, on stock recommendations, while the Male-Male connections translate into a 1.1% improvement in price impact, the Female-Female connections effect is a positive 0.4%, albeit insignificant. The weaker significance of the Female-Female connection could be due to small sample: only 4% of connections are Female-Female; 80% are Male-Male. However the evidence suggests that while addressing the basis problem might help closing the gender gap, the "old boys club" has an undeniable strength.

E. Heckman Correction

In our final robustness check, we explicitly address the concern that our results may be driven by the endogenous self-selection of analysts covering different stocks. In our regressions, we have used numerous techniques to address endogeneity, including using the standardized performance ranks, and controlling for a combination of analyst, industry, firm and year fixed effects. In this section, we use the Heckman 2-stage technique to explicit address the endogenous mapping between analysts and firms they cover.

To implement the Heckman procedure, we first regress the percentage of female analysts covering a firm on exogenous factors that could otherwise affect female participation in covering that firm. Our key instrumental variable is the female labor force participation rate in the county where company is head-quartered in 1990, the beginning of our sample period. While this variable is likely to affect female analysts' presence in covering the firm, it is unlikely to affect individual analysts' performance and furthermore how connections affect the performance. In Panel A of Table 12, indeed we find that female labor force participation significantly predicts the percentage of female analysts coving the firm. In addition, we also find that larger firms and value (high book-to-market) firms tend to have higher female coverage.

We then compute the inverse Mill's ratio from the first stage and include it as an additional variable in the second-stage regression. In Panel B, we find that our main result—namely that the interaction term between male and connections significantly reduces forecast error and increase recommendation price impact—remain true after the endogeneity correction.

V. **Conclusions**

Connections help people relate to each other and in the finance profession, they facilitate the transmission of useful information. Using a sample of Wall Street analysts, we document that the extent to which male and female analysts benefit from their connections is different. Connections help male analysts improve their forecast accuracy more than in the overall population. Connections increase male analysts' recommendation price impact but this effect is absent for female analysts. These effects are stronger in firms with more opaque information environment, indicating that the effectiveness of social connections as information channels differs across gender.

Furthermore, controlling for job performance, connections per se significantly enhances male analysts' odds of being voted as star analysts by institutional investors, while they have no effect on female analysts' odds. For female analysts, education and job performance are significant predictors of election probability. We provide an intriguing piece of evidence that the asymmetric effect of connection on star-status is absent in another, algorithm-based analyst ranking. This suggests that investors subjectively value connections among men more than they do among women. Finally, the asymmetric impact of connections on performance is especially evident among young analysts.

We believe our findings can help explain the persistent gap in long term career trajectories between young male and female workers, and by implication, ultimately the stubborn gender gap at the top of the business world. Young graduates out of college or business school have similar credentials regardless of gender; in our sample, if anything, the female analysts on the margin have higher education attainment. However if men are better able to capitalize on connections for job performance and career gains, especially when young, it could set off a self-reinforcing cycle, maintaining and enlarging the gender gap observed later.

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Figure 1 Gender Distribution

This figure plots the percentage of female analysts in the overall analyst pool and the star (AA) analyst pool. AA analysts are identified from the October issues of the *Institutional Investor* magazine.

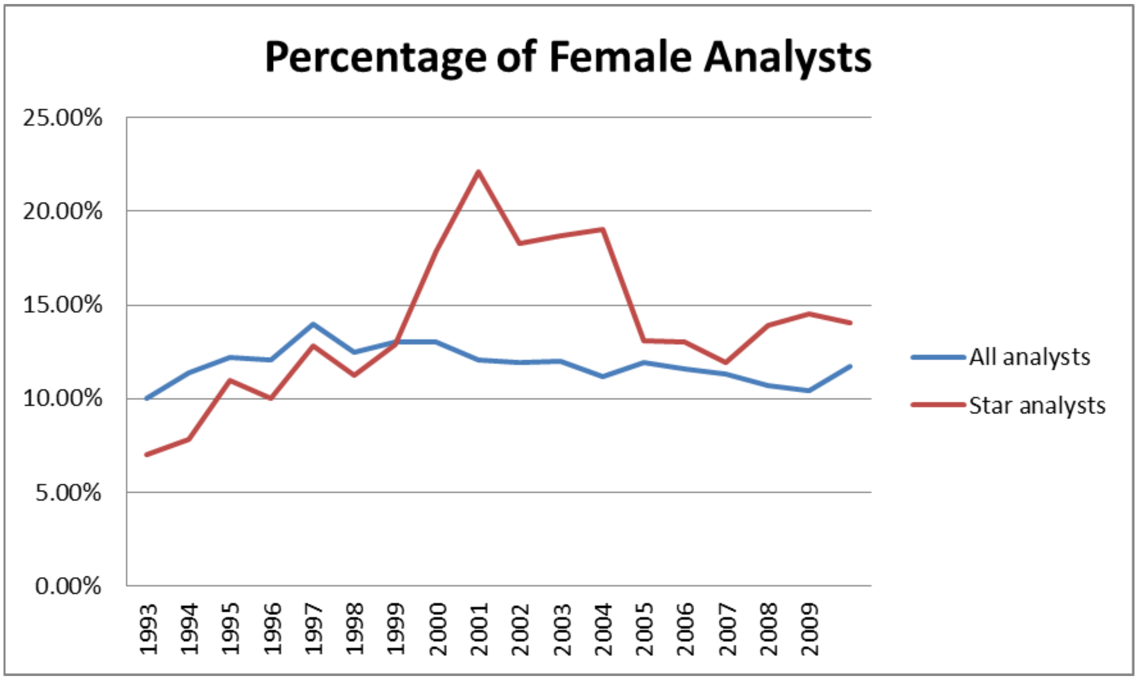
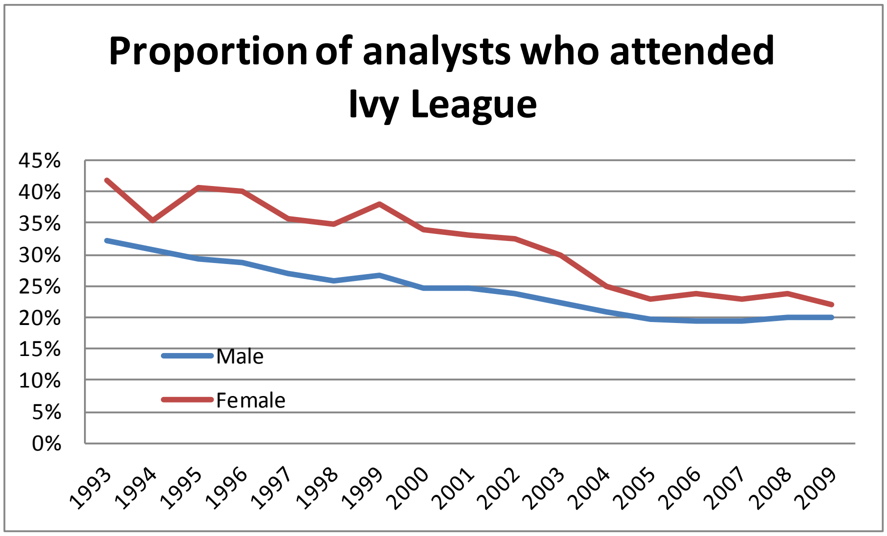


Figure 2 Comparing Education

This figure plots the fraction of male and female analysts who have ever attended an Ivy League school. Star analysts are identified from the October issues of the *Institutional Investor* magazine.



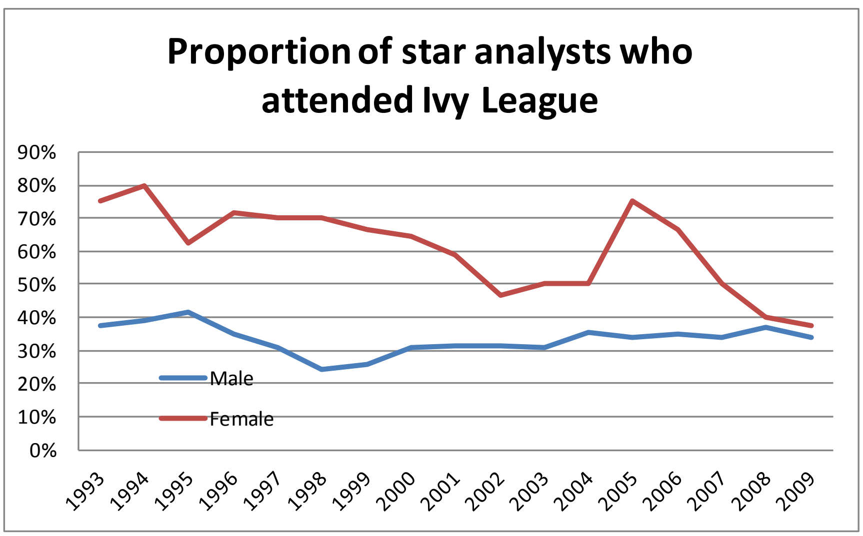


Table 1 Gender Distribution

This table reports the percentage of female analysts in the overall analyst pool and the star (AA) analyst pool. Star analysts are identified from the October issues of the *Institutional Investor* magazine.

	All Analysts			Star Analysts		
Year	Male	Female	% Female	Male	Female	% Female
1993	215	24	10.04%	53	4	7.02%
1994	264	34	11.41%	59	5	7.81%
1995	302	42	12.21%	65	8	10.96%
1996	364	50	12.08%	63	7	10.00%
1997	432	70	13.94%	68	10	12.82%
1998	506	72	12.46%	79	10	11.24%
1999	554	83	13.03%	81	12	12.90%
2000	609	91	13.00%	78	17	17.89%
2001	642	88	12.05%	60	17	22.08%
2002	681	92	11.90%	67	15	18.29%
2003	762	104	12.01%	61	14	18.67%
2004	859	108	11.17%	51	12	19.05%
2005	937	127	11.94%	53	8	13.11%
2006	832	109	11.58%	60	9	13.04%
2007	722	92	11.30%	59	8	11.94%
2008	633	76	10.72%	62	10	13.89%
2009	548	64	10.46%	47	8	14.55%
Average	580	78	11.75%	63	10	14.03%

Table 2 Connection Statistics

This table presents statistics on analyst connections. *Connect1* is an indicator variable that equals 1 if an analyst covering a stock attended the same university as one of the officers/directors of the company. *Connect2* is an indicator variable that equals 1 if an analyst covering a stock attended the same degree program in the same university as one of the officers/directors of the company. *Connect3* is an indicator variable that equals 1 if an analyst covering a stocks attended in the same degree program in the same university as one of the officers/directors of the company over overlapping periods. P-values from t-tests of equality are reported.

Panel A: Number of connections by gender									
	Connect1			*Connect2*			*Connect3*		
Year	Male	Female	p-value (diff.=0)	Male	Female	p-value (diff.=0)	Male	Female	p-value (diff.=0)
1993	1.73	1.54	0.73	0.93	0.88	0.87	0.07	0.08	0.84
1994	1.59	1.38	0.67	0.83	0.65	0.52	0.06	0.06	0.98
1995	1.70	1.67	0.94	0.89	0.83	0.84	0.08	0.02	0.39
1996	1.62	1.74	0.77	0.87	0.96	0.75	0.09	0.04	0.39
1997	1.53	1.61	0.82	0.87	0.97	0.66	0.10	0.03	0.18
1998	1.48	1.96	0.15	0.88	1.11	0.32	0.10	0.07	0.60
1999	1.71	2.29	0.05	0.99	1.39	0.07	0.13	0.12	0.90
2000	1.89	2.35	0.14	1.06	1.47	0.05	0.14	0.11	0.65
2001	2.10	2.67	0.07	1.22	1.56	0.12	0.14	0.14	0.96
2002	2.19	2.42	0.47	1.27	1.38	0.61	0.15	0.13	0.75
2003	2.30	2.01	0.34	1.31	1.14	0.43	0.14	0.08	0.26
2004	2.47	2.26	0.53	1.39	1.32	0.77	0.15	0.06	0.15
2005	2.54	2.45	0.76	1.41	1.35	0.75	0.15	0.07	0.13
2006	2.89	3.00	0.75	1.59	1.56	0.88	0.16	0.08	0.18
2007	3.20	3.37	0.67	1.75	1.75	1.00	0.19	0.08	0.12
2008	3.14	3.28	0.74	1.72	1.78	0.84	0.17	0.04	0.08
2009	3.32	3.30	0.97	1.83	1.67	0.62	0.15	0.05	0.13
Average	2.21	2.33	0.21	1.24	1.30	0.31	0.13	0.08	0.00

Table 2 Connection Statistics, Continued

Panel B: Number of connections by star status									
	Connect1			*Connect2*			*Connect3*		
Year	AA	Non-AA	p-value (diff.=0)	AA	Non-AA	p-value (diff.=0)	AA	Non-AA	p-value (diff.=0)
1993	2.65	1.42	0.00	1.40	0.77	0.01	0.12	0.05	0.16
1994	2.59	1.28	0.00	1.39	0.65	0.00	0.09	0.05	0.34
1995	2.96	1.35	0.00	1.64	0.68	0.00	0.15	0.05	0.03
1996	3.16	1.33	0.00	1.71	0.72	0.00	0.16	0.07	0.09
1997	3.23	1.24	0.00	1.96	0.68	0.00	0.21	0.07	0.01
1998	2.96	1.28	0.00	1.96	0.72	0.00	0.20	0.07	0.01
1999	3.53	1.49	0.00	2.17	0.85	0.00	0.28	0.10	0.00
2000	3.81	1.66	0.00	2.26	0.93	0.00	0.29	0.11	0.00
2001	4.53	1.89	0.00	2.77	1.08	0.00	0.42	0.11	0.00
2002	4.24	1.98	0.00	2.68	1.12	0.00	0.37	0.13	0.00
2003	4.12	2.09	0.00	2.57	1.17	0.00	0.27	0.12	0.04
2004	4.44	2.31	0.00	2.73	1.29	0.00	0.43	0.12	0.00
2005	5.11	2.37	0.00	3.05	1.30	0.00	0.57	0.12	0.00
2006	4.77	2.75	0.00	2.87	1.49	0.00	0.45	0.13	0.00
2007	4.84	3.07	0.00	2.93	1.64	0.00	0.39	0.16	0.01
2008	4.11	3.04	0.01	2.40	1.65	0.01	0.26	0.15	0.14
2009	4.31	3.22	0.04	2.36	1.76	0.08	0.15	0.14	0.96
Average	3.83	2.04	0.00	2.29	1.12	0.00	0.28	0.11	0.00

Table 3 Demographic and Work Patterns

This table reports demographic and work patterns by analyst gender. *Ivy League* is an indicator variable that equals 1 if the analyst has ever attended an Ivy League school and 0 otherwise. *Number of qualifications* is the number of college degrees an analyst has. *Postgrad Degree* is a dummy equal to one if an analyst holds at least one postgraduate degree. *MBA degree* is a dummy equal to one if an analyst holds MBA degree. *Number of Stocks Covered* is the number of firms for which an analyst provides earnings per share (EPS) forecasts. *Number of Ind Covered* is the number of industries that an analyst cover, where industry is defined based on Fama-French 48 industries classification. *Brokerage size* is the number of analysts working for the brokerage firm that the analyst works for. *Experience* is the number of years since an analyst first appears in the I/B/E/S database. P-values from t-test for differences are reported.

	Male	Female	p-value (diff.=0)
Ivy League	0.24	0.30	0.00
Number of qualifications	1.62	1.64	0.00
Postgrad Degree	0.60	0.62	0.00
MBA degree	0.42	0.48	0.00
Num of Stocks Covered	18.15	15.26	0.00
Num of Ind Covered	3.92	3.46	0.00
Brokerage Size	14.68	16.43	0.00
Experience	5.14	4.71	0.00

Table 4 Connection and Forecast Accuracy

This table examines the effect of connections on analysts' forecast accuracy. The dependent variables is the standardized percentage forecast error, calculated as the absolute forecast error scaled by price, standardized across analysts covering the same firm same year (Equation (1)). *Connect1*, *Connect2*, and *Connect3* are as defined in Table 2. *Male* is an indicator variable that equals one for male analysts and zero for female analysts. *Ivy League* is an indicator variable that equals one if the analyst attended one of the Ivy League schools and zero otherwise. *All Star* is an indicator variable that equals 1 if the forecast is made by an AA analyst and 0 otherwise. *Experience* is the number of years the analyst appears in the I/B/E/S database. *Brokerage size* is the number of analysts working for the brokerage firm employing the analyst. *Number of Ind Covered* is the number of Fama-French industries represented by the firms the analyst covers in the year. *Number of Stocks Covered* is the number of stocks the analyst covers in the year. *Size* is the natural log of market capitalization of equity. *BTM* is the natural log of the book-to-market ratio of the stock. *Past Returns* is the natural log of the past 12-month return of the stock. Constants are included but not reported in the regression. All explanatory variables are standardizes as in Equation (1). Standard errors are corrected for heteroscedasticity and are clustered at analyst level. *t*-statistics are reported in parentheses. *, ** and *** denote significance level at 10%, 5% and 1% respectively.

Panel A: Results using Connect1				
	(1) *Fore Error*	(2) *Fore Error*	(3) *Fore Error*	(4) *Fore Error*
Connect1	-0.045	-0.030	-0.029	-0.034
	(-3.916)***	(-5.454)***	(-5.491)***	(-6.585)***
Male	-0.010	-0.006		-0.006
	(-3.442)***	(-1.847)*		(-2.058)**
*Male*Connect1*		-0.018	-0.019	-0.011
		(-3.093)***	(-3.329)***	(-2.119)**
All Star	-0.004	-0.004		-0.003
	(-1.521)	(-1.565)		(-1.275)
Ivy League	-0.002	-0.002		-0.001
	(-0.920)	(-0.909)		(-0.693)
Experience	0.000	0.000	-0.001	-0.000
	(1.500)	(1.482)	(-2.083)**	(-2.119)**
Brokerage Size	0.004	0.004	0.003	0.002
	(1.961)*	(1.900)*	(1.311)	(0.955)
Num of Ind Covered	0.008	0.008	0.005	0.006
	(3.848)***	(3.798)***	(2.365)**	(3.087)***
Num of Stocks Covered	0.005	0.005	0.005	0.004
	(2.299)**	(2.329)**	(2.311)**	(1.964)**
Size	-0.009	-0.009	-0.010	-0.021
	(-17.522)***	(-17.511)***	(-18.271)***	(-13.451)***
BTM	0.020	0.020	0.021	0.028
	(20.187)***	(20.163)***	(21.000)***	(18.266)***
Past Returns	-0.010	-0.010	-0.010	-0.009
	(-28.470)***	(-28.490)***	(-28.485)***	(-25.742)***
Observations	381,556	381,556	381,556	381,556
R-squared	0.024	0.024	0.034	0.051
Fixed Effects	Year+Industry	Year+Industry	Year+Industry+Analyst	Year+Firm

Table 4 Connection and Forecast Accuracy, Continued

Panel B: Results using Connect2				
	(1)	(2)	(3)	(4)
Connect2	-0.039	-0.020	-0.020	-0.024
	(-6.581)***	(-2.872)***	(-3.204)***	(-3.549)***
Male	-0.009	-0.006		-0.006
	(-3.167)***	(-2.140)**		(-2.306)**
*Male*Connect2*		-0.022	-0.020	-0.013
		(-3.064)***	(-2.991)***	(-1.873)*
Controls	Yes	Yes	Yes	Yes
Observations	381,556	381,556	381,556	381,556
R-squared	0.022	0.022	0.033	0.050
Fixed Effects	Year+Industry	Year+Industry	Year+Industry+Analyst	Year+Firm
Panel C: Results using Connect3				
	(1)	(2)	(3)	(4)
Connect3	-0.111	-0.055	-0.061	-0.045
	(-4.061)***	(-2.189)**	(-3.065)***	(-2.307)**
Male	-0.008	-0.007		-0.006
	(-2.934)***	(-2.739)***		(-2.507)**
*Male*Connect3*		-0.061	-0.055	-0.067
		(-2.406)**	(-2.684)***	(-3.346)***
Controls	Yes	Yes	Yes	Yes
Observations	381,556	381,556	381,556	381,556
R-squared	0.022	0.022	0.033	0.050
Fixed Effects	Year+Industry	Year+Industry	Year+Industry+Analyst	Year+Firm

Table 5 Connections and Buy Recommendations

This table examines the effect of connections on analysts' buy recommendation impact. The dependent variables is the *CAR [0,1]*, 2-day cumulative abnormal return immediately after the release of the analyst recommendation. *Connect1*, *Connect2*, and *Connect3* are as defined in Table 2. *Male* is an indicator variable that equals one for male analysts and zero for female analysts. *Ivy League* is an indicator variable that equals one if the analyst attended one of the Ivy League schools and zero otherwise. *All Star* is an indicator variable that equals 1 if the forecast is made by an AA analyst and 0 otherwise. *Experience* is the number of years the analyst appears in the I/B/E/S database. *Brokerage size* is the number of analysts working for the brokerage firm employing the analyst. *Number of Ind Covered* is the number of Fama-French industries represented by the firms the analyst covers in the year. *Number of Stocks Covered* is the number of stocks the analyst covers in the year. *Size* is the natural log of market capitalization of equity. *BTM* is the natural log of the book-to-market ratio of the stock. *Past Returns* is the natural log of the past 12-month return of the stock. Constants are included but not reported in the regression. All explanatory variables are standardizes as in Equation (1). Standard errors are corrected for heteroscedasticity and are clustered at analyst level. *t*-statistics are reported in parentheses. *, ** and *** denote significance level at 10%, 5% and 1% respectively.

Panel A: Results Using Connect1				
	(1)	(2)	(3)	(4)
	CAR[0,1]	*CAR[0,1]*	*CAR[0,1]*	*CAR[0,1]*
Connect1	0.009	-0.002	-0.002	-0.001
	(8.828)***	(-0.741)	(-0.729)	(-0.409)
Male	0.004	0.001		0.002
	(3.484)***	(1.016)		(1.337)
*Male*Connect1*		0.012	0.013	0.011
		(4.884)***	(4.206)***	(4.599)***
All Star	0.002	0.002		0.002
	(2.083)**	(2.234)**		(1.872)*
Ivy League	0.001	0.001		0.001
	(0.955)	(0.864)		(1.538)
Experience	0.000	0.000	-0.000	0.000
	(2.850)***	(2.745)***	(-1.377)	(3.292)***
Brokerage Size	0.002	0.002	0.000	0.003
	(2.568)**	(2.569)**	(0.262)	(2.843)***
Num of Ind Covered	-0.002	-0.002	-0.001	-0.002
	(-1.951)*	(-2.015)**	(-0.456)	(-1.710)*
Num of Stocks Covered	-0.003	-0.003	-0.004	-0.003
	(-2.964)***	(-2.951)***	(-3.309)***	(-2.715)***
Size	-0.002	-0.002	-0.002	-0.009
	(-6.954)***	(-6.911)***	(-7.291)***	(-9.588)***
BTM	0.001	0.001	0.001	-0.000
	(1.966)**	(1.911)*	(1.714)*	(-0.334)
Past Returns	0.001	0.001	0.001	0.001
	(3.679)***	(3.685)***	(3.364)***	(3.698)***
Observations	29,302	29,302	29,302	29,302
R-squared	0.030	0.031	0.091	0.169
Fixed Effects	Year+Industry	Year+Industry	Year+Industry+Analyst	Year+Firm

Table 5 Connections and Buy Recommendations, Continued

Panel B: Results using Connect2				
	(1)	(2)	(3)	(4)
	CAR[0,1]	*CAR[0,1]*	*CAR[0,1]*	*CAR[0,1]*
Connect2	0.010	0.000	0.001	-0.000
	(8.642)***	(0.138)	(0.220)	(-0.067)
Male	0.004	0.003		0.003
	(3.489)***	(2.266)**		(2.304)**
*Male*Connect2*		0.011	0.009	0.011
		(3.452)***	(2.582)***	(3.767)***
Control variables	Yes	Yes	Yes	Yes
Observations	29,302	29,302	29,302	29,302
R-squared	0.029	0.030	0.090	0.168
Fixed Effects	Year+Industry	Year+Industry	Year+Industry+Analyst	Year+Firm
Panel C: Results using Connect3				
	(1)	(2)	(3)	(4)
	CAR[0,1]	*CAR[0,1]*	*CAR[0,1]*	*CAR[0,1]*
Connect3	0.012	-0.004	-0.008	-0.004
	(3.148)***	(-0.566)	(-1.974)**	(-0.664)
Male	0.004	0.004		0.004
	(3.366)***	(3.241)***		(3.418)***
*Male*Connect3*		0.017	0.022	0.019
		(2.242)**	(3.445)***	(2.593)***
Control variables	Yes	Yes	Yes	Yes
Observations	29,302	29,302	29,302	29,302
R-squared	0.027	0.027	0.088	0.166
Fixed Effects	Year+Industry	Year+Industry	Year+Industry+Analyst	Year+Firm

Table 6 Connections and Sell Recommendations

This table examines the effect of connections on analysts' sell recommendation impact. The dependent variables is the *CAR [0,1]*, 2-day cumulative abnormal return immediately after the release of the analyst recommendation. *Connect1*, *Connect2*, and *Connect3* are as defined in Table 2. *Male* is an indicator variable that equals one for male analysts and zero for female analysts. *Ivy League* is an indicator variable that equals one if the analyst attended one of the Ivy League schools and zero otherwise. *All Star* is an indicator variable that equals 1 if the forecast is made by an AA analyst and 0 otherwise. *Experience* is the number of years the analyst appears in the I/B/E/S database. *Brokerage size* is the number of analysts working for the brokerage firm employing the analyst. *Number of Ind Covered* is the number of Fama-French industries represented by the firms the analyst covers in the year. *Number of Stocks Covered* is the number of stocks the analyst covers in the year. *Size* is the natural log of market capitalization of equity. *BTM* is the natural log of the book-to-market ratio of the stock. *Past Returns* is the natural log of the past 12-month return of the stock. Constants are included but not reported in the regression. All explanatory variables are standardizes as in Equation (1). Standard errors are corrected for heteroscedasticity and are clustered at analyst level. *t*-statistics are reported in parentheses. *, ** and *** denote significance level at 10%, 5% and 1% respectively.

Panel A: Results using Connect1				
	(1) *CAR[0,1]*	(2) *CAR[0,1]*	(3) *CAR[0,1]*	(4) *CAR[0,1]*
Connect1	-0.002	0.000	0.003	0.001
	(-1.582)	(0.047)	(0.680)	(0.234)
Male	-0.002	-0.001		0.000
	(-0.707)	(-0.398)		(0.023)
*Male*Connect1*		-0.003	-0.004	-0.003
		(-0.685)	(-0.902)	(-0.750)
All Star	0.002	0.002		-0.001
	(1.359)	(1.356)		(-0.354)
Ivy League	0.001	0.001		0.000
	(0.456)	(0.469)		(0.303)
Experience	-0.000	-0.000	-0.002	-0.000
	(-2.422)**	(-2.408)**	(-2.492)**	(-2.722)***
Brokerage Size	-0.002	-0.002	-0.002	-0.003
	(-1.395)	(-1.401)	(-1.097)	(-1.788)*
Num of Ind Covered	0.001	0.001	0.000	0.001
	(0.929)	(0.936)	(0.104)	(0.381)
Num of Stocks Covered	0.004	0.004	0.005	0.004
	(2.195)**	(2.197)**	(2.565)**	(2.443)**
Size	0.006	0.006	0.005	-0.017
	(12.791)***	(12.791)***	(8.922)***	(-9.490)***
BTM	0.008	0.008	0.007	0.002
	(8.089)***	(8.088)***	(6.673)***	(1.087)
Past Returns	0.003	0.003	0.003	0.003
	(7.242)***	(7.238)***	(5.751)***	(6.014)***
Observations	28,407	28,407	28,407	28,407
R-squared	0.040	0.040	0.118	0.272
Fixed Effects	Year+Industry	Year+Industry	Year+Industry+Analyst	Year+Firm

Table 6 Connections and Sell Recommendations, Continued

	Panel B: Results using Connect2			
	(1)	(2)	(3)	(4)
	CAR[0,1]	*CAR[0,1]*	*CAR[0,1]*	*CAR[0,1]*
Connect2	-0.001	0.000	0.004	0.003
	(-0.736)	(0.027)	(0.727)	(0.516)
Male	-0.002	-0.001		-0.000
	(-0.697)	(-0.588)		(-0.107)
*Male*Connect2*		-0.002	-0.004	-0.003
		(-0.299)	(-0.750)	(-0.591)
Control variables	Yes	Yes	Yes	Yes
Observations	28,407	28,407	28,407	28,407
R-squared	0.040	0.040	0.118	0.272
Fixed Effects	Year+Industry	Year+Industry	Year+Industry+Analyst	Year+Firm
	Panel C: Results using Connect3			
	(1)	(2)	(3)	(4)
	CAR[0,1]	*CAR[0,1]*	*CAR[0,1]*	*CAR[0,1]*
Connect3	0.005	-0.011	0.021	-0.006
	(1.097)	(-0.664)	(0.898)	(-0.315)
Male	-0.002	-0.002		-0.001
	(-0.698)	(-0.764)		(-0.371)
*Male*Connect3*		0.017	-0.013	0.013
		(1.000)	(-0.539)	(0.670)
Control variables	Yes	Yes	Yes	Yes
Observations	28,407	28,407	28,407	28,407
R-squared	0.040	0.040	0.118	0.272
Fixed Effects	Year+Industry	Year+Industry	Year+Industry+Analyst	Year+Firm

Table 7 Connections and AA Election

This table reports probit regression results of analysts career outcomes. The dependent variable *Elected as AA* is an indicator variable that equals 1 if an analyst is elected as an All-American winner by institutional investors in a year and 0 otherwise. The dependent variable *Promote to AA* is an indicator variable that equals 1 if an analyst was not an AA last year and is an AA this year and 0 otherwise. *Connect1* is an indicator variable that equals 1 if an analyst attended the same university as one of the senior officers and directors of the company and 0 otherwise. For each analyst-year, we treat analyst as connected if he/she has at least one connection with the firms he/she covers. *Ivy League* equals 1 if the analyst attended one of the Ivy League schools and zero otherwise. *Experience* is the number of years the analyst appears in the I/B/E/S database. *Num of Ind Covered* is the number of industry sectors covered by the analyst in the preceding year. *Num of Stocks covered* is the number of stocks the analysts issued earnings forecast on in the preceding year. *Forecast error last year* is the average standardized accuracy measure across all stocks covered by the analyst in the preceding year. *Rec impact last year* is the average two-day cumulative abnormal returns across all recommendations issues by the analyst during the preceding year. *AA last year* is an indicator variable that equals 1 if the analyst was an AA in the last year and 0 otherwise. Standard errors are corrected for heteroscedasticity t-statistics are reported in parentheses. *, ** and *** denote significance level at 10%, 5% and 1% respectively.

Panel A: Results using Connect1				
	Male analysts		Female analysts	
	(1)	(2)	(3)	(4)
	Elected as AA	*Promote to AA*	*Elected as AA*	*Promote to AA*
Connect1	0.163	0.243	0.066	0.205
	(2.278)**	(3.475)***	(0.367)	(1.034)
Ivy League	0.078	0.039	0.303	0.286
	(1.113)	(0.595)	(2.055)**	(1.792)*
Experience	-0.200	-0.058	0.075	0.221
	(-2.229)**	(-0.720)	(0.336)	(0.947)
Num of Ind Covered	-0.268	-0.322	0.090	-0.167
	(-2.862)***	(-3.399)***	(0.393)	(-0.684)
Num of Stocks Covered	0.376	0.454	0.453	0.699
	(3.576)***	(4.495)***	(1.688)*	(2.311)**
Forecast error last year	-1.979	-0.898	-6.904	-8.751
	(-1.181)	(-0.654)	(-1.917)*	(-2.544)**
Rec impact last year	0.013	0.016	-1.467	-0.869
	(0.019)	(0.021)	(-0.921)	(-0.518)
AA last year	2.808		2.388	
	(39.439)***		(14.977)***	
Observations	6,615	7,874	916	909
Pseudo R2	0.552	0.0424	0.479	0.105
Fixed Effects	Year	Year	Year	Year

Table 7 Connections and AA Election, Continued

Panel B: Results using Connect2

	Male Analysts			Female Analysts	
	(1)	(2)		(1)	(2)
	Elected as AA	*Promote to AA*		*Elected as AA*	*Promote to AA*
Connect2	0.124	0.158	*Connect2*	-0.215	-0.189
	(1.932)*	(2.552)**		(-1.499)	(-1.136)
Ivy League	0.082	0.055	*Ivy League*	0.394	0.412
	(1.173)	(0.822)		(2.720)***	(2.568)**
Experience	-0.201	-0.056	*Experience*	0.080	0.238
	(-2.237)**	(-0.689)		(0.361)	(1.032)
Num of Ind Covered	-0.265	-0.313	*Num of Ind Covered*	0.095	-0.138
	(-2.849)***	(-3.326)***		(0.412)	(-0.570)
Num of Stocks Covered	0.376	0.461	*Num of Stocks Covered*	0.501	0.768
	(3.555)***	(4.540)***		(1.924)*	(2.599)***
Forecast error last year	-1.930	-0.843	*Forecast error last year*	-7.737	-9.459
	(-1.160)	(-0.625)		(-2.183)**	(-2.781)***
Rec impact last year	-0.019	-0.015	*Rec impact last year*	-1.373	-0.591
	(-0.029)	(-0.020)		(-0.863)	(-0.360)
AA last year	2.805		*AA last year*	2.393	
	(39.369)***			(15.022)***	
Observations	6,615	7,874	Observations	916	909
Pseudo R2	0.552	0.0397	Pseudo R2	0.481	0.105
Fixed Effects	Year	Year	Fixed Effects	Year	Year

Panel C: Results using Connect3

	Male Analysts			Female Analysts	
	(1)	(2)		(1)	(2)
	Elected as AA	*Promote to AA*		*Elected as AA*	*Promote to AA*
Connect3	0.159	0.335	*Connect3*	-0.164	-0.368
	(1.620)	(3.888)***		(-0.744)	(-1.260)
Ivy League	0.098	0.061	*Ivy League*	0.345	0.398
	(1.442)	(0.954)		(2.428)**	(2.587)***
Experience	-0.211	-0.084	*Experience*	0.070	0.217
	(-2.331)**	(-1.025)		(0.317)	(0.943)
Num of Ind Covered	-0.253	-0.300	*Num of Ind Covered*	0.083	-0.158
	(-2.713)***	(-3.191)***		(0.360)	(-0.662)
Num of Stocks Covered	0.394	0.477	*Num of Stocks Covered*	0.479	0.784
	(3.777)***	(4.788)***		(1.838)*	(2.665)***
Forecast error last year	-1.917	-0.826	*Forecast error last year*	-7.223	-9.506
	(-1.149)	(-0.607)		(-2.031)**	(-2.712)***
Rec impact last year	-0.003	-0.068	*Rec impact last year*	-1.396	-0.626
	(-0.004)	(-0.089)		(-0.871)	(-0.374)
AA last year	2.808		*AA last year*	2.396	
	(39.429)***			(15.056)***	
Observations	6,615	7,874	Observations	916	909
Pseudo R2	0.552	0.0430	Pseudo R2	0.479	0.106
Fixed Effects	Year	Year	Fixed Effects	Year	Year

Table 8 Quality of Information

This table compares the effect of connections on job performance in firms with different disclosure and information quality. *Accrual Quality* is constructed following Dechow and Dechiv (2002). It is the (negative of) standard deviation of the residual change in working capital unexplained by changes in cash flows, revenue and PPE in the past 5 years. *10-K Disclosure Quality* measures disclosure transparency using textual analysis of 10-K filings. It is based on Li (2008) and obtained from Li's website. *Stock Volatility* is log of one plus stock volatility. *Tangibility* is measured by market to book ratio. All regressions contain same set of controls as in Tables 4-6. All explanatory variables are standardizes as in Equation (1). Industry fixed effects is based on Fama-French 48 industry classification. Standard errors are corrected for heteroscedasticity and are clustered at analyst level. *t*-statistics are reported in parentheses. *, ** and *** denote significance level at 10%, 5% and 1% respectively.

Panel A: Forecast accuracy

	Accrual Quality		*10-K Disclosure Quality*		*Stock Volatility*		*Asset Tangibility*	
	High	Low	High	Low	Low	High	High	Low
Connect1	-0.035	-0.019	-0.038	-0.015	-0.030	-0.029	-0.036	-0.022
	(-5.749)***	(-2.025)**	(-4.807)***	(-2.448)**	(-4.760)***	(-4.194)***	(-6.341)***	(-3.480)***
Male	-0.002	-0.012	-0.006	-0.001	-0.007	-0.005	-0.004	-0.007
	(-0.490)	(-2.956)***	(-1.364)	(-0.394)	(-1.544)	(-1.423)	(-1.556)	(-1.833)*
*Male*Connect1*	-0.015	-0.031	-0.010	-0.032	-0.017	-0.037	-0.010	-0.023
	(-2.352)**	(-3.152)***	(-1.194)	(-5.087)***	(-2.476)**	(-5.069)***	(-1.599)	(-3.445)***
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	156,969	151,667	133,402	133,698	186,022	191,998	167,585	181,036
R-squared	0.023	0.028	0.023	0.025	0.020	0.033	0.028	0.024
Test of interaction coefficient equality								
P-value		0.0576		0.0101		0.0057		0.0698

Panel B: Recommendation impact

	Accrual Quality		*10-K Disclosure Quality*		*Stock Volatility*		*Asset Tangibility*	
	High	Low	High	Low	Low	High	High	Low
Connect1	-0.002	0.000	-0.001	0.000	0.002	-0.006	0.001	-0.004
	(-0.648)	(0.002)	(-0.187)	(0.117)	(0.819)	(-1.581)	(0.169)	(-1.244)
Male	0.003	0.002	0.003	0.002	0.002	0.000	0.001	0.002
	(1.414)	(1.028)	(1.435)	(0.846)	(1.876)*	(0.157)	(0.405)	(1.327)
*Male*Connect1*	0.007	0.020	0.007	0.016	0.003	0.022	0.009	0.016
	(1.658)*	(4.313)***	(1.763)*	(4.273)***	(1.373)	(5.339)***	(2.427)**	(4.047)***
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	12,354	11,621	10,565	10,827	14,118	15,173	11,427	14,189
R-squared	0.031	0.043	0.039	0.045	0.030	0.041	0.039	0.036
Test of interaction coefficient equality								
P-value		0.0217		0.0996		0.0004		0.0838

Table 9 Young versus Old Analysts

This table examines the effect of connections on job performance among young and old analysts. Young (old) analysts are defined as those with less (more) than five years of experience in the IBES sample. All variables, including unreported controls, are as defined in Table 4. For brevity we report regression results only use Model (1) in Table 4. Standard errors are corrected for heteroscedasticity and are clustered at analyst level. *t*-statistics are reported in parentheses. *, **, *** indicates statistical significance at the 10%, 5%, and 1% levels, respectively.

	Old Analysts			Young Analysts		
	(1)	(2)	(3)	(4)	(5)	(6)
	Connect1	Connect2	Connect3	Connect1	Connect2	Connect3
	Fore Error	*Fore Error*	*Fore Error*	*Fore Error*	*Fore Error*	*Fore Error*
Connection	-0.036	-0.026	-0.081	-0.024	-0.012	-0.043
	(-4.832)***	(-3.893)***	(-2.733)***	(-3.184)***	(-1.984)**	(-1.998)**
Male	-0.010	-0.010	-0.011	-0.002	-0.003	-0.005
	(-2.304)**	(-3.686)***	(-4.269)***	(-0.611)	(-1.323)	(-2.348)**
*Male*Connection*	-0.013	-0.019	-0.034	-0.022	-0.026	-0.078
	(-1.705)*	(-2.593)***	(-1.121)	(-2.785)***	(-4.001)***	(-3.320)***
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	191,946	191,946	191,946	189,610	189,610	189,610
R-squared	0.025	0.024	0.024	0.023	0.022	0.022
Fixed Effects	Year+Industry	Year+Industry	Year+Industry	Year+Industry	Year+Industry	Year+Industry

Table 10 A Placebo Test –The Wall Street Journal Top Analyst Ranking

This table reports probit regression results on the Wall Street Journal's annual analyst rankings. The specification is identical to Table 7. The dependent variable *WSJ Top* is an indicator variable that equals 1 if an analyst is ranked as a top analyst by the WSJ and zero otherwise. *WSJ Top last year* is an indicator variable that equals 1 if the analyst was a top analyst ranked by the WSJ in the last year and zero otherwise. All the other variables are defined under Table 7. Standard errors are corrected for heteroscedasticity. t-statistics are reported in parentheses. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Male Analysts	Female Analysts
	(1)	(2)
	WSJ Top	*WSJ Top*
Connect1	0.028	0.313
	(0.403)	(1.432)
Ivy League	-0.103	-0.045
	(-1.489)	(-0.249)
Experience	-0.052	-0.217
	(-0.578)	(-0.890)
Num of Ind Covered	-0.013	0.645
	(-0.136)	(2.200)**
Num of Stocks Covered	0.513	0.758
	(4.702)***	(2.302)**
Forecast error last year	-2.783	-10.754
	(-1.785)*	(-2.016)**
Rec impact last year	-0.063	1.369
	(-0.087)	(0.642)
WSJ Top last year	0.105	0.049
	(1.325)	(0.220)
Observations	2,698	377
Pseudo R2	0.0308	0.121
Fixed Effects	Year	Year

Table 11 Same-gender Connections

This table examines the impact of same-gender connection on job performance. The dependent variables are standardized forecast error and the 2-day cumulative abnormal returns. All variables are as defined in Table 4. The connection measure used is *Connnect1*. *Male-Male (Female-Female) connection* is an indicator variable that equals one if both the analyst and the connected officer/director are male (female) and zero otherwise. *Male-Female connection* is an indicator variable that equals one if a male analyst is connected to a female officer/board member and zero otherwise. Standard errors are corrected for heteroscedasticity and are clustered at analyst level. t-statistics are reported in parentheses. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Regression results

	(1) *Fore Error*	(2) *Buy CAR[0,1]*
Male-Male Connection	-0.047	0.011
	(-23.385)***	(9.468)***
Male-Female Connection	-0.039	0.002
	(-10.095)***	(1.041)
Female-Female Connection	-0.025	0.004
	(-3.248)***	(1.230)
Male	-0.007	0.002
	(-2.479)**	(2.007)**
All Star	-0.004	0.002
	(-1.590)	(2.216)**
Ivy League	-0.002	0.001
	(-0.907)	(0.860)
Experience	0.000	0.000
	(1.478)	(2.687)***
Brokerage Size	0.004	0.002
	(1.914)*	(2.562)**
Num of Ind Covered	0.008	-0.002
	(3.796)***	(-1.979)**
Num of Stocks Covered	0.005	-0.003
	(2.325)**	(-2.971)***
Size	-0.009	-0.002
	(-17.565)***	(-6.886)***
BTM	0.020	0.001
	(20.173)***	(1.946)*
Past Returns	-0.010	0.001
	(-28.475)***	(3.687)***
Observations	381,556	29,302
R-squared	0.024	0.031
Fixed Effects	Year+Industry	Year+Industry

Panel B. F Tests of Equality of Coefficients

	Fore Error p-value	*CAR[0,1]* p-value
Male-Male Connection=Female-Female Connection	0.0052	0.0332
Male-Male Connection=Male-Female Connection	0.0581	0.0001
Male-Female Connection=Female-Female Connection	0.0618	0.6072

Table 12 Heckman Correction

This table re-examines main regression results using the Heckman correction to account for endogeneity in analyst coverage. Panel A reports first stage Heckman model, where we regress percentage of female analysts covering a firm on female labor force participation rate in the county where company headquarter is located and other firm level characteristics. Panel B reports main coefficient from the second stage Heckman model, where *Inverse Mill's Ratio* is calculated from first stage regression. *Female participation rate* is percentage of female participating in labor force at US county level from 1990 census. All other variables (including unreported controls) are the same as in Table 4. Standard errors are corrected for heteroscedasticity and are clustered at analyst level. t statistics are presented beneath the coefficients within parentheses. *, ** and *** denote significance level at 10%, 5% and 1% respectively.

Panel A. First Stage Heckman

	(1)
	% of Female Analysts
Female participation rate	0.002
	(3.126)***
Size	0.008
	(10.895)***
BTM	0.006
	(3.287)***
Past Returns	-0.002
	(-0.841)
Observations	42,964
R-squared	0.035
Fixed effects	Year+Industry

Panel B. Second Stage Heckman

	(1)	(2)	(1)	(2)
	Fore Error	*Fore Error*	*Buy CAR[0,1]*	*Buy CAR[0,1]*
Connect1	-0.045	-0.030	0.009	-0.003
	(-23.678)***	(-5.150)***	(8.366)***	(-1.098)
Male	-0.009	-0.005	0.004	0.001
	(-3.320)***	(-1.630)	(3.443)***	(0.708)
*Male*Connect1*		-0.018		0.013
		(-2.968)***		(5.052)***
Inverse's Mill's Ratio	0.863	0.876	0.046	0.034
	(2.911)***	(2.958)***	(0.408)	(0.298)
Controls	Yes	Yes	Yes	Yes
Observations	353,195	353,195	27,621	27,621
R-squared	0.024	0.024	0.030	0.031
Fixed Effects	Year+Industry	Year+Industry	Year+Industry	Year+Industry