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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. Connections improve analysts' forecasting accuracy and recommendation impact, but the effect is two to three times as large for men as for women. Connections also contribute to analysts' likelihood of being voted by institutional investors as "star" analysts, but act as a partial substitute to performance for men, while a complement to performance for women. Our evidence indicates that men benefit more than women from connections in both job performance and the subjective evaluation by others. (*JEL* G24, J16, J24)

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> I love my job [as an analyst]. The market doesn't know what sex I am, it only knows whether I'm right or wrong.
>
> Kate Reddy, Sarah Jessica Parker's character in *I Don't Know How She Does It*

Women are now the majority among college graduates and in the American workforce.[1] Despite women's advancements in education and labor participation, a persistent gender gap remains in business, especially at the

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[1] Goldin, Katz, and Kuziemko (2006) report that as of 2003, there were 1.35 female graduates from four-year colleges for every male graduate. According to a report by the *Economist*, women constituted the majority of the U.S. workforce as of 2009.

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top echelons of the business world: The percentage of women in corporate leadership positions remains in the single digits and low teens.[2] That gender diversity initiatives are ubiquitous testifies to the wide recognition of women's lackluster advancement in business.

In this paper, we explore the idea that the persistent gender gap in business is partially attributable to the differential way in which men and women benefit from their connections in the business community. In other words, social capital (connections) is converted into human capital (career advancements) at different rates for men and women.

Our focus on connections complements a number of explanations that economists have put forward for the gender gap in business. First, Barber and Odean (2001) and Niederle and Vesterlund (2007) show that women are more risk averse than men, and they are less willing to engage in competition. If risk-taking is rewarded, then women's higher aversion to risk and competition contributes to a gender gap in business (Huang and Kisgen 2012). Second, a woman's career is more likely to be interrupted by child-rearing, leading to less experience and less advancement (Bertrand, Goldin, and Katz 2010). Third, some women may rationally give up a high-powered career in exchange for personal happiness (Bertrand 2013); thus, the perceived gender gap may reflect a preference rather than inequality. Last but not least of all, societal norms, whereby women and men are uncomfortable with a wife earning more than a husband, may also play a role (Bertrand, Kamenica, and Pan 2015). These findings provide powerful explanations for the low percentage of women in business, in general, and at the top levels, in particular.

Our paper focuses on a conditional analysis: Taking the percentage of women in a particular line of work as given, do we see *differential* rates *and* paths of career success between the two genders? Specifically, do connections have different impacts on men's and women's career outcomes? We contribute to the literature by studying how social networks might mitigate or exacerbate the gender gap, an important topic hitherto unexplored.

The context of our study is Wall Street analysts; we examine the interplay among 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, because it is a highly demanding work environment, only the most competitive women will enter this work force (Kumar 2010). This self-selection removes the large gender difference in risk aversion and competitiveness that the literature has documented in the general population. The homogeneity between the men and women on Wall Street in terms of education, competitiveness, and as we will show later, even how connected they are, ensures that the differences we document are not driven by these basic factors.

[2] According to a 2013 *Bloomberg* report, the fraction of female CFOs in S&P 500 firms reached a record high of 10.8% in 2012; at the same time, the fraction of female CEOs was 4%, also a record high.

Second, information is of paramount value on Wall Street, and, as documented by Cohen, Frazzini, and Malloy (2008, 2010), connections—in the form of alumni ties—facilitate the transmission of information, enabling connected analysts to make more impactful stock recommendations and connected mutual fund managers to make more profitable trades. Our paper builds on this work and asks whether women and men benefit from their social networks professionally *to the same extent*. We use the same alumni ties as in Cohen, Frazzini, and Malloy (2008, 2010).

Third, for analysts' career advancement, reputation matters, but reputation is more than Kate Reddy's statement above that it is only a question of whether an analyst is right or wrong; instead, the evaluation of analysts has a large subjective element. A key marker of analysts' career success is achieving the status of "All American" (AA). Not only do AAs command higher pay—a 2007 compensation survey indicates that AAs, on average, command three times the pay of other analysts in the same bank—but they are also coveted by rival banks. AA status is determined by investor voting, which involves subjective evaluations.[3] For example, institutional investors frequently say that, in voting for the best analysts, industry knowledge and communication are the most important criteria, while accurate earnings forecasts are less important.[4]

We empirically examine the following questions:

1. What is the gender distribution among Wall Street analysts? And among the subsample of AA analysts? Is there a gender gap in the AA pool?
2. Do connections help improve men's and women's job performance—earnings forecast accuracy and recommendation price impact—*equally*?
3. Do connections help improve men and women's career advancement—being voted as AA analysts—*equally*?

There are three (nonmutually exclusive) mechanisms through which connections can be associated with both better performance (which we measure as forecast accuracy and recommendation impact) and better career outcomes (which we measure as being voted AAs by investors). First, there can be a causal relation between connections and performance. As Cohen, Frazzini, and Malloy (2010) show, connections are valuable information channels that help analysts improve their performance. Second, there might be a correlation between an analyst's connectedness and his or her unobserved skill. For instance, having gone to a top university and thus having certain connections may be an indicator that an analyst is smart, which also drives good performance. Third, investors may care about connections for nonperformance reasons and therefore may use connections as a substitute for performance in their voting for AAs.

[3] Voting is organized each year by the influential *Institutional Investor*, with the winner list published in the October issues. See Fang and Yasuda (2009, 2014) for more details about the AA voting.

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

In relation to the AA voting, if the only effect of connections is to improve analysts' performance (the first mechanism) and if investors care only about performance in their votes, then, after controlling for performance, connections should not further contribute to analysts' chances of becoming AAs. If connections are proxies of analysts' unobserved skill (the second mechanism) and our performance metric is not a complete statistic of what investors care about, then connections will further enhance analysts' chances of being voted as AAs. But as long as connections are positively correlated with skill, which is also positively correlated with performance, then the interaction term between connections and performance should contribute to the odds of being elected in the same direction as the performance metric; in other words, connections and performance are complements. Finally, if investors use connections as a substitute for performance (the third mechanism) in voting for AAs, then the interaction term between connections and performance should contribute in the opposite direction from the performance metric. In sum, the AA election process is a noisy selection on analyst skill; more skillful analysts should more likely be elected AAs. The key questions are whether connections sharpen or blunt this selection on skill, and whether the effect is symmetric for men and women.

Our findings indicate that, at least in one respect, there appears to be no gender gap among Wall Street analysts. Women represent about 12% of analysts in our sample period (1993-2009); this low percentage is similar to their representation in corporate management. During the same period, they account for about 14% of AA analysts. Thus, women are as likely as men to obtain the coveted AA title, the marker of career success.

When we examine the impact of connections, however, we find two significant differences. First, the value of connections as an information channel is much higher for men than for women. While connections improve both men's and women's job performance (forecast accuracy and recommendation impact), the effect is two to three times as big for men as for women. For example, while connections lead to a 2% improvement in forecast accuracy in general, among men, there is a further 4% improvement. For stock recommendations, while connections are associated with a 50-basis-point (bp) increase in price impact (two-day cumulative abnormal return), there is a further 50-bp gain for male analysts. These patterns are stronger for informationally opaque firms, where the value of connections as a channel of information transmission is higher. While we do not rule out a positive correlation between connections and general skill, our evidence suggests a causal impact of connections on performance because our empirical design identifies with-in analyst variation in performance associated with connections. Thus our findings are consistent with Cohen, Frazzini, and Malloy (2010) whereby analysts obtain useful information through connections, but indicate that the effect is much larger for men than for women.

Second, connections play a different role in male and female analysts' odds of winning the coveted AA title. While connections contribute to both men's and women's odds of success, there is a substitutive effect between connections and past performance for men, and a complementary effect between connections and past performance for women. Our estimates suggest that a one-standard-deviation increase in past average forecast errors would reduce a male analyst's odds of being elected as an AA by over 7%. But a one-standard-deviation increase in a male analyst's connectedness will reduce this negative effect by roughly half. For women, connections appear to accentuate, rather than attenuate, the effect of forecast errors. In additional analyses, we find a similar asymmetric effect in other career outcome measures such as job terminations and assignments to cover visible and large stocks.

Taken together, our results indicate that among Wall Street analysts, men reap more benefits from their connections than women. Although women as a group seem to be succeeding on Wall Street – they are just as likely to be voted AAs as men are—the factors behind their success are different. Connections are not only less valuable as an information channel that directly contributes to better job performance for women, but they also do not enhance their overall career success in the subjective evaluation by investors the same way that they do for men.

In a 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 AA analysts: Women are not underrepresented among AAs. The gender gap in our paper is thus much more subtle: We uncover an asymmetry in the factors that drive male and female analysts' success.

Our findings offer a potential explanation for the gender gap beyond Wall Street, including the thin ranks of women at the top in business, despite women's advancement in education and the work force. Career advancement both on Wall Street and elsewhere requires not only good job performance but also the favorable subjective evaluations by others. If men reap more benefits from connections both directly in terms of job performance and indirectly in the subjective evaluation by others, their advantage can persist and even widen as their careers progress.

1. 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 Levi, 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 gap in the business world. 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. This gap is largely explained by women's career interruptions due to motherhood. Bertrand (2013) shows that some women may rationally choose a curtailed career in exchange for overall well-being. Bertrand, Kamenica, and Pan (2015) shows that social norms regarding gender identity may also discourage women from high powered careers that lead to higher earnings than their husbands.

Our paper compliments this existing literature by offering another channel—social networks—through which the gender gap may develop and persists. Focusing narrowly on Wall Street analysts helps us reduce some of the confounding effects due to, for example, men and women's different risk aversion and willingness to compete. Since Wall Street jobs are highly competitive, analysts' self-selection to enter this labor market reduces the gender differences in these characteristics relative to the overall population.

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.

2. Data and Descriptive Statistics

2.1 Sample selection and variable measurement

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 *Institutional Investor* each year.

To identify analyst gender, we obtain full names of AA analysts from *Institutional Investor*. When the name alone is ambiguous, we check the accompanying articles in *Institutional Investors* 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, 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*).[5] 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.

To measure analysts' performance on earnings forecasts, we use the de-meaned absolute forecast error as in Clement (1999):

$$Fore\_error_{i,j,t} = \left(AFE_{i,j,t} - \overline{AFE_{J,t}}\right) / \overline{AFE_{J,t}} \quad (1)$$

where $AFE_{i,j,t}$ is the absolute forecast error (the absolute difference between the analyst's average forecasted earnings per share, or EPS, and the firm's actual EPS) for analyst i's forecasts of firm j in year t and $\overline{AFE_{J,t}}$ is the mean absolute forecast error for firm j in year t among all analysts covering firm j.[6] *Fore_error* is thus a percentage measure of how much bigger or smaller an analyst's forecast is compared to the average analyst performance. Positive (negative) values of the variable indicate that an analyst's forecast error is larger (smaller) than the average. The smaller the measure, the more accurate is the analyst.

To measure the impact of analysts' stock recommendations, we follow a large body of literature and focus on the two-day cumulative abnormal return

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[5] We consider six degrees: MBA, MA (general), PhD, MD, JD, and undergraduate degrees (BA, BS).

[6] In the reported result, we keep all forecasts made by an individual analyst for a given firm in a given year and use the average to calculate his or her forecast error. Results are robust if we use only the last forecast made by each analyst for each firm each year.

Table 1
Gender distribution

	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

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

immediately after a recommendation change, using the daily Daniel et al. (1997) (DGTW) characteristics-based benchmarks.[7] Specifically,

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

where [0,1] is the two-day window from the date of the recommendation release to one 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 removes expected stock movements associated with stocks' size, book-to-market ratio, and momentum, leaving only stock-specific abnormal returns that reflect market's reactions to analyst recommendation changes.[8]

2.2 Descriptive statistics

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

[7] In robustness checks, we use a 180-day window and find qualitatively similar results. We also use the same calendar-time portfolios as in Cohen, Frazzini, and Malloy (2010) where each recommendation change enters a buy or sell portfolio the day after it is issued and remains in the portfolio until the analyst updates it. Results are qualitatively the same.

[8] The DGTW benchmarks (Daniel et al. 1997) were downloaded from http://www.smith.umd.edu/faculty/rwermers/ftpsite/Dgtw/coverpage.htm.

period, however. Also reported in Table 1 is the number of AA analysts and the gender distribution in this subsample. Each year around 73 analysts 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. Given that females are 12% of the overall analyst pool, it follows that judging by percentages alone, there is no gender gap: Female analysts are as likely to be elected AAs as male analysts.

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, the number of connections is unsurprisingly smaller across both genders: 1.24 for male and 1.33 for female. Turning to *Connect3*—the 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 1(A) 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 1(B) 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 2
Connection statistics

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

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

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

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

Table 3
Demographic and work patterns

	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

This table reports demographic and work patterns by analyst gender. *Ivy League* is an indicator variable that equals one if the analyst attended an Ivy League school and zero otherwise. *Number of qualifications* is the number of college degrees an analyst holds. *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 an 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 covers, where an industry's definition is based on Fama-French's 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 appeared in the I/B/E/S database. p-values from t-test for differences are reported.

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.

3. Main Findings

3.1 Connections and forecast accuracy

Table 4 presents regressions results on forecast accuracy. Panesl A, B, and C report results using *Connect1*, *Connect2*, and *Connect3* as measures of analyst-firm connection, respectively. For brevity, the latter two panels report the key coefficients only. In Model (1), connection and gender enter the regression separately without interaction term. In Models (2)-(4), the interaction term is included. We use industry and year fixed effects in Model (1) and (2), and we further include analyst fixed effects in Model (3) to absorb any performance difference that is driven by latent analyst traits. In Model (4), we use firm fixed

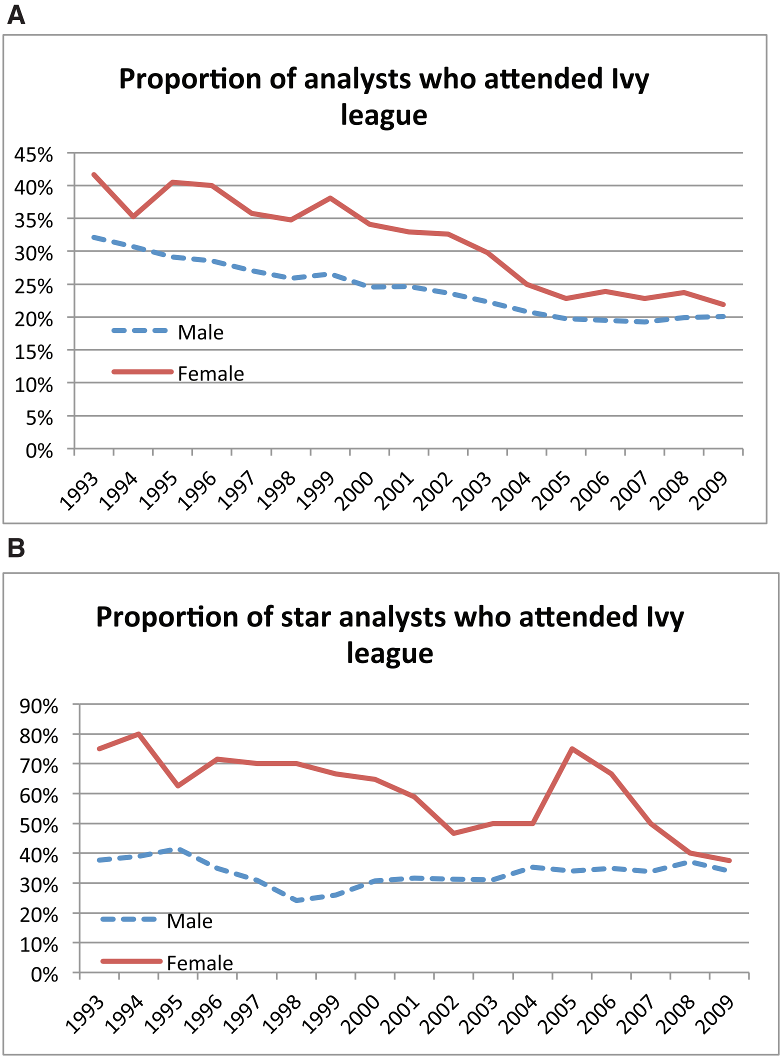

Figure 1
Comparing education
This figure plots the fraction of male and female analysts who attended an Ivy League school (A) and the fraction of male and female star analysts who attended an Ivy League school (B). The data sample is from 1993 to 2009. Star analysts were identified from the October issues of *Institutional Investor*.

effects to mitigate the concerns that the observed performance difference is related to unobservable time-invariant firm characteristics.[9]

[9] We perform extensive robustness checks, including keeping only stocks covered by five or more analysts; keeping only stocks covered by both male and female analysts; using joint industry-year fixed effects; and using joint firm-year fixed effects. Our results are robust to all alternative specifications.

Table 4
Connection and forecast accuracy

A. Results using the Connect1 measure

	(1) *Fore error*	(2) *Fore error*	(3) *Fore error*	(4) *Fore error*
Connection	−0.064	−0.026	−0.024	−0.029
	(−5.58)***	(−3.48)***	(−2.63)***	(−3.34)***
Male	−0.007	0.003		0.001
	(−1.33)	(0.61)		(0.24)
*Male*Connection*		−0.044	−0.046	−0.042
		(−5.38)***	(−4.77)***	(−4.52)***
All Star	−0.007	−0.007		−0.008
	(−1.56)	(−1.62)		(−1.60)
Ivy League	0.001	0.001		0.000
	(0.17)	(0.17)		(0.01)
General exp	0.002	0.002	0.002	0.002
	(3.02)***	(2.99)***	(3.39)***	(2.99)***
Brokerage size	0.000	0.000	0.000	0.000
	(0.43)	(0.35)	(0.67)	(0.43)
Num of ind	0.003	0.003	0.000	0.003
	(2.81)***	(2.77)***	(0.28)	(2.73)***
Num of stocks	−0.000	−0.000	0.000	−0.000
	(−0.13)	(−0.07)	(1.60)	(−0.09)
Num of analyst	−0.001	−0.001	−0.001	−0.001
	(−1.95)*	(−1.90)*	(−2.09)**	(−1.66)*
Size	0.002	0.002	0.002	0.020
	(2.15)**	(2.11)**	(1.62)	(6.95)***
BTM	0.010	0.010	0.011	0.027
	(6.15)***	(6.12)***	(6.44)***	(9.75)***
Past returns	0.011	0.011	0.011	0.012
	(14.90)***	(14.90)***	(14.85)***	(15.23)***
Observations	462,993	462,993	462,993	462,993
R-squared	0.002	0.002	0.010	0.004
Fixed effects	Year+Industry	Year+Industry	Year+Industry+Analyst	Year+Firm
Cluster	Analyst	Analyst	Analyst	Analyst

B. Results using the Connect2 measure

	(1)	(2)	(3)	(4)
Connect2	−0.064	−0.022	−0.024	−0.023
	(−8.68)***	(−2.36)**	(−2.20)**	(−2.12)**
Male	−0.006	0.000		−0.002
	(−1.13)	(0.06)		(−0.27)
*Male*Connect2*		−0.048	−0.042	−0.046
		(−4.78)***	(−3.60)***	(−4.04)***
Controls	Yes	Yes	Yes	Yes
Observations	462,993	462,993	462,993	462,993
R-squared	0.002	0.002	0.009	0.004
Fixed effects	Year+Industry	Year+Industry	Year+Industry+Analyst	Year+Firm

(*continued*)

From panel A, the immediate observation is that connection is strongly associated with better forecasting performance. In all regressions, the connection variable is negative (i.e., associated with smaller forecast errors) and highly significant. The male indicator is insignificant, indicating that gender is not associated with performance. In Models (2)-(4), the interaction term between gender and connection is significantly negative, indicating that for male analysts, there is a larger association between connection and performance.

Table 4
Continued

C. Results using the Connect3 measure

	(1) *Fore error*	(2) *Fore error*	(3) *Fore error*	(4) *Fore error*
Connect3	−0.135	−0.071	−0.062	−0.075
	(−11.54)***	(−2.18)**	(−1.77)*	(−2.27)**
Male	−0.005	−0.004		−0.006
	(−0.96)	(−0.85)		(−1.08)
*Male*Connect3*		−0.069	−0.075	−0.060
		(−1.97)**	(−2.04)**	(−1.71)*
Controls	Yes	Yes	Yes	Yes
Observations	462,993	462,993	462,993	462,993
R-squared	0.002	0.002	0.009	0.003
Fixed effects	Year+Industry	Year+Industry	Year+Industry+Analyst	Year+Firm

This table examines the effect of connections on analysts' forecast accuracy. The dependent variable is the standardized percentage forecast error, calculated as the absolute forecast error scaled by price, standardized across analysts covering the same firm in the same year (Equation (1)). *Connect1*, *Connect2*, and *Connect3* are 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 one if the forecast is made by an AA analyst and zero 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 are not reported in the regression. All explanatory variables are standardized like in Equation (1). Standard errors are corrected for heteroscedasticity and are clustered at the analyst level. t-statistics are reported in parentheses. *, **, and *** represent significance at the 10%, 5%, and 1% level, respectively.

The economic magnitudes of the connection effect and its asymmetry across genders are large. The coefficient on the connection variable in Models (2)-(4) is about −0.02, meaning that being connected to a company's board improves an analyst's forecast accuracy for that company by 2%. The interaction term between gender and connection has a coefficient of about -0.04, meaning that for male analyst, connection is related to a further improvement of 4%, leading to a total improvement of 6%. In other words, the connection effect is roughly three times as large for men as for women. Results in panels B and C are similar.

It is important to note that the connection variables are constructed at the analyst-firm-year level. Thus, the same analyst has different connection 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. Furthermore, Model (3) includes analyst-year fixed effects, absorbing cross-analyst variations and the result in this model is the same as in other models. Thus, while it is plausible that connection is related to unobserved analyst talent which drives better performance, the association between connection and performance documented here is not explained by this cross-sectional sorting effect. Instead, connections *improve* analyst performance (as is the conclusion in Cohen, Frazzini, and Malloy (2010), and the improvement is larger for men

Table 5
Connections and the price impact of recommendations

A. Buy recommendations

	(1) *CAR[0,1]*	(2) *CAR[0,1]*	(3) *CAR[0,1]*	(4) *CAR[0,1]*
Connection	0.010	0.005	0.004	0.005
	(12.72)***	(2.52)**	(2.07)**	(2.29)**
Male	0.002	0.001		0.001
	(1.80)*	(0.60)		(0.79)
*Male*Connection*		0.006	0.007	0.006
		(3.08)***	(3.07)***	(2.97)***
All star	0.003	0.003		0.003
	(3.60)***	(3.67)***		(2.92)***
Ivy League	0.001	0.001		0.001
	(1.26)	(1.22)		(1.50)
General exp	0.000	0.000	−0.000	0.000
	(2.53)**	(2.49)**	(−0.21)	(2.70)***
Brokerage size	0.000	0.000	0.000	0.000
	(3.05)***	(3.07)***	(0.47)	(3.58)***
Num of ind	−0.001	−0.001	0.000	−0.001
	(−2.40)**	(−2.41)**	(0.52)	(−2.41)**
Num of stocks	−0.000	−0.000	−0.000	−0.000
	(−3.93)***	(−3.92)***	(−4.50)***	(−3.82)***
Num of analyst	0.000	0.000	−0.000	−0.000
	(0.69)	(0.68)	(−0.55)	(−1.95)*
Size	−0.003	−0.003	−0.003	−0.011
	(−12.80)***	(−12.77)***	(−12.57)***	(−13.20)***
BTM	0.001	0.001	0.002	0.001
	(3.03)***	(2.99)***	(3.82)***	(1.47)
Past returns	0.000	0.000	0.000	0.001
	(1.36)	(1.35)	(1.59)	(2.01)**
Observations	46,273	46,273	46,273	46,273
R-squared	0.031	0.031	0.076	0.182
Fixed effects	Year+Industry	Year+Industry	Year+Industry+Analyst	Year+Firm

(*continued*)

than for women, indicating that the value of connections as an information channel is significantly higher for men than for women.

3.2 Connections and recommendation impact

Tables 5 examines how connections affect the price impact of analysts' buy (panel A) and sell recommendations (panel B). For brevity, we only report result using the coarser Connect1 measure; results using Connect2 and Connect3 are qualitatively similar. The regression models are the same as in Table 4, except that the dependent variable is now the two-day cumulative abnormal return following each stock recommendation.

Similar to Table 4, results in panel A of Table 5 indicates that connections have a strong positive effect on the price impact of analysts' buy recommendations. The coefficient on the connection variable ranges between 0.005 and 0.01, indicating that connections increase analysts' recommendation impact by 50 bps to 1%. Gender alone does not have a significant effect, suggesting that, on average, male and female analysts' recommendations generate similar abnormal returns. The coefficient on the interaction term between gender

Table 5
Continued

B. Sell recommendations

	(1) *CAR[0,1]*	(2) *CAR[0,1]*	(3) *CAR[0,1]*	(4) *CAR[0,1]*
Connection	0.001	0.001	0.002	0.003
	(0.55)	(0.34)	(0.52)	(0.82)
Male	−0.000	−0.000		0.000
	(−0.17)	(−0.10)		(0.15)
*Male*Connection*		−0.001	−0.000	−0.003
		(−0.16)	(−0.02)	(−0.97)
All star	0.001	0.001		−0.002
	(0.57)	(0.57)		(−1.24)
Ivy League	0.001	0.001		0.002
	(0.78)	(0.78)		(1.84)*
General exp	−0.001	−0.001	−0.000	−0.001
	(−4.11)***	(−4.11)***	(−2.01)**	(−4.02)***
Brokerage size	−0.000	−0.000	−0.000	−0.000
	(−2.17)**	(−2.17)**	(−2.71)***	(−2.12)**
Num of ind	−0.000	−0.000	−0.001	−0.000
	(−0.90)	(−0.90)	(−1.83)*	(−0.93)
Num of stocks	0.001	0.001	0.001	0.000
	(4.89)***	(4.89)***	(5.26)***	(4.73)***
Num of analyst	−0.001	−0.001	−0.000	−0.001
	(−3.13)***	(−3.13)***	(−1.13)	(−2.97)***
Size	0.005	0.005	0.004	−0.013
	(12.81)***	(12.81)***	(8.92)***	(−9.46)***
BTM	0.007	0.007	0.007	0.003
	(8.43)***	(8.43)***	(7.35)***	(2.36)**
Past returns	0.003	0.003	0.002	0.002
	(7.51)***	(7.50)***	(6.01)***	(6.31)***
Observations	42,999	42,999	42,999	42,999
R-squared	0.035	0.035	0.095	0.270
Fixed effects	Year+Industry	Year+Industry	Year+Industry+Analyst	Year+Firm

This table examines the effect of connections on analysts' buy and sell recommendations. The dependent variables is the *CAR [0,1]*, two-day cumulative abnormal return immediately after the release of the analyst recommendation. Connection is the Connect 1 measure 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 one if the forecast is made by an AA analyst and zero 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 are not reported in the regression. All explanatory variables are standardized like in Equation (1). Standard errors are corrected for heteroscedasticity and are clustered at the analyst level. t-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

and connection is positive and significant, indicating that for male analysts, connections are associated with a higher increase in price impact. Specifically, in Models (2)-(4), the coefficient on the interaction term is around 0.006, whereas that on the connection variable itself is 0.005. Thus, while connections are associated with a 50-bp higher two-day price impact, for male analysts, there is an additional 60-bp improvement, leading to a total improvement of over 1%. Thus, parallel the conclusions from Table 4, the value of connections as an information channel is about twice as high as for female analysts. Notably, the coefficient magnitudes are consistent across all four models, even in Model (3) which contains analyst-year fixed effect which means the coefficient picks up within analyst variations due to connection.

Results in panel B show that connections do not affect the price impact of analysts' sell recommendations in any significant way. This is consistent with results in Cohen, Frazzini, and Malloy (2010) and other papers that examine recommendation impact (e.g., Fang and Yasuda 2014).[10]

Together, results in Tables 4 and 5 point to a consistent conclusion: Connections improve analysts job performance (consistent with Cohen, Frazzini, and Malloy (2010)), but the effect is two to three times as large for men as for women. Thus, the value of connections as an information channel that improves job performance is much higher for men than for women.

3.3 Connections and the AA election

There are three mechanisms through which connections can enhance an analyst's odds of being voted an AA by institutional investors. First, connections are valuable information channels that improve analysts' performance as we documented in the previous subsection. But if investors care only about performance in their voting, then after controlling for performance, connections should not further contribute to analysts' chances of becoming AAs. Second, connections can also be a proxy for an analyst's talent. For instance, having gone to a top university and hence having certain connections may indicate that an analyst is "smart", which also drives performance. In this case, if our performance metric is not a complete statistic of what investors care about, then connections will further enhance analysts' chances of being voted AAs. But as long as connections are positively correlated with skill, which is also positively correlated with performance, then the interaction term between connections and performance should contribute to the odds of being elected in the same direction as the performance metric; in other words, connections and performance are complements. Finally, investors may view connections as a substitute to performance. If this is the case, then the interaction term between connections and performance should contribute in the opposite direction from the performance metric. In sum, the AA election is an imperfect selection on analyst skill; more skilled analysts should more likely be elected. The key question is whether connections sharpen or dampen this selection on skill.

[10] 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 has some restrictions on short-selling, making negative views less of a research focus for analysts. Second, firms (and insiders) are more wary of disclosing material negative information and of 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 are positive opinions.

To investigate, we estimate the following probit regression for male and female analysts:

$$Prob(AA_{i,t}) = \alpha + \beta * \%Connection_{i,t-1} + \gamma * Error_{i,t-1} + \theta * \%Connection_{i,t-1} * Error_{i,t-1} + Controls + \epsilon_{i,t}. \quad (3)$$

The unit of this analysis is analyst-year, since the AA election occurs once a year. The independent variable is whether an analyst is elected an AA in a year. The key independent variables are *%Connection*, an analyst-year-level connection measure calculated as the percentage of an analyst's covered firms that he/she is connected to; *Error*, which is the analyst's average forecast errors in the past year, a proxy for performance; and the interaction term between the two. Control variables follow prior literature (e.g., Fang and Yasuda 2014) and include variables such as experience, breadth of coverage, and the brokerage firm that the analyst works for.

Table 6 reports probit regression results. The left (right) panel pertains to male (female) analysts, respectively. Results in this table indicate that connections positively contribute to both male and female analysts' odds of being elected as AAs, and poor performance (forecast error) negatively affects the odds.

However, the interaction term between connection and past performance has opposing signs in the male and female analysis. In the male sample, this interaction term has a positive sign, the opposite of the sign on the forecast error variable. This means that for male analysts, being highly connected helps counter the negative effects of poor past performance. Specifically, the marginal probabilities (unreported) from the probit (Model (2)) implies that a one-standard-deviation increase in past forecast error reduces the unconditional probability of being elected by 0.875%. Given that the average unconditional odds is about 12% (12% of AAs each year get elected), this is a reduction of 7.29% (0.875%/12%). But for male analysts, a one-standard-deviation increase in connection would reduce that negative effect to −0.42%, or 3.5% of the unconditional probability. Thus, a one-standard-deviation increase in connections reduces the effect of bad performance by about half. In contrast, in the female sample, the interaction term has a negative sign, the same as on the forecast error variable, indicating that connections are a complement to performance. In fact, once the interaction term is included, the past forecast error itself becomes insignificant, the negative effect is loaded on the interaction term. This means that for female analysts, being well connected only aggravates the negative effect of poor performance. These results indicate that connections act as a partial substitute for performance for male analysts while they are a complement to performance for female analysts.

To shed more light on our findings, Table 7 directly compares the average (de-meaned) forecast error across various analyst groups in double-sorts. We calculate various difference-in-differences to shed light on the gender difference in the relation between connections and performance, and in the relation between AA star status and performance.

Table 6
Connections and the AA election

	Male analysts			Female analysts		
	Probit	Probit	OLS	Probit	Probit	OLS
	(1) Elect_AA	(2) Elect_AA	(3) Elect_AA	(1) Elect_AA	(2) Elect_AA	(3) Elect_AA
% connection	0.282	0.479	0.031	1.741	1.631	0.146
	(2.036)**	(3.271)***	(2.968)***	(4.315)***	(4.043)***	(3.164)***
Fore error	−0.411	−0.591	−0.015	−1.195	−0.299	−0.005
	(−3.236)***	(−3.987)***	(−2.756)***	(−3.290)***	(−0.477)	(−0.323)
*% connection*Fore error*	1.398	0.068		−3.828	−0.343	
	(2.208)**	(1.891)*		(−1.796)*	(−2.322)**	
Ivy League	0.037	0.016	−0.003	0.229	0.259	0.019
	(0.523)	(0.221)	(−0.630)	(1.168)	(1.312)	(1.117)
Experience	0.005	0.006	0.001	−0.022	−0.024	−0.001
	(0.750)	(0.899)	(1.913)*	(−1.153)	(−1.252)	(−0.549)
Brokerage size	0.037	0.038	0.002	0.043	0.043	0.003
	(12.018)***	(12.272)***	(10.459)***	(5.354)***	(5.498)***	(3.603)***
Num of ind	−0.022	−0.022	−0.001	0.052	0.047	0.004
	(−1.536)	(−1.568)	(−1.310)	(1.094)	(0.992)	(0.935)
Num of stocks	0.008	0.007	0.001	0.042	0.042	0.002
	(1.488)	(1.417)	(1.031)	(3.059)***	(3.044)***	(1.924)*
AA last year	3.178	3.169	0.812	2.709	2.752	0.686
	(36.561)***	(36.331)***	(68.619)***	(12.092)***	(12.048)***	(20.012)***
Observations	10,453	10,453	10,453	1,353	1,353	1,353
R-squared	0.681	0.682	0.687	0.666	0.670	0.621
Fixed effects	Year	Year	Year	Year	Year	Year
Cluster	Analyst	Analyst	Analyst	Analyst	Analyst	Analyst

This table reports regression results of analysts' career outcomes. The dependent variable *Elect_AA* is an indicator variable that equals one if an analyst is elected as an All-American analyst by institutional investors in a year and zero otherwise. % connection is the percentage of the stocks covered by an analyst with which the analyst has an alumni connection. Reported results are based on the Connect 1 definition, which is an indicator variable that equals one if an analyst attended the same university as one of the senior officers and directors of the company and zero otherwise. *Fore error* is the average demeaned forecast error across all stocks covered by an analyst in the preceding year. *Ivy League* equals one 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* is the number of industry sectors covered by the analyst in the preceding year. *Num of stocks* is the number of stocks the analysts issued earnings forecast on in the preceding year. *AA last year* is an indicator variable that equals one if the analyst was an AA in the last year and zero otherwise. Standard errors corrected for heteroscedasticity t-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

In panel A of Table 7, we tabulate forecast errors for all analysts (AAs and non-AAs). We examine performance differentials along two dimensions: AAs versus non-AAs, and connected analysts versus nonconnected analysts. For this exercise, we define an analyst as connected if he/she is connected to at least one of the companies that he/she covers (we refine this definition in panel B). Since the numbers tabulated are forecast errors, the smaller the value, the better is the performance.

The tabulation in panel A yields a number of observations. First, AAs perform significantly better than non-AAs (rows [1] versus [2]), and this is true for both men and women. For men, the average (de-meaned) forecast errors are −0.009 and −0.001 for stars and non-stars respectively. For women, they are −0.023 and 0.006 respectively. Thus, the AA voting process does select analysts on ability. Second, women outperform men among AAs (−0.023 versus −0.009) but lag behind men among non-AAs (0.006 versus −0.001). The rank order of

Table 7
Forecast error comparisons: Double sorts

A. All analysts

		Female		Male		Male - Female	p-value	
[1]	AA	−0.023		−0.009		0.014	0.074	*
[2]	Non-AA	0.006		−0.001		−0.006	0.089	*
						Diff-in-diff		
	[1] - [2]	−0.028		−0.008		0.021	0.022	**
	p-value	0.001	***	0.015	**			
[3]	Connected analyst	−0.006		−0.008		−0.002	0.621	
[4]	Nonconnected analyst	0.017		0.012		−0.005	0.421	
						Diff-in-diff		
	[3] - [4]	−0.023		−0.020		0.003	0.679	
	p-value	0.002	***	0.000	***			

B. AA analysts

		Female		Male		Male - Female	p-value	
	All	−0.023		−0.009		0.014	0.074	*
[5]	Connected analysts	−0.020		−0.013		0.008	0.335	
[6]	Nonconnected analysts	−0.060		0.010		0.070	0.033	**
						Diff-in-diff		
	[5]-[6]	0.039		−0.023		−0.062	0.058	*
	p-value	0.198		0.002	***			
[7]	Connected analysts, on their connected stock	−0.040		−0.067		−0.026	0.035	**
[8]	Connected analysts, on their nonconnected stock	−0.007		0.009		0.016	0.133	
						Diff-in-diff		
	[7]-[8]	−0.034		−0.076		−0.043	0.012	**
	p-value	0.0228	**	0.000	***			

This table compares de-meaned forecast errors between different analyst groups. De-meaned forecast errors are calculated according to Equation (1). *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively, using a two-tailed test.

performance (from best to worse) by analyst group is female AAs, male AAs, male non-AAs, and female non-AAs. Thus, women exhibit a wider performance variance in the cross-section, and the AA election effectively selects highly skilled women.

The comparison along the connection dimension (rows [3] versus [4]) indicates that connected analysts perform significantly better than nonconnected analysts, and controlling for connection, there is no performance difference between male and female analysts. Both these results are consistent with earlier regression results.

Panel B of Table 7 focuses on AA analysts and sheds light on the effect of connections on performance for this select group of winners. First, the top row of this panel reiterates the result that among AAs, female analysts outperform male analysts but lines [5] and [6] show that this difference is driven by nonconnected analysts. For nonconnected AAs (row [6]), the female versus male performance comparison is −0.06 versus +0.01, a difference of 0.07 and highly significant. Among connected AAs (row [5]), male and female perform equally well. Second, we observe that connection is not associated with performance among female AAs (the connected versus nonconnected female AA comparison is −0.02 versus −0.06 and statistically insignificant), but it is strongly associated with performance among male AAs (the connected versus nonconnected male AA comparison is −0.013 versus 0.01, a difference of

0.023 and significant at the 1% level). Thus connection is more correlated with performance in the cross-section of male AA analysts than it is in the cross-section of female AA analysts.

Finally, in rows [7] and [8], we further unpack the performance of connected analysts into their performance on the stocks they are connected to, and other stocks in their coverage portfolio that they are not connected to. Here, we see that on connected stocks, male AAs outperform female AAs (row [7], −0.067 versus −0.04). On the stocks that the analysts are not connected to however, male analysts' performance lags behind female analysts (row [8], 0.009 versus −0.007), although the difference is insignificant due to small sample. Finally, we see that AAs' performances are better on their connected stocks than their nonconnected stocks (rows [7] versus [8]), and notably, the connection-related performance gap is twice as large for men as for women ([7] – [8], −0.076 versus -0.034).

Collectively, these results show that while female analysts exhibit a wider performance variance than male analysts in the overall population, female AAs' performance are more consistent across stocks and less dependent on connections than male AAs. These results help explain the fact that even though female analysts benefit less from connections, they are as likely as male analysts to be voted AAs overall. They also offer a possible explanation for why investors might use connections as a partial substitute for performance for men. Connections are strongly associated with performance for men. But the true effect of connections is at the stock level. If investors view connections as an analyst attribute instead, they could give an analyst too much credit for his connectedness; in doing so, connections become a substitute for performance.

Overall, the results in this subsection indicate that while the odds of being voted AAs are similar between men and women, the factors driving their success is somewhat different. Benefiting less from connections, female AAs exhibit superior and more consistent performance than their male counterparts.

4. Additional Analyses

4.1 Quality of information

If connections are a useful channel of information, and if male analysts benefit more from this channel than female analysts, our results should hold more strongly in the set of stocks that are informationally more opaque. To test this, we examine four information proxies and sort stocks into high and low information quality according to each measure and compare the results across the subsamples. The first information proxy we use is a financial reporting quality measure based on Dechow and Dichev (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). We use stock volatility and asset tangibility as two additional measures of the firms' information environment. The value of private information is higher for volatile and opaque firms that are harder to understand and predict.

Table 8 reports subsample regression results on earnings forecast accuracy (comparable to Table 4) in panel A and results on recommendation values (comparable to Table 5) in panel B. For brevity, we report results using *Connect1*. Other connection measures yields similar results. Results in panel A are consistent with baseline results in Table 4: Connections improve performance; gender is not associated with performance; the interaction term between gender and connections is significantly negative, indicating larger performance improvement associated with connections for men than for women. The new result here is that the interaction effect is significantly stronger in informationally opaque firms than transparent firms, consistent with the idea that connections facilitates information transmission, and that men benefit more from this communication channel.

Results in panel B using stock recommendations lead to similar qualitative conclusions: Connections are associated with stronger buy recommendation impact, especially for male analysts, and the interaction effect is again significantly stronger among informationally opaque firms than transparent firms.

4.2 Job terminations and other career outcome measures

In the previous section we examined analysts' winning the AA title as a positive career outcome. If the effect we document is robust, we should observe similar patterns in job terminations, a negative career outcome. Indeed we should observe similar effects in other career outcome measures, such as being assigned to cover highly visible stocks, large stocks, and working for top-tier brokerage houses.[11]

In general it is difficult to identify job terminations. The existing literature has used the analysts' disappearance from the I/B/E/S data set as a proxy for job termination. But this approach is inaccurate at best. In many instances, high performing analysts were promoted to be department heads and as a result no longer publish research report under their names. In other cases, analysts may move to the buy side or become an independent consultant, or even staring their own research firms that do not submit to I/B/E/S. In all these cases, the analysts will disappear from the I/B/E/S data set, but none of the situations described above correspond to termination, or bad career outcomes.

To better identify job terminations, we rely on mergers between brokerage houses. Brokerage mergers inevitably result in redundancies. For instance, both merging firms have a telecom analysts; the merged entity is unlikely to

11 Hong and Kubik (2003) consider these three career outcome measures.

Table 8
Quality of information

A. Forecast error

	Accrual quality		10-K disclosure quality		Stock volatility		Assets tangibility	
	High	Low	High	Low	High	Low	High	Low
Connection	−0.040	−0.014	−0.031	−0.014	−0.031	0.006	−0.031	−0.022
	(−3.97)***	(−0.95)	(−2.49)**	(−1.22)	(−2.83)***	(0.65)	(−3.29)***	(−1.91)*
Male	0.013	−0.007	0.004	0.008	−0.003	0.007	0.000	0.006
	(1.96)*	(−0.79)	(0.65)	(0.98)	(−0.41)	(1.13)	(0.05)	(0.94)
*Male*Connection*	−0.033	−0.074	−0.038	−0.081	−0.078	−0.038	−0.040	−0.066
	(−2.97)***	(−4.89)***	(−2.90)***	(−6.65)***	(−6.55)***	(−3.62)***	(−3.89)***	(−5.44)***
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	184,181	181,682	159,353	157,492	226,333	229,812	236,675	225,638
R-squared	0.003	0.003	0.003	0.004	0.004	0.003	0.002	0.004
Fixed effects	Year+Industry	Year+Industry	Year+Industry	Year+Industry	Year+Industry	Year+Industry	Year+Industry	Year+Industry
Cluster	Analyst	Analyst	Analyst	Analyst	Analyst	Analyst	Analyst	Analyst
Test of equality of interaction coefficients								
p-value		0.0261**		0.0069***		0.008***		0.0803*

B. Recommendation impact

	High	Low	High	Low	High	Low	High	Low
Connection	0.005	0.005	0.006	0.006	0.009	0.000	0.005	0.003
	(1.88)*	(1.66)*	(2.07)**	(2.34)**	(2.52)**	(0.14)	(2.11)**	(1.31)
Male	0.001	0.002	0.002	0.001	−0.000	0.002	0.001	0.001
	(0.30)	(1.10)	(1.35)	(0.51)	(−0.17)	(0.76)	(0.44)	(0.47)
*Male*Connection*	0.008	0.015	0.008	0.015	0.011	0.002	0.003	0.011
	(2.60)***	(4.35)***	(2.44)**	(5.36)***	(3.01)***	(1.71)*	(1.06)	(3.90)***
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	18,678	17,950	16,562	15,929	23,529	22,608	24,774	21,110
R-squared	0.041	0.035	0.041	0.049	0.035	0.040	0.022	0.047
Fixed effects	Year+Industry	Year+Industry	Year+Industry	Year+Industry	Year+Industry	Year+Industry	Year+Industry	Year+Industry
Cluster	Analyst	Analyst	Analyst	Analyst	Analyst	Analyst	Analyst	Analyst
Test of equality of interaction coefficients								
p-value		0.0992*		0.0754*		0.0317**		0.0337**

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 standard deviation of (negative of) the residual change in working capital unexplained by changes in cash flows, revenue, and PPE in the past five 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 Web site. *Stock volatility* is the log of one plus stock volatility. *Tangibility* is measured by the market-to-book ratio. All regressions contain same set of controls as in Tables 4–6. All explanatory variables are standardized like in Equation (1). Industry fixed effects is based on Fama-French's 48-industry classification. Standard errors are corrected for heteroscedasticity and are clustered at the analyst level. t-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

retain both. Hong and Kacperczyk (2010) document that brokerage mergers are associated with significant job terminations for analysts. An added advantage of using mergers to study terminations is that the events are exogenous to an individual analyst's performance. Merger-related terminations are less driven by poor performance compared to normal terminations; they also reflect the subjective evaluation of analysts by their superiors in which analysts' network and connections could play a role.

To conduct this analysis, we use brokerage mergers information provided by Hong and Kacperczyk (2010). For each merger, we identify the analysts working in either merging entities before the merger but disappeared from the database within three years after the merger. We use three years to ensure that disappearance of analysts from IBES is likely to be related to brokerage mergers. We then estimate a probit regression for termination identical to the probit regression for AA election except for the different dependent variable.

Table 9, panel A, reports the results on job terminations. Mirroring the results on AA elections, we find that connections are negatively related to job terminations, although the coefficients are statistically insignificant. Past forecast errors, a proxy for poor performance, increases the odds of termination. The interaction term between forecast error and connections in the male sample is negative, suggesting that connections help dampen the negative effect of poor performance. This effect, however, is absent from the female sample. Overall these results are consistent with the AA election analysts and with the conclusion that men benefit more from their connections than women in the subjective evaluation by others.

Following Hong and Kubik (2003), in Table 9, panel B, we investigate three additional career outcome measures: being assigned to cover highly visible stocks, big stocks, and working for top tier banks. Highly visible (big) stocks are those that rank in the top quartile in terms of analyst coverage (market cap) in a given year. We use the list of top-tier banks in Fang and Yasuda (2009), which is based on investment banks' league table rankings.[12] Results in panel B are largely consistent with those in panel A and the AA election results: In the stock assignment analyses, the interaction term between forecast error and connections have opposite signs in the male and female samples, suggesting a substitutive effect for men and a complementary effect for women. The only case in which this effect is not observed is the analysis of analysts' employment at top-tier banks. This could be due to the difficulty and noises in defining top-tier banks,[13] and as Hong and Kubik (2003) show, working for top-tier banks

[12] League table rankings measure banks' market share in securities business. Top-tier banks in the list include Goldman Sachs & Company, Morgan Stanley & Company, Merrill Lynch, J. P. Morgan, Credit Suisse First Boston, UBS, Hambrecht & Quist, Prudential Securities, Deutsche Bank, and Salomon Smith Barney.

[13] We use the list of top-tier banks from Fang and Yasuda (2009) as an exogenous list to avoid identifying top-tier banks in-sample which can be endogenous to analyst behavior. The trade-off is that such a top-tier bank list may not be the same as the top-tier bank list based on analyst research quality.

Table 9
Job terminations and other career outcome measures

A. Job terminations

	Male	Female
% connection	−0.502	−0.419
	(−1.38)	(−1.00)
Fore error	0.440	1.501
	(1.83)*	(3.06)***
*% connection*Fore error*	−1.261	2.153
	(−2.45)**	(0.96)
Ivy League	−0.463	−0.316
	(−2.19)**	(−1.48)
General exp	0.013	0.055
	(1.02)	(2.24)**
Brokerage size	0.030	0.017
	(5.00)***	(2.78)***
Num of ind	0.009	0.036
	(0.16)	(0.62)
Num of stocks	−0.030	−0.091
	(−2.00)**	(−3.74)***
Observations	1,743	451
R-squared	0.201	0.244
Fixed effects	Year	Year
Cluster	Analyst	Analyst

B. Other career outcome measures

	Covering visible stocks		Covering big stocks		Working for top-tier banks	
	Male	Female	Male	Female	Male	Female
% connection	0.312	0.408	0.484	0.538	−0.129	−0.489
	(3.274)***	(1.530)	(5.640)***	(2.029)**	(−0.719)	(−1.022)
Fore error	−0.213	−0.312	−0.379	−0.286	−0.035	−0.167
	(−1.954)*	(−1.837)*	(−4.631)***	(−1.720)*	(−0.266)	(−0.524)
*% connection*Fore error*	0.514	−1.732	0.466	−1.762	−0.717	1.207
	(1.790)*	(−1.980)**	(1.888)*	(−1.868)*	(−1.433)	(0.643)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	10,453	1,353	10,453	1,353	10,453	1,353
R-squared	0.0784	0.0976	0.0804	0.0922	0.715	0.739
Fixed effects	Year	Year	Year	Year	Year	Year
Cluster	Analyst	Analyst	Analyst	Analyst	Analyst	Analyst

This table reports probit regression results of analysts' job terminations (panel A) and other career outcome measures (panel B). In panel A, the dependent variable *Termination* is an indicator variable that equals one1 if an analyst disappears from the I/B/E/S data set within three years after the brokerage house he/she works for goes through a merger (as either an acquirer or a target) and zero otherwise. In panel B, the dependent variable *Covering visible (big) stocks* is an indicator variable that equals one if an analyst covers at least one stock that ranks in the top quartile by total analyst coverage (market capitalization) across all stocks in a given year and zero otherwise. The variable *Working for top-tier banks* is an indicator that equals one if an analyst works for one of the top banks as defined in Fang and Yasuda (2009) and zero otherwise. *% connection* is the percentage of the stocks covered by an analyst with which the analyst has an alumni connection. Reported results are based on the Connect 1 definition, which is an indicator variable that equals one if an analyst attended the same university as one of the senior officers and directors of the company and zero otherwise. *Fore error* is the average demeaned forecast error across all stocks covered by an analyst in the preceding year. *Ivy League* equals one 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* is the number of industry sectors covered by the analyst in the preceding year. *Num of stocks* is the number of stocks the analysts issued earnings forecast on in the preceding year. *AA last year* is an indicator variable that equals one if the analyst was an AA in the last year and zero otherwise. Standard errors corrected for heteroscedasticity t-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

also depend on other factors such as analyst optimism. Overall the results in this section are consistent with the results on AA elections.

4.3 Placebo test: A different star-selection

We have shown that connections differentially affect male and female's chance of being voted by institutional investors as AA analysts. Connections have a substitutive effect with performance for men but a complementary effect with performance for women.

If this asymmetry reflects a bias in investor's subjective evaluation of analysts, then the same asymmetry should not be present in a contest that does not involve voting. To test this idea, we turn to a separate star-ranking published by 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".

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. Results here are different from the AA voting results in Table 6. First, connections have no significant impact on analysts' odds of being on the WSJ's top list. Second, the interaction term between performance and connections also do not have a significant impact. Forecast error (the performance proxy) negatively predict being on the list, although the coefficients are sometimes insignificant. This could be because the WSJ list focuses on recommendations, and there is an imperfect correlation between forecast errors and recommendation values.

Overall, however, the evidence here indicates that the asymmetric effect of connections on making the list in the AA voting is absent from a contest that does not involve voting.

4.4 Homophily: Same-sex connections

One reason female analysts may benefit less from connections is homophily: the tendency for people to bond with those similar to them (i.e., same gender). To test this hypothesis, we unpack the connection variable into four gender-classified connections: male-male; male analyst-female director, female analyst-male director, and female-female, and re-estimate the forecast error and recommendation impact regressions. Table 11 reports the results. For brevity, we only report the key coefficients on the various connection variables. The same control variables used in Tables 4 and 5 are included but unreported.

Table 10
A placebo test of the *Wall Street Journal*'s top analyst rankings

	Male analysts			Female analysts		
	Probit	Probit	OLS	Probit	Probit	OLS
	(1) WSJ top	(2) WSJ top	(3) WSJ top	(1) WSJ top	(2) WSJ top	(3) WSJ top
% connection	−0.012	0.019	0.007	−0.155	−0.333	−0.123
	(−0.086)	(0.133)	(0.200)	(−0.419)	(−0.776)	(−1.353)
Fore error	−0.302	−0.210	−0.019	−1.092	−2.659	−0.248
	(−1.925)*	(−1.152)	(−1.104)	(−1.733)*	(−2.984)***	(−1.668)
*% connection*Fore error*	−0.225	−0.101		4.164	0.261	
	(−0.312)	(−0.860)		(1.509)	(0.533)	
Ivy League	−0.089	−0.093	−0.022	0.022	0.120	0.019
	(−1.408)	(−1.475)	(−1.570)	(0.156)	(0.779)	(0.601)
General exp	−0.006	−0.006	−0.002	−0.024	−0.031	−0.004
	(−0.926)	(−0.966)	(−1.042)	(−1.801)*	(−2.206)**	(−1.535)
Brokerage size	0.005	0.005	0.001	0.008	0.004	0.001
	(2.220)**	(2.217)**	(2.151)**	(1.172)	(0.508)	(0.803)
Num of ind	0.007	0.006	0.001	0.064	0.083	0.013
	(0.418)	(0.408)	(0.366)	(2.688)***	(3.260)***	(2.426)**
Num of stocks	0.025	0.025	0.006	0.022	0.025	0.004
	(5.112)***	(5.051)***	(4.735)***	(3.561)***	(4.074)***	(2.528)**
WSJ top last year	0.089	0.088	0.020	0.047	−0.002	−0.015
	(0.944)	(0.932)	(0.777)	(0.228)	(−0.007)	(−0.274)
Observations	2,952	2,952	2,952	411	411	411
R-squared	0.0383	0.0377	0.038	0.0892	0.118	0.085
Fixed effects	Year	Year	Year	Year	Year	Year
Cluster	Analyst	Analyst	Analyst	Analyst	Analyst	Analyst

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

Consistent with homophily, analysts tend to derive larger benefits from same-gender connections. For female analysts, connections with a female director reduces forecast errors by 3.8% and enhances recommendation impact by 70 bps as opposed to by 2.1% and 40 bps when she is connected to a male director. Thus the magnitude of the female-female connection effect is nearly twice as large as the female-male connection (although these differences are insignificant due to the small sample of female-female connections). Male analysts also benefit more from same-gender connections. The male-male connection is associated with a 7% reduction in forecast error and 1.1% improvement in recommendation impact, as opposed to 6.7% and 80 bps when the connection is with a female director. The difference on the recommendation impact is significant at the 10% level.

Despite homophily, the most striking difference is that male analysts benefit more from connections than female analyst. The male-male connection is associated with performance improvements that are roughly twice as large as even the female-female connection (7% reduction in forecast error, 1.1% improvement in recommendation values, compared to 3.8% and 70 bps),

Table 11
Same-gender connections

	(1) *Fore error*	(2) *CAR[0,1]*
Male-male connection	−0.070	0.011
	(−5.829)***	(5.620)***
Male analyst-female dir connection	−0.067	0.008
	(−8.206)***	(4.406)***
Female analyst-male dir connection	−0.021	0.004
	(−2.400)**	(1.685)*
Female-female connection	−0.038	0.007
	(−3.181)***	(2.376)**
Controls	Yes	Yes
Observations	462,993	46,273
R-squared	0.002	0.031
Fixed effects	Year+Industry	Year+Industry
Cluster	Analyst	Analyst
F-test for coefficient equality	*p*-value	*p*-value
Male-male connection = Female-female connection	0.010*	0.182
Male-male connection = Male analyst-female dir connection	0.735	0.098*
Male-male connection = Female analyst-male dir connection	0.000*	0.001*
Female-female connection = Male analyst-female dir connection	0.044**	0.773
Female-female connection = Female analyst-male dir connection	0.219	0.332

This table examines the impact of same-gender connection on job performance. The dependent variables are standardized forecast error and the two-day cumulative abnormal returns. Table 4 defines all variables. *Connnect1* is the connection measure. *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 analyst-female dir connection is an indicator variable that equals one if the analyst is a male and the connected director is a female. Female analyst-male dir connection is similarly defined. The set of unreported control variables are the same as those used in Tables 4 and 5. Standard errors are corrected for heteroscedasticity and are clustered at the analyst level. t-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

and about three times as large as the female-male connection (2.1% and 40 bps). These differences are highly significant. Thus, homophily only partially explains why men benefit more from connections than women.[14]

4.5 Heckman correction

In our final robustness check, we use Heckman's two-stage technique to address the concern that male and female analysts cover different stocks. Our regressions include industry and firm fixed effects; nevertheless, we use the Heckman procedure to directly account for this type of endogeneity. 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

[14] Numerous hypotheses can be put forward as to why men benefit more than women from connections. One is that even though female analysts gain more from female connections, female directors might, on average, hold less influential roles on the boards, limiting that benefit. Another is that men are more aggressive in using their networks to push for information and advantages. They might also have more opportunities to do so, via, for example, country clubs and sporting events. Yet another possibility is that men use more effective communication and networking skills. These effects are impossible to dissect empirically, at least without more detailed board composition data than is available and without micro-level data on conversations, private meetings, and the like.

Table 12
Heckman correction

A. First-stage Heckman

	(1) % female analyst
Female participation rate	0.002
	(3.13)***
Size	0.008
	(10.89)***
BTM	0.006
	(3.29)***
Past returns	−0.002
	(−0.84)
Observations	42,964
R-squared	0.035
Fixed effects	Year+Industry

B. Second-stage Heckman

	Fore error	*Fore error*	*Buy CAR[0,1]*	*Buy CAR[0,1]*
Connect1	−0.025	−0.029	0.004	0.004
	(−3.10)***	(−3.17)***	(1.97)**	(1.86)*
Male	0.005	0.002	0.000	0.001
	(0.98)	(0.39)	(0.11)	(0.49)
*Male*Connect1*	−0.045	−0.042	0.007	0.007
	(−5.25)***	(−4.27)***	(3.40)***	(3.22)***
Inverse Mill's ratio	4.890	13.012	0.129	0.164
	(8.20)***	(8.63)***	(1.29)	(1.00)
Controls	Yes	Yes	Yes	Yes
Observations	425,121	425,121	42,987	42,987
R-squared	0.003	0.005	0.032	0.180
Fixed effects	Year+Industry	Year+Firm	Year+Industry	Year+Firm

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

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.

5. Conclusions

Connections help people relate to each other, and, in the world of finance, they facilitate the transmission of useful information. Focusing on a sample of Wall Street analysts, we document that while connections are valuable to all analysts, the extent to which male and female analysts benefit from their connections is different. First, connections, as valuable information channels, improve analysts' forecast accuracy and recommendation impact. But this effect is at least twice as large for men compared with women. Second, connections, as important social and human capital, improve an analyst's odds of being voted by institutional investors as star analysts (known as All-Americans, or AAs); they act as a partial substitute to performance for men, but a complement to performance for women.

These findings suggest that on Wall Street, men benefit more from connections, both in terms of job performance and in terms of the subjective evaluation by others. Strikingly, judging from numbers alone, there appears no gender gap among Wall Street analysts: Female analysts are as likely to be voted AAs as their male colleagues are. But our results highlight the fact that the factors driving success are not entirely the same between men and women.

Beyond Wall Street, our findings have broad implications about the persistent gender gap in business, especially the fact that very few women are at the top, even though women have surpassed men in both education and labor force participation. Climbing the corporate ladder requires both stellar performance and favorable subjective evaluation by others. If men benefit more from connections on both fronts—as suggested by our findings—their advantages can persist and even widen as their careers progress.

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