Gender and Connections among Wall Street Analysts[1]

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Abstract

We study how the interplay between gender and connections affect career outcomes and performance among Wall Street analysts. We measure connections using alumni ties between analysts and the firms they cover. Male and female analysts are equally connected on average. Connection is associated with more accurate earnings forecasts for men, but not for women. Controlling for accuracy, connection is important in explaining men's, but not women's, probability of being voted by institutional investors as "star" analysts, an important measure of career success. For women, education achievements and accurate forecasts are important factors that determine voting outcomes. This asymmetry in the effect of connections between the two genders does not exist in an alternative, computerized process of evaluating analysts, and is most pronounced among young analysts. Our results suggest that men reap higher returns from connections than women, and that investors are more willing to rely on soft information such as connections to evaluate men than women.

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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

Women now account for 60% of four-year college graduates, 30% of MBA classes, 14% of senior executive positions at Fortune 500 firms, and 3% of Fortune 500 CEOs. These numbers have been steadily (if slowly) increasing in the last couple of decades (Carter and Silva (2010), Korkki (2011)). Despite these progresses, there remains a perception that women, more than men, face glass ceilings. This paper explores the idea that the observed "gender inequality" in career advancement, i.e., human capital, is at least partially explained by how men and women benefit *differentially* from their connections in the business community, i.e., social capital.

To do so, we study how connections affect the performance and career outcomes *differently* for male and female Wall Street Analysts. Wall Street is a fascinating and important setting to study gender issues and social capital, not the least for its reputation as a male-dominated world, a men's club. It might be expected that there is a big gender difference: men may be more connected than women, for example. At the same time, Wall Street is highly competitive and performance-driven. Labor market competition and self-selection can reduce observed gender differences if only the most competitive and well-connected women are in the profession. Are Wall Street men more connected than women? Does connection improve performance more for men than women? The answer to the first question relates to the gender difference in the amount of social capital, whereas the second addresses whether men and women reap differential returns from their social capital.

What makes Wall Street analyst an interest subject to study our question is that there are two types of performance metrics for analysts. On the one hand, the accuracy of analysts forecast, and the price impact of analysts' stock recommendations, for example, are fairly objective measures of "performance" and "competence". An extensive body of literature uses them to measure the informativeness or quality of analyst research. On the other hand, being voted by thousands of institutional investors as a "star analyst" involves far more subjective human judgments.[1] Since "star analyst" status is one of the most important determinants of analyst pay, it is clearly an important measure of career advancement. How does connection affect both types of performance metrics for men and women *differently*?

To study these questions, we construct a dataset that consists of 1,815 unique analysts covering 8,242 unique firms for the period between 1993 and 2009. There are over 41,000 analyst-firm pairs in our data, and nearly half a million forecast and recommendations. We first examine if men are more "connected" than women—an important question to address potential selection bias, and then examine whether connections affect the earnings accuracy and career outcomes differently for men and women. Following Cohen, Frazzini, and Malloy (2010), we measure analysts' connections by their school ties (i.e., alumni networks) with the senior officers and directors of the companies they cover. Their work establishes an important link between social capital—connections, and human capital—research informativeness. They find that more impactful recommendations are made by analysts who are connected with company insiders through alumni networks. We use the same data of connections in this paper, and extend their

[1] The most influential star-analyst election is conducted annually by the *Institutional Investor* magazine, in which thousands of buy-side institutional investors (mutual funds and hedge funds) are polled to name the "best" analyst in their opinion. The poll results are aggregated and prominently announced in the October issues of the *Institutional Investor* each year, and the winning analysts are called "All American" (AA) analysts. The AA title is associated with not only celebrity status but also outsized pay even by Wall Street standards. Fang and Yasuda (2009) report that less than 8% of all analysts ever attain the AA title. The *Institutional Investor's* 2007 analyst compensation survey reports that the average cash compensation for AA analyst was \$1.4 million in 2006, compared to \$0.5 million for all senior analysts (including AAs). Top analysts on the AA ranking often get paid tens of millions of dollars.

study by examining whether men and women reap differential returns from their social connections.

Based on this large data set, we find no evidence of men being more connected than women. The average analyst, both men and women, have school tie connections to about two firms they cover; men cover about nine firms on average while women cover eight firms. Thus, female analysts do not have less social capital than their male colleagues.

But connection helps improve men's forecast accuracy, but not women's. For men, forecasts made on a connected firm is typically 4% more accurate in relative terms compared to forecasts made on a non-connected firm, meaning that in a ranking from 0 to 100, 0 being the worst forecast for a given firm in a given period and 100 being the best forecast, the rankings of connected forecasts are 4% ahead of the rankings of non-connected forecasts. The number is highly significant statistically. For women, there is no difference. Analysis of stock recommendations yields similar conclusions. For men, recommendations made on a connected firm have immediate (1-day) impact that is about 25 basis points (0.25%) bigger for both buy and sell recommendations, compared to recommendations made by the same analysts on non-connected firms. For women, there is no difference.[2] Thus, overall, while connections—social capital—is converted into research informativeness—human capital—for men, the same is not true for women, even though the two samples are similarly connected.

We further examine broader career outcomes in terms analysts' odds of being elected a star. We find that in the pooled regression, gender per se has no impact on election outcomes. This is good news – there is no gender difference in the odds of becoming a star. This means that the popular claims and beliefs that women are promoted less than men (e.g., Carter and Silva

[2] There is some evidence that *same-sex* connection is associated with stronger price impacts for women, but the differences are not statistically significant.

(2010)) are myths, at least in the analyst context.[3] Connection per se also does not matter in the pooled regression which controls for other analyst characteristics. But when we look at the evidence in the male and female sub-samples separately, we find an important asymmetry. Among men, after controlling for accuracy, connection *per se* contributes to significantly higher odds (15%) of being elected as a star, whereas for women, connection has a *negative* (though insignificant) coefficient. Instead, for women, the factors that matter in star-election was precise earnings forecasts and Ivy League education (neither of which is significant in explaining men's election odds). In other words, while men and women on average have equal odds of success, their paths are different. Women's career advancement appears more dependent on measureable competence, whereas men's is more related to their social capital.

Does this pattern reflect a systematic bias in investors' subjective evaluation of analysts? This is an important question because an alternative possibility is simply that connections are a proxy for analyst ability. We check this hypothesis by using an alternative, algorithm-based evaluation of analysts. Each year, the *Wall Street Journal* publishes a separate list of top analysts called "Best on the Street". Unlike the results from *Institutional Investor,* this list is based on an algorithm that combines the analysts' forecast and recommendation qualities. The bottom line is that this list is not generated by a voting process. We show that the aforementioned asymmetry in what contributes to successful outcomes does not exist in this list. Thus, this placebo test offers evidence that the asymmetry we find is due to subjective voting. We also show that the asymmetry is particularly pronounced among young analysts, whose qualities are largely unknown to investors, but disappears for senior analysts with significant track record.

[3] One difference maybe that the basic inequality claims are often made for the corporate context in which politics, inertia, and culture play important roles, whereas here we are looking at reactions from outside investors who are primarily focused on market outcomes.

Collectively, our evidence is consistent with the notion that men and women extract differential returns from their social connections (Ibarra (1992)). However, it goes further to suggest that investors may rely on connections—analysts' social capital—to infer analyst ability; however, they seem more willing to put weight on this soft information in the evaluation of men than in the evaluation of women. One plausible explanation for this asymmetry is that male analysts, being the majority on Wall Street, are more familiar to investors than female analysts. Burt (1998) argues that people are more willing to rely on soft information when evaluating "familiar" subjects.

Our findings provide significant insight into our business and society. The "gender gap" has disappeared in many areas, including education. However, it still persists in the top echelons of business. Our evidence suggests that people's differential willingness to rely on soft information to evaluation others, coupled with the minority status of women in such top positions, may help explain the still persistent gender gap at the top of the business world.

The rest of the paper is organized as follows. Section 1 reviews related literature. Section 2 discusses our data. Section 3 presents our findings and Section 4 concludes.

1. Literature

Gender has been a largely neglected topic in the study of financial markets until recently. An emerging literature on gender and finance suggests that there is clearly a gender difference, but the focal point of the existing work has been men and women's different attitude towards risk. Men seem to embrace risk more than women, and men tend to be more over-confident than women.

In their influential work, Barber and Odean (2001) use a large sample of trading data from individual brokerage accounts and find that men tend to trade more frequently than women. Men also invest in riskier stocks (such as small firm stocks) and have more concentrated portfolios. While gross return are slightly higher for men than for women—as would be expected since their portfolios are more risky, this advantage is eroded by the higher trading costs that men incur; net of transaction costs, men and women have similar investment performance. Niederle and Vesterlund (2007) use experimental data to study men and women's attitudes towards competition. In the first stage of their experiment, a flat rate is paid on completing a task (no competition). Men and women exhibit no difference in performance. In the second stage, compensation is determined in a competitive tournament for the same task. Men enter the tournament twice as likely as women. Thus, men are more willing to embrace competition, even though there is no gender difference in competence, consistent with the notion that men are more over-confident. Two very recent empirical studies provide evidence of the relative over-confidence of men compared to women among senior corporate executives. Huang and Kisgen (2011) document that male executives undertake more acquisitions and issue more debt than female executives, and acquisition and debt issuance announcements by male executives are associated with lower return than those made by female executives. Levy, Li, Zhang (2011) find that boards with more female representation tends to be less acquisitive and pay a lower acquisition premium to target firms.

Direct comparisons of gender differences in performance are fraught with data limitations and self-selection biases. As a result, the existing literature does not provide consistent evidence on whether women "perform" better than men in various settings. In carefully calibrated lab environments such as Niederle and Vesterlund (2007), men and women are equally competent.

Similarly, the real life trading results in Barber and Odean suggests that male and female individual investors exhibit the same investment performance. On the other hand, a few studies suggest female executives are associated with lower corporate valuation and performance (Adams and Ferreira (2009), Ahern and Dittmar, (2011), and Kulich et al. (2010)). However this conclusion is at odds with the evidence in Huang and Kisgen (2011) and Levy, Li, and Zhang (2011) which suggests the opposite.

We know of two studies that directly compare male and female analysts' performance, and they reach different conclusions. Kumar (2010) finds that female analysts tend to be more accurate than male and he attributes this finding to the competitive nature of the analyst profession and to self-selection: Only very competitive and competent women will enter the profession, giving rise to their superior performance. Green, Jegadeesh, and Tang (2007) use more recent data than Kumar (2010) and find that female analysts are less accurate than their male counterparts. Overall it seems that the relation between gender and performance per se is context-specific and difficult to generalize.

In our paper, the direct comparison between male and female performance is not the main goal. Rather, our focus is on how social capital influences performance differently for men and women. That is, how the interaction between gender and social connections affect performance and career outcomes. Our work draws from the seminal work of Ibarra (1992), one of the earliest papers to coin the notion that men reap greater returns from networks than women. In particular, she finds 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”; but while connections are associated with better performance and career outcomes for men, it is not the case for women.

2. Data

Detailed data on analysts’ earnings forecasts and stock recommendations are obtained from the I/B/E/S database for the years 1993-2009. Our sample starts in 1993 because I/B/E/S started providing detailed coverage on stock recommendation in that year. I/B/E/S provides data on different types of forecasts, for example quarterly earnings forecasts and long-term target prices. We focus on forecasts of fiscal year-end earnings per share (EPS), which is the most common type of forecast made by an analyst covering a firm with the best data coverage.

To construct connections between analysts and the companies they cover, we obtain education data for analysts and companies’ senior officers and directors. For analysts’ education information, we use the dataset from Cohen, Frazzini, and Malloy (2010). For officers and directors’ education informaiton, we use data from BoardEx. An analyst is “connected” to an officer or director in the BoardEx database if he/she has attended the same school as the officer/director. We construct the “connection” variable at two levels. At the coarser level, we code a pair as connected as long as the two people have attended the same university. At a finer level, we code a pare as connected if they have attended the same degree program at the same university. We consider 6 types of degrees—MBA, general master, PhD, medical degree, law degree, and undergrad degree. Finally, because officers and directors of a firm change over time, we refine the connection variables constructed at the individual level to reflect these changes. Specifically, we update the connection variables between analysts and companies they cover annually, every year checking whether the analyst is connected to an officer or director of the firm during that time. For example, if analyst Amy Cohen is connected to firm ABC Corp through director John Smith, but John Smith served on the board of ABC Corp only through the years 1999-2003, then Amy Cohen is "connected" to ABC Corp for 1999-2003, but not other years.

We code gender for analysts, officers, and directors based on the individuals' names. For star analysts, we have full names from the *Institutional Investor* magazine. For other analysts, we use the same data as in Kumar (2010), which is also coded by name. BoardEx provides full names of directors and officers, from which we code their gender. One interesting question is whether same-sex connections are special. Thus gender information for both analysts and firm insiders allow us to identify same-sex connections.

One of the most important career outcomes for an analyst is being elected an "All American" (AA) analyst. We obtain the annual election results from the October issues of the *Institutional Investor* magazine each year. The AA titles are given to top analysts in 60 or so industries defined by *Institutional Investor*[4]: 1^{st}-place, 2^{nd}-place, 3^{rd}-place, and runners-up. While the 1^{st} and 2^{nd}-place titles are awarded to one analyst per industry per year, the 3^{rd}-place and runners-up titles are often shared by multiple individuals. Thus, the 1^{st}- and 2^{nd}-place titles are special, representing the "cream of the crop". To distinguish between the 1^{st} and 2^{nd}-place titles with the rest, we classify these two titles are high-rank. Fang and Yasuda (2009) report that AAs and high-rank AAs represent 8% and 2% of the entire analyst population, respectively. We use the AA information to identify positive career outcomes for analysts.

[4] For more details of the All American analyst election process, see, for example, Fang and Yasuda (2009, 2011).

Table 1 shows the gender distribution in our merged analyst sample. Between 1993 and 2009, female analysts account for 12% of all analysts, and 14% of star analysts (AAs).[5] Thus, unconditionally, it seems that women are more likely to be elected a star. This pattern has been also documented by Kumar (2010) and Green et al. (2009). For both percentages, we see a notable rise and fall through our sample period. Female presence in the overall analyst population increased throughout the 90s, but fell after 2000. The rise and fall is particular notable in the star analyst population (Figure 1). The figure also reveals that female presence in the star analyst population exceeds female presence in the overall population after year 2000, indicating that the higher (unconditional) odds for women to be elected as stars is a relatively recent phenomenon.

Table 2 tabulates the number of stocks the average analyst is "connected" to, and compares this statistics across gender and across star status (p-values for differences are reported). For brevity, we report statistics using the coarser measure of connection—at the university level. The finer connection measure at the degree level gives similar results. For both men and women, the number of connections steadily increased in the sample period. In 1993, men had 1.73 connections versus women's 1.54; by 2009, men have 3.21 connections compared to women's 3.25. But the most salient observation is that we do not observe a gender difference in analysts' connections. The p-values for the male-female differences are generally insignificant. For two years—1999 and 2001—the p-values are significant at the 10% level, but both instances indicate more connections among women than men. If we instead consider number of connections as a percentage of total number of firm covered (statistics unreported), the

[5] The 12% figure for the overall population is slightly lower than previous reports. Green et al. (2007) find that females account for 16% of analysts in top-tier brokerages and 13% in other brokerages. Kumar (2010) reports female to represent 16% of his sample. One reason for the difference is that our data is a merged set between the I/B/E/S analyst file and analysts' education data, which is compiled from websites. The discrepancy suggests that female analysts' education profiles are slightly under sampled in the websites. Our figures on the female presence on star analysts (14%), however, match more closely with prior evidence, suggesting that the under-sampling is less of a problem with more visible female analysts.

conclusion is similar, if not suggesting that women tend to be slightly more connected. This is because women on average tend to cover fewer firm (statistics shown in Table 3 below).

In conclusion, men do not have more connections than women. This result is important and suggests that the difference between men and women is not in terms of their degrees of connection. In contrast, star analysts are significantly more connected that non-star analysts. In 1993, stars and non-stars had 2.65 and 1.42 connections respectively, and in 2009 the numbers are 4.27 versus 3.11. Both differences are significant. This is what we might expect, if connection is a valuable social and human capital for analysts.

Panel B of Table 2 further investigates the gender difference in connections within the star and non-star population. Again, we find no evidence that men are more connected than women, in either population. In the star population, women have more connections than men for years 1998-2000, and 2002. In the non-star population, none of the years exhibit any significant difference.

Our data allows us to examine gender differences in the analysts' education qualification. Figure 2 graphs the fraction of analysts who attended Ivy League schools. The graph indicates a clear downward trend in the percentages of analysts with Ivy League education. Among female analysts, this fraction decreased from 42% in 1993 to 23% in 2009. Among men, the figure declined from 32% to 20%. But throughout the entire period, Ivy League education has always been more common in women than men. If education is a proxy or signal for aptitude (Spence (1973), Chevalier and Ellison (1999)), then these facts indicate that the pool of female analysts is at least as competent, if not more so, than men.

Table 3 compares a number of other statistics between men and women. For brevity, we collapse and compare the statistics over the entire sample period, rather than for individual years.

The table confirms our observation that female analysts tend to be slightly "better" educated than men—more of them have Ivy League education and the difference is significant at the 10% level. While men and women tend to be connected to the same number of stocks (slightly under 2 for both samples over the entire period), since women cover fewer stocks than men (8.58 versus 9.79, significant at 1%), on a percentage basis, women are connected to a larger fraction of the firms they cover than men. Using the coarser university level connection, women are connected to 24% of the firms they cover compared to men's 20%. Using the finer degree level connection, the figures are 13%, and 11%, respectively, both differences are significant at 1%.

A few other demographic and work patterns are consistent with prior evidence. Women tend to be slightly less experienced than men: 4.32 years of experience versus 4.73 years, a small difference in magnitude, but statistically significant. Women notably seem to work less than men: they cover fewer firms and fewer industries. But for each firm covered, women and men issue the same number of forecasts and recommendations per year. Thus, overall female analysts have a lighter work load then men, but per firm covered, they do not work less intensely. The fact that female cover fewer firms is also documented by Green et al. (2009).

In summary, while we find some demographic and work-pattern differences between the genders, there is no evidence that female analysts are less connected, or that they are less well-educated than their male colleagues. In fact, if anything, the opposite seems true.

3. Connections, Performance, and Career Outcomes

A. Forecast Accuracy

In this section, we examine how connection affects forecast accuracy, and in particular, how this relation differs in the male and female sample.

We define forecast accuracy as the absolute difference between an analyst's forecast of a firm's earnings per share (EPS) and the actual reported EPS, scaled by stock price. Thus, the basic forecast accuracy measure is a percentage forecast error; the smaller this number, the more accuracy is the forecast.

It is important to note that the analyst forecast data set is highly heterogeneous. Analysts cover different firms that vary in forecasting difficulty. Thus, a simple percentage forecast error may not be comparable across firms. For example, whereas a 5% forecast error may be quite good for a complex and volatile technology company, it may be very large for a stable and simple utility business. A firm is typically covered by a number of analysts. For the analysts that provide coverage for the same firm, it is the relative accuracy of one analyst versus another that matters. From investors' perspective, it is also natural for them to compare analysts providing coverage for the same firm. While analysts providing coverage for IBM may be directly compared with one another, it is not reasonable to directly compare analyst covering IBM with an analyst covering GE, for example.

For these reasons, we follow existing literature (e.g., Clement and Tse (2005)) and compute a standardized forecast accuracy as follows:

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

where Raw Accuracy$_{i,\,j,\,t}$ is the scaled forecast error measure defined above based 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.

This standardization thus converts the simple percentage error measure into a ranking, which is comparable across analysts and firms. All analysts covering IBM in the same time period are ranked relative to one another. Thus the standardization controls for firm-period effects across analysts. Moreover, the ranking is also more comparable across firms. But in order to calculate the measure, we require that the firm is covered by at least 5 analysts in a given year. Thus, thinly covered firms are dropped in our final sample.

Table 4 provides summary statistics for the raw (unstandardized) forecast error, and the standardized error. The table shows that standardization is important. Panel A shows that the mean raw forecast error is 0.02 (or 2%). That is, the average forecast error as a percentage of the prevailing stock price is 2%. The minimum is 0 (the analyst's forecast matched the actual reported EPS exactly), and the maximum is slightly over 75%. Notably, the mean raw forecast error for men is 2%, slightly larger than women's 1.9% (the difference is statistically significant at 1%). Turning to standardized errors, we find its mean is 0.391 (39.1%), which means that the distance between the average forecast and the best forecast (minimum raw forecast error) is just under 40% of the distance between the best and the worst forecasts, for the same firm during the same period. Notably, for women the average is 0.402, slightly larger than men's 0.389 (the difference is statistically significant at 1%).

Because the standardized error measure provides a ranking of all analysts covering the same firm in the same year, it is more informative about the relative performance among analysts. We will focus on this measure in the remainder of the paper (rank-based measure has become the standard, see, for example, Clement and Tse (2005), Hong et al. (2000)).

Table 5 tests the difference in standardized forecast error between genders, and between connected versus non-connected forecasts. First, on a standardized basis, men appear more accurate than women. Men's average standardized error is 0.389, versus women's 0.402. This is a small difference in magnitude, but statistically significant at 1%. Economically, it means that men on average are 3% ((0.402-0.389)/0.40) closer to the “best” forecast than women. Overall the gender difference in forecast accuracy exists, but is not overwhelming: among the 17 years in our sample, the difference is significant at the 10% or lower level for 9 years.

On the other hand, there is a clear difference associated with connection. The standardized error for connected forecasts is 0.377, 4% lower than the 0.394 figure for non-connected forecasts, the difference being significant at 1%. Over the 17 years, this difference is significant at the 5% level or lower in all but 2 years. This result on the relation between connection and forecast accuracy is consistent with evidence from Cohen, Frazzini, and Malloy (2008, 2010), and suggests that connections, which are important links for informal communication, contributes positively to information discovery.

Panel B of the table further examines the connection-related difference in the male and female sub-samples. In the male sample, the conclusion mirrors the whole sample: connection is associated with significantly smaller forecast errors. The average standardized error for forecasts made by connected male is 0.375, compared to 0.393 for non-connected male, a 5% economic difference. In sharp contrast, we fail to see a connection-related advantage in the female sample: the average standardized error for connected and non-connected forecasts made by female analysts are 0.399 and 0.403 respectively, with a *t*-stat of only 1.21 for the difference. Connection is associated with significantly better forecast accuracy in only 1 out of the 17 years—1994, and the significance is marginal (10%). In two other years—2007 and 2008, connection is associated with significantly *worse* forecast errors.

In conclusion, the uni-variate tests indicate that on standardized errors, men seem more accurate than women on average; but the bigger and stronger effect is that connected forecasts are more accurate than non-connected forecasts.[6] However, the connection effect is present only among men but not women. Though not our focus, the finding of higher accuracy among men is consistent with prior reports (e.g. Green et al. (2009)). That connection is associated with higher accuracy is consistent with findings in Cohen, Malloy, and Frazzini (2008) and (2010), and indicates that social connections positively contributes to analysts' human capital. But our result suggests that there is a gender asymmetry in the social capital to human capital relation: The positive link only exists for men but not women.

Table 6 corroborates the above findings in regression analysis. The dependent variable is standardized forecast error. The key independent variables are the male dummy, connection, and the interaction between the two. Model (1) includes only the male dummy as a benchmark model. Models (2) and (3) introduce the connection dummies and the interaction term. Model (2) uses the university-level connection (Connect1) and Model (3) uses the degree-level connection (Connect2). In our panel regression specification, we include a host of analyst, forecast, and firm characteristics that have been identified to affect forecast accuracy. Analyst characteristics include an Ivy League dummy, an All-star dummy, the analyst's general as well as stock-specific experience, the size of the broker she/he works for, etc. Forecast characteristics include days since last forecast (by the same analyst for the same firm), forecast horizon, and forecast frequency. Firm characteristics include firm size, book-to-market ratio, and past returns. We include joint firm-year fixed effects, and cluster the standard errors by analyst-year.

[6] We emphasize that the differences show in our analysis is difference by forecast, not by analyst. That is, it is not driven by the connected sample being populated by a different group of analysts than the non-connected sample. Connection is defined for analyst-firm-year triplets; so the same analyst appears in both the "connected" sample and the "non-connected" sample. Recall that on average, an analyst is connected to about 30% of the stocks he/she covers (Table 3). Even for the same analyst-firm, some forecasts will be connected and others will be unconnected, due to the movements of officers and directors at the firms. Finally, comparisons between firms and analysts are facilitated by the use of standardized forecast errors, which rank analysts covering the *same* firm for the *same* year. It could be the case that a subset of analysts only appears in the connected sample—the analysts who only cover stocks that he/she has a connection to, and that another subset only appears in the non-connected sample—those analysts who is not connected to any stock he/she covers. Unreported results confirm that when we drop these analysts the results are unaffected.

Results in Table 6 confirm the univariate results in Table 5. The gender coefficient is negative and significant, indicating that men are more accurate than women, on average. The coefficient on Connect1 is positive and marginally insignificant and it is positive and significant at the 5% level for Connect2. This variable captures the effect of connection among females, and indicates that connection does not translate into more accurate forecasts in the female sample. On the other hand, the interaction term between both connection measures and the gender dummy is negative and significant, meaning that connection is related to more accurate forecasts for male analysts.

As a further test, we examine the likelihood that men and women make forecasts that correctly *anticipate* the upcoming earnings news. We examine forecasts made 1 and 2 days before firms release earnings numbers, and code it as “correct” if the forecast revision is in the same direction as the earnings surprise (in other words, if an analyst revised his/her forecast upwards, and the actual released earning two days later is indeed higher than the prevailing consensus, then the analyst is “correct” in his/her revision; such revisions are informative). We find (unreported), that among male analysts, connection improves his odds of being informative and correct by 3% (significant at 5%), but the effect is absent for female analysts.

We also looked at forecast revisions made 1-2 days *after* the companies’ release of earnings. This would not be a measure of forecast informativeness, but a measure of analysts’ piggyback on public information. We find that connections does not increase men’s probability of “piggyback” (ie, revise forecasts in the same direction as the earnings surprise); but connection does increase women’s probability of “piggyback”. Thus, these analysis reveal that male analysts were able to translate “connections” into more informative forecasts that anticipate earnings news, rather than merely follow suit. This in turn suggests that men are more efficient at converting social capital into human capital.[7]

B. Recommendation Impact

Table 7 investigates whether connection is related to the price impact of stock recommendations. We measure price impact by the abnormal stock returns around the days when the analyst issues a new buy or sell recommendation. Specifically, we use event study methodology and calculate the cumulative abnormal returns (CAR) using the Daniel, Grinblatt, Titman, and Wermers (1997) (DGTW) characteristics-based benchmarks that takes into account the expected stock movement attributable to firm size, book-to-market, and momentum.[8]

Results in Table 7 echo the conclusions from Tables 5 and 6 that for men, connection seems to translate into higher recommendation price impact, but not for women. We examine two event windows. The CAR[0,+1] (Panel A) is the immediate one-day window after the analyst issues a recommendation. Price impact should be concentrated in this window. Extensive prior literature documents that the market is efficient with respect to public information such as analyst recommendations; any information contained in analyst recommendations is quickly incorporated into prices within one day (Barber et al. (2001), Green (2006), Fang and Yasuda (2011), among others). The CAR[+1, +30] window is the subsequent 30-day window. While we do not expect additional price impact in this window, it is important to look at this window to see if there is any sign of price reversal. The idea is that if the price impact in day 1 is due to incremental information (rather than over-reaction or hubris of any

[7] It is possible that women might benefit more from same-gender connections: female analysts may be more comfortable with female executives and may be able to obtain useful soft information through informal communications. In unreported analysis, we focus on same-sex networks and did not find it to play a stronger role for women.

[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) and Wermers (2004).

kind), then we should not see return reversal in the subsequent days. But if the initial price impact is due to market over-reaction (to analyst status, or gender, for example), such movement should be spurious and will be corrected (reversed) in subsequent days.

Table 7 indicates that for male analysts, connection is associated with significantly higher price impact. For connected recommendations made by male analysts, CAR[0, +1] is 1.58%, 24 basis points higher than the 1.33% price impact of non-connected male recommendations. The difference is significant at the 5% level. For sells, connected recommendations by male analysts have an average CAR[0, +1] of -2.55%, 26 basis points bigger than the -2.29% figure exhibited by non-connected recommendations. Economicly, these effects are large: a 24 basis points difference in daily returns implies an annual return difference of 60%. For female analysts, on the other hand, connection is not associated with stronger price impact in either buys or sells.

We also examined whether special role is played by same-sex connections. We find some evidence of this, but the effect is not statistically significant. In unreported analysis, we find that CAR[0, +1] for buy recommendations from female analysts with same-sex connection is 1.44%, 40 basis points bigger than the non-connected female's 1.03%, but the difference is unfortunately insignificant at the 10% level, possibly indicating a small sample of female same-sex connections. For sells, females with same-sex connections exhibit CAR[0, +1] of -2.93%, a huge 77 basis points larger (in magnitude) than the -2.16% shown by non-connected women, but again while large in magnitude, the effect is not significant statistically.

C. Career Outcomes – Star Status by Investor Voting

The previous two sections examined relatively objective measures of analysts' research quality – earnings forecast accuracy and buy/sell recommendation impact. We find that for men, connection is associated with more accurate forecasts and more impactful recommendations. These results indicate that there is a positive link between analysts' social capital and human capital, a finding consistent with Cohen, Frazzini, and Malloy (2008, 2010). But the fact that such a positive link exists for men but not for women indicates that men and women reap differential returns from their social connections (Ibarra (1992)).

In this section, we examine what could be considered as the ultimate definition of "success" for analysts – the promotion to star status by institutional investors through opinion polls. Even though the outcome of the star elections rests on institutional investors' subjective opinions, it is one of the most important factors affecting analyst pay. What are the factors that help get a man elected? Are there a different set of factors that matter for women? Does connection affect analysts' election odds over and above the effects of better research quality? Answers to these questions not only add another dimension to the evidence that men and women extract differential returns from social connections, in a more broad sense, they are pre-requisite in understanding any gender "inequality" in career paths. These questions are no longer just about whether analysts can convert social capital into higher human capital; rather, they shed light on the opinions of the investors, who are the ultimate "judges" of the analysts.

We define three favorable career outcomes in relation to star-analyst election and use them as dependent variables in probit analysis. We define "Promotion1" as the event that an analyst who is a non-star in last year gets elected as a star this year. "Promotion2" is defined as an analyst who is a low-rank star (3rd-place or runner-up title holder) last year who gets upgraded to a high-rank star (1st or 2nd-place winner) this year. "All star" is simply indicates whether an analyst is elected as a star. As explanatory variables, we include measures of analyst work quality and characteristics. Specifically, we include the analyst's experience, the number of stocks and industries he/she covers, his/her track record in terms of past forecast accuracy, and education – whether he/she has attended Ivy League school. Probit regressions are estimated for the whole sample, as well as the male and female sub-samples.

Table 8 reports the estimation results. In the whole sample (Panel A), we find that neither gender, nor connection, nor the interaction between the two are significant in determining the election outcomes. The male dummy is negative, and just marginally insignificant with t-stats of about 1.4 in the All-star model ("allstar"). This indicates that there is no gender difference per se in election odds; if anything, female analysts are slightly more likely to get elected than male, which is consistent with univariate results earlier and prior evidence (e.g. Green et al (2007)). This is important. It indicates that there is no gender "inequality" per se in the odds of being promoted as a star. Connection per se also does not matter in the whole sample. Experience, especially firm-specific experience is highly valued by investors, as is the number of stocks covered by the analysts. Number of industries covered, however, has a negative impact on being elected. This possibly reflects investor preference for deep industry expertise over broad coverage.

One striking observation is low magnitudes of the pseudo-R^2 in the regressions. For the promotion regressions, the pseudo-R2 is below 10%; for the All-star equation, it is over 50% but this is mainly due to the inclusion of the lagged star status. These results indicate that observable analyst characteristics explain a very small fraction of analysts' promotions; much of what determines star election outcomes are unknown. Changes in star status (captured by the two promotion variables) are particularly difficult to predict, and there is considerable persistence in star status. These patterns are consistent with what we know (or not know) about the star-election from earlier work (e.g., Fang and Yasuda (2009), (2011)).

Panel B reports the probit regression results for the gender sub-samples. Results here reveal a most interesting asymmetry. In the male sample, connection *per se* is highly valued by investors. The connection indicator has coefficients in the range of 0.15-0.17, indicating that being connected improves the odds by roughly 15% after other effects are controlled for. The coefficient is significant in all equations. In contrast, connection per se is not valued at all in the female sample by investors. In fact, the variable has a negative sign in all equations. For women, two other variables matter: Ivy League education, and past forecasting accuracy. Ivy League has a coefficient ranging from 0.33 to 0.54 in the different equations, indicating a huge economic effect. Past forecast error has a significantly negative coefficient in the promotion from non-star to star, and from the promotion from the low-rank star status to the high-rank star status. Thus, inaccurate forecasts are penalized (alternatively stated, accurate forecasts are rewarded) in the female sample. Interestingly, the impact of forecast quality is especially significant for the promotion from non-star to star status, but less so for the promotion from low-rank star to high-rank star, suggesting that quantifiable competence plays a particularly important role in the promotion of relatively novice stars. Notably, neither Ivy League education nor forecast accuracy is significant in determining men's odds of promotion or being elected a star.

These results reveal that investors value analysts of different genders differently: While connection is valued by investors and affects career outcomes positively for men, for women, it is measurable achievements and competence that seem to play a larger role. Overall, an interpretation of the findings in this section is that while there is no gender inequality per se in the odds of obtaining the crown jewel of success in the analyst profession, the paths getting there seem differ somewhat for the two sexes.

D. A Placebo Test

Does the fact that men directly benefit from connections whereas women need to rely on demonstrated performance reflect a bias in investors' subjective evaluations of analysts? To check this, we rely on an alternative, computer-based "best analyst" list as a placebo test. Each year, Wall Street Journal publishes its own "Best on the Street" list of the top analysts for the year. Unlike the Institutional Investor list which is based on human voting, this list is based on an algorithm that considers the analysts' forecast and recommendation performance during the past 12 months. We repeat the probit analysis using this list as the outcome variable, and report the results in Table 9.

Results here indicate that the aforementioned asymmetry in the factors influencing men and women's odds of becoming a star does not exist in this alternative ranking. Notably, connections per se do not matter for either populations. The contrast between this result and that in Table 8 indicates that the asymmetry exists in subjective voting.

E. Young versus old

If investors rely on connections-a type of social capital-to infer analyst ability, this may matter more for young analysts with little track record than for older analysts. To examine this, we split the sample into the "young" versus "old" population, by the median of experience (6 years). We repeat the election results regression in Panel B of Table 8 for the two sub-samples, and report the results in Table 10. Consistent with the notion that investors rely on connections to evaluate analysts, we see that the previously documented asymmetry exists primarily in the young analyst population, but largely disappears for the older analyst population. Thus, young male analysts directly benefit from connections while young female analysts do not.

4. Conclusions

Using a large sample of Wall Street analysts, we analyze how connections (social capital) affect performance (human capital) and career outcomes differently for men and women. Our findings support the notion that men reap higher returns from their social capital than women (Ibarra 1992). We document that the male and female analysts in our sample do not exhibit differential amount of social capital; if anything, women are somewhat more connected than men; women in our sample are also more likely to have had an Ivy League education. But connections are related to performance and career outcomes in different ways for the different genders. While for men, connections are associated with more accurate earnings forecasts and more impactful buy and sell recommendations—both of which indicate more informative and thus more valuable research done by the analysts, this association does not exist for women.

For broader career outcomes, we examine the odds for the analysts to be promoted to star status by institutional investors through opinion polls. We find an asymmetry in what matters for men and women's success of being voted as a "star". Among men, connections directly contributes to higher odds of becoming a star. In contrast, for women, while Ivy League education and accurate past forecasts are rewarded, connections per se does not matter. To check that this asymmetry indeed reflects a "bias" that exists only in subjective voting, we use a placebo test. We utilize the algorithm-based best analyst list generated by the Wall Street Journal. We show that the aforementioned bias does not exist in this alternative evaluation mechanism, and thus it indeed reflects a subjective bias. We also document that the bias is most pronounced among young analysts whose qualities are mostly unknown to investors, but disappears among senior analysts with significant track records.

Collectively, these results go beyond the notion that men reap higher returns from social capital than women. Investors may be relying on connections (a form of social capital) to help resolve uncertainties about analyst ability. However, the asymmetry in the factors that contribute to men and women's star status, and the striking fact that this asymmetry exists only in subjective voting, indicates that investors are somehow more willing to put weight on soft information such as connection when evaluating men than when evaluating women. One explanation is that people are more willing to rely on soft information when evaluating subjects that are more "familiar" (Burt 1998). Men, being the majority on Wall Street, are more familiar to investors. Such a bias—which arises purely from information problems and human psychology—may inadvertently lead to a pattern whereby men appear to be evaluated on "potential" whereas women are evaluated on demonstrated "performance". This in turn may explain why while the gender gap has closed in many areas including education, it persists in the top echelons of the business world.

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Figure 1. Gender Distribution

This figure plots the fraction of females in the general analyst population and the star analyst (AA) population. The sample of analyst is from our merged sample between I/B/E/S file, the analyst education file, and the BoardEx file. Star analysts are identified from the October issues of the *Institutional Investor* magazine.

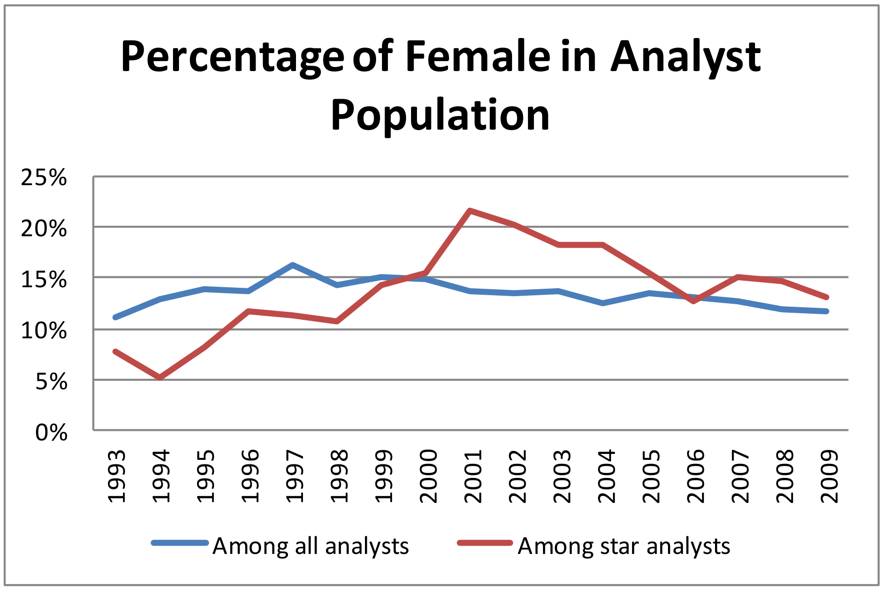
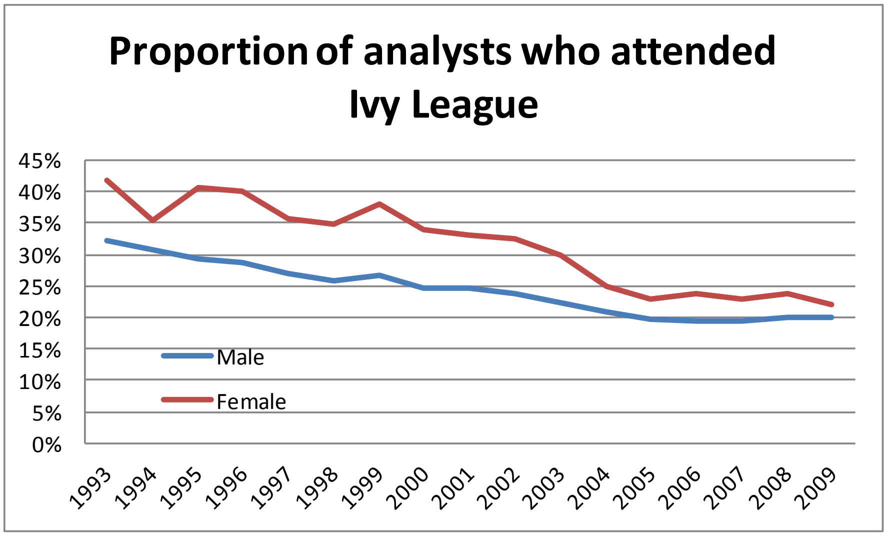


Figure 2. Comparing Education

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.



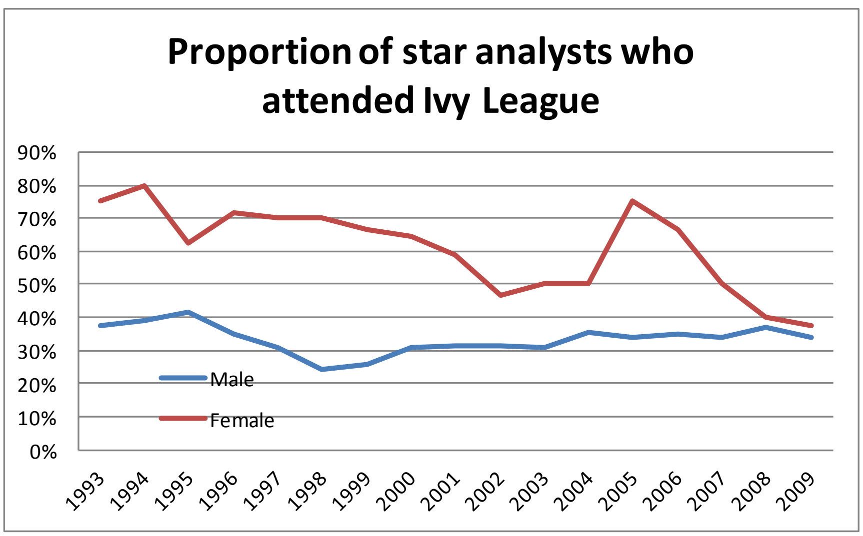


Table 1. Gender Distribution

This table reports the number of male and female analysts in the general population and the star analyst population. 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%	48	4	7.69%
1994	264	34	11.41%	55	3	5.17%
1995	302	42	12.21%	57	5	8.06%
1996	364	50	12.08%	53	7	11.67%
1997	432	70	13.94%	55	7	11.29%
1998	506	72	12.46%	66	8	10.81%
1999	554	84	13.17%	66	11	14.29%
2000	610	91	12.98%	71	13	15.48%
2001	642	88	12.05%	51	14	21.54%
2002	681	92	11.90%	51	13	20.31%
2003	762	104	12.01%	49	11	18.33%
2004	859	108	11.17%	45	10	18.18%
2005	937	127	11.94%	44	8	15.38%
2006	832	109	11.58%	48	7	12.73%
2007	722	92	11.30%	45	8	15.09%
2008	633	76	10.72%	52	9	14.75%
2009	548	64	10.46%	33	5	13.16%
Average	580	78	11.85%	52	8	13.76%

Table 2. Comparing Connections

This table compares the number of connections between male and female analysts, and between star and non-star analysts. A connection means the analyst shares a school tie—he or she has attended the same university—with an officer or director of a firm he/she covers. Star analysts are identifies from the October issues of the *Institutional Investor* magazine. *, **, *** denotes statistical significance of the difference at the 10%, 5%, and 1% levels based on two-tailed tests, respectively.

Panel A: Comparing connections						
year	Male	Female	*p* -value (diff.)	Star	Non-star	*p* -value (diff.)
1993	1.73	1.54	0.73	2.65	1.42	0.00 ***
1994	1.59	1.35	0.62	2.59	1.28	0.00 ***
1995	1.69	1.64	0.91	2.96	1.34	0.00 ***
1996	1.61	1.74	0.75	3.16	1.31	0.00 ***
1997	1.52	1.60	0.81	3.22	1.22	0.00 ***
1998	1.46	1.94	0.14	2.92	1.27	0.00 ***
1999	1.68	2.23	0.06 *	3.48	1.46	0.00 ***
2000	1.85	2.33	0.12	3.77	1.62	0.00 ***
2001	2.05	2.63	0.07 *	4.48	1.84	0.00 ***
2002	2.16	2.40	0.44	4.17	1.95	0.00 ***
2003	2.25	2.01	0.43	4.08	2.05	0.00 ***
2004	2.41	2.22	0.57	4.41	2.25	0.00 ***
2005	2.46	2.40	0.83	5.08	2.30	0.00 ***
2006	2.78	2.94	0.66	4.72	2.65	0.00 ***
2007	3.08	3.32	0.55	4.78	2.95	0.00 ***
2008	3.03	3.22	0.63	4.08	2.93	0.01 ***
2009	3.21	3.25	0.93	4.27	3.11	0.03 **

Panel B: Comparing conenctions in star and non-star sub-samples						
	Star Analysts			Non-star Analysts		
year	Male	Female	*p* -value (diff.)	Male	Female	*p* -value (diff.)
1993	2.72	1.75	0.59	1.41	1.50	0.86
1994	2.63	2.20	0.79	1.29	1.21	0.86
1995	2.82	4.13	0.33	1.38	1.06	0.43
1996	2.94	5.14	0.18	1.33	1.19	0.68
1997	2.99	4.80	0.21	1.24	1.07	0.54
1998	2.59	5.50	0.02 **	1.25	1.37	0.70
1999	3.20	5.42	0.04 **	1.42	1.69	0.32
2000	3.40	5.47	0.03 **	1.63	1.61	0.95
2001	4.23	5.35	0.32	1.83	1.97	0.64
2002	3.73	6.13	0.03 **	1.99	1.68	0.33
2003	4.00	4.43	0.66	2.10	1.63	0.14
2004	4.41	4.42	1.00	2.28	1.95	0.34
2005	4.94	6.00	0.44	2.31	2.16	0.60
2006	4.52	6.11	0.22	2.65	2.65	1.00
2007	4.71	5.25	0.73	2.93	3.13	0.62
2008	3.89	5.30	0.23	2.93	2.91	0.96
2009	4.02	5.75	0.21	3.13	2.89	0.65

Table 3. Summary Statistics

This table reports demographic and work pattern statistics of male and female analyst samples. Ivy League is an indicator variable that equals 1 if the analyst has ever attended an Ivy League school and 0 otherwise. Ever was star is an indicator variable that equals 1 if the analyst has ever been elected as a star analyst and 0 otherwise. Star analysts are identified from the October issues of the *Institutional Investor* magazine. Connect1 is an indicator variable that equals 1 if the analyst covering a firm has attended the same university as one of the active senior officer and directors of the firm and 0 otherwise. Connect2 is an indicator variable that equals 1 if the analyst covering a firm has attended the same degree program in the same university as one of the active senior officers and directors of the firm and 0 otherwise. Number of firms connected to is the sum of Connect1 among all firms covered by an analyst. % of firms connected to is the number of connections an analyst has, defined above, divided by the total number of stocks the analyst covers. No. of firms covered is the number of firms for which an analyst provides earnings per share (EPS) forecasts. No. of industries covered is the number of industries, according to the Fama French 48 industries classification, represented by the firms that the analyst covers. No. of earnings forecast made per firm per year is the number of year-end EPS forecasts made by an analyst for a firm in a given year. No. of recs issued per firm per year is the number of buy/sell stock recommendations that an analyst issues for a firm in a given year. Years of experience measure the number of years an analyst appears in the I/B/E/S database. *, **, *** denotes statistical significance of the difference at the 10%, 5%, and 1% levels based on two-tailed tests, respectively.

	Male	Female	t-stat	
Ivy league	21.98%	26.97%	1.72	*
Ever was star	12.83%	14.11%	0.55	
% of firms connected to - University (Connect1)	20.21%	23.86%	19.07	***
% of firms connected to - Degree (Connect2)	11.49%	13.35%	12.23	***
Number of firms connected to	1.89	1.96	0.39	
Avg no. of firms coverred	9.79	8.58	-3.26	***
Avg no. of industries	2.63	2.29	-3.41	***
Avg no. of earnings forecasts made per firm per year	3.29	3.28	-0.09	
Avg no. of recs issued per firm per year	1.36	1.35	0.50	
Avg years of experience	4.73	4.32	4.21	***

Table 4. Forecast Error Statistics

This table reports summary statistics of the forecast errors of analysts' earnings per share (EPS) forecasts. Raw Forecast Error is the absolute difference between an analyst's forecast of the company's year-end EPS and the firm's actual reported year-end EPS, scaled by the prevailing stock price in the quarter before the release of the actual EPS. Standardized Forecast Error is calculated using Equation (1). Specifically, it is the Raw Forecast Error minus the minimum Raw Forecast Error among all forecasts issued by all analysts for the same firm in the same year, divided by the difference between the maximum and minimum Raw Forecast Error among all forecasts issued by all analysts for the same firm in the same year.

Summary statistics of forecast errors							
	mean	sd	min	p25	p50	p75	max
Raw Forecast Error							
Female	0.019	0.054	0.000	0.001	0.004	0.013	0.743
Male	0.020	0.058	0.000	0.001	0.004	0.014	0.747
All	0.020	0.058	0.000	0.001	0.004	0.014	0.747
Standardized Forecast Error							
Male	0.389	0.337	0.000	0.083	0.304	0.657	1.000
Female	0.402	0.338	0.000	0.093	0.327	0.676	1.000
All	0.391	0.337	0.000	0.084	0.307	0.659	1.000

Table 5. Univariate Comparisons of Standardized Forecast Error

This table compares Standardized Forecast Errors between male and female analysts, and between connected and non-connected analysts. Standardized Forecast Error is calculated using Equation (1). Specifically, it is the Raw Forecast Error minus the minimum Raw Forecast Error among all forecasts issued by all analysts for the same firm in the same year, divided by the difference between the maximum and minimum Raw Forecast Error among all forecasts issued by all analysts for the same firm in the same year. Raw Forecast Error is the absolute difference between an analyst's forecast of the company's year-end EPS and the firm's actual reported year-end EPS, scaled by the prevailing stock price in the quarter before the release of the actual EPS. A forecast is made by a "Connected" analyst if at the time of the forecast, the analyst shares a school tie—has attended the same university—with one of the active senior officers and directors of the firm. *, **, *** denotes statistical significance of the difference at the 10%, 5%, and 1% levels based on two-tailed tests, respectively.

Panel A: Overall gender and connection effects									
	Male	Female	t-stat (Diff)		Connected	Non-connected	t-stat (Diff)	
1993	0.4155	0.4669	4.28	***	0.3893	0.4243	3.38	***
1994	0.4089	0.4237	1.40		0.3816	0.4143	3.30	***
1995	0.4046	0.4108	0.70		0.3948	0.4071	1.40	
1996	0.4198	0.4266	0.77		0.3966	0.4247	3.36	***
1997	0.4100	0.4187	1.07		0.3893	0.4149	3.27	***
1998	0.4099	0.4238	1.89	*	0.3964	0.4148	2.69	***
1999	0.4015	0.4151	1.84	*	0.3930	0.4058	2.00	**
2000	0.3988	0.4079	1.25		0.3897	0.4027	2.16	**
2001	0.3838	0.3978	2.13	**	0.3744	0.3887	2.80	***
2002	0.3916	0.4070	2.43	**	0.3820	0.3966	2.95	***
2003	0.3684	0.3728	0.68		0.3612	0.3712	2.18	**
2004	0.3903	0.3943	0.71		0.3781	0.3945	4.04	***
2005	0.3848	0.3804	-0.84		0.3705	0.3886	4.74	***
2006	0.3827	0.3960	2.59	***	0.3698	0.3884	4.97	***
2007	0.3987	0.4120	2.40	**	0.3941	0.4018	1.98	**
2008	0.3972	0.4141	3.08	***	0.3987	0.3989	0.05	
2009	0.3394	0.3575	3.16	***	0.3316	0.3437	3.04	***
All years	0.3894	0.4021	7.87	***	0.3777	0.3943	13.33	***

Panel B: Effects of connection in gender subsamples									
	Male				Female				
	Connected	Non-Connected	t-stat (Diff)		Connected	Non-Connected	t-stat (Diff)		
1993	0.3851	0.4198	-3.20	***	0.4341	0.4712	-1.03		
1994	0.3827	0.4125	-2.88	***	0.3694	0.4294	-1.72	*	
1995	0.3915	0.4067	-1.62		0.4183	0.4098	0.34		
1996	0.3969	0.4237	-3.01	***	0.3949	0.4321	-1.55		
1997	0.3875	0.4137	-3.06	***	0.3984	0.4234	-1.29		
1998	0.3926	0.4131	-2.77	***	0.4167	0.4255	-0.50		
1999	0.3867	0.4049	-2.60	***	0.4239	0.4123	0.73		
2000	0.3850	0.4023	-2.64	***	0.4139	0.4058	0.53		
2001	0.3720	0.3871	-2.76	***	0.3883	0.4015	-0.96		
2002	0.3778	0.3953	-3.30	***	0.4085	0.4065	0.14		
2003	0.3621	0.3702	-1.66	*	0.3542	0.3800	-1.94		
2004	0.3746	0.3949	-4.67	***	0.4026	0.3913	0.97		
2005	0.3698	0.3893	-4.81	***	0.3761	0.3819	-0.53		
2006	0.3668	0.3874	-5.17	***	0.3921	0.3974	-0.48		
2007	0.3898	0.4014	-2.81	***	0.4269	0.4063	1.76	*	
2008	0.3944	0.3980	-0.84	***	0.4297	0.4084	1.78	*	
2009	0.3283	0.3424	-3.36	***	0.3595	0.3568	0.22		
All years	0.3746	0.3932	-14.03	***	0.3988	0.4031	-1.21		

Table 6. Standard Forecast Error Regressions

This table reports panel regression analysis of Standardizes Forecast Errors. Standardized Forecast Error, is calculated using Equation (1). Male is an indicator variable if the analyst is a man and 0 otherwise. Connect1 is an indicator variable that equals 1 if the analyst covering a firm has attended the same university as one of the active senior officer and directors of the firm and 0 otherwise. Connect2 is an indicator variable that equals 1 if the analyst covering a firm has attended the same degree program in the same university as one of the active senior officers and directors of the firm and 0 otherwise. All star is an indicator variable that equals 1 if the forecast is made by a star analyst and 0 otherwise. Star analysts are identified from the October issues of the *Institutional Investor* magazine. Star status is valid from the October each year to the end of September of the following year. 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 degrees an analysts have. Bus is an indicator variable if the analyst has attended a business school and 0 otherwise. Experience–general is the number of years the analyst appears in the I/B/E/S database. Experience-firm specific is the number of years he/she provides EPS forecasts for the stock. Broker size is the number of analysts working for the brokerage firm that the analyst works for. Number of firms covered is the number of stocks the analyst provides EPS forecasts in the year. Number of industries covered is the number of Fama French industries represented by the firms the analyst covers in the year. Last year's average forecast error is lagged valued of the analyst's average standardized forecast error in the year before. Average forecasting frequency is the average number of times the analyst issues EPS forecasts for the firm covered. Number of days since last forecast is the number of days between the current forecast and the last forecast made by the same analyst for the same firm. Forecast horizon is the number of days between the forecast date and the actual earnings report date. Ln_firm size is the natural log of market capitalization of equity. Ln_bm is the natural log of the book-to-market ratio of the stock. Ln_past return is the natural log of the past 12-month return of the stock. All explanatory variables are standardizes as in Equation (1). *t*-statistics are in parenthesis and are calculated based on robust standard errors clustered at the analyst-year level are reported. *, **, *** denotes statistical significance of the difference at the 10%, 5%, and 1% levels based on two-tailed tests, respectively.

	(1)	(2)	(3)
Male	-0.007	-0.005	-0.005
	(-3.189)***	(-2.111)**	(-2.180)**
Connect 1		0.007	
		(1.60)	
Male * Connect 1		-0.008	
		(-1.860)*	
Connect 2			0.012
			(2.266)**
Male * Connect 2			-0.013
			(-2.389)**
Analyst characteristics:			
All Star	-0.002	-0.002	-0.002
	(-0.964)	(-1.016)	(-1.047)
Ivy League	0.000	0.000	0.000
	(-0.078)	(-0.026)	(-0.097)
Number of qualifications	0.001	0.001	0.001
	-0.476	-0.539	-0.488
Bus	-0.001	-0.001	-0.001
	(-0.501)	(-0.521)	(-0.553)
Experience - general	0.002	0.002	0.002
	-1.368	-1.36	-1.361
Experience - stock specific	-0.011	-0.011	-0.011
	(-7.466)***	(-7.440)***	(-7.436)***
Broker size	-0.002	-0.002	-0.002
	(-1.522)	(-1.547)	(-1.544)
Number of stocks covered	0.006	0.006	0.006
	(3.186)***	(3.202)***	(3.214)***
Number of industries covered	-0.001	-0.001	-0.001
	(-0.510)	(-0.518)	(-0.537)
Last year's average forecast error	0.002	0.002	0.002
	(1.546)	(1.536)	(1.529)
Forecast characteristics:			
Number of days since last forecast	0.034	0.034	0.034
	(20.366)***	(20.366)***	(20.364)***
Forecast horizon	0.455	0.455	0.455
	(181.076)***	(181.073)***	(181.070)***
Forecast frequency	-0.002	-0.002	-0.002
	(-1.202)	(-1.185)	(-1.185)
Stock characteristics:			
Ln_size	-0.091	-0.091	-0.091
	(-10.189)***	(-10.189)***	(-10.189)***
Ln_bm	0.091	0.091	0.091
	(10.973)***	(10.973)***	(10.975)***
Ln_past return	-0.009	-0.009	-0.009
	(-23.131)***	(-23.133)***	(-23.135)***
Constant	1.596	1.594	1.594
	(12.695)***	(12.681)***	(12.682)***
Clustered errors	Analyst-year	Analyst-year	Analyst-year
Fixed effects	Firm-year	Firm-year	Firm-year
Observations	309,206	309,206	309,206
R-squared	0.375	0.375	0.375

Table 7. Recommendation Impact

This table compares the price impact of the buy and sell recommendations issued by male and female analysts, and by connected and non-connected analysts. Buy and sell recommendations are identified from the I/B/E/S database. Recommendation codes 1 and 2 (strong buys and buys) are considered as "Buy recommendations" below, and codes 3, 4, and 5 (hold, sells, and strong sells) are classified as "Sell recommendations" below. A recommendation is issued by a connected analyst if at the time of the recommendation, the analyst shares a school tie—has attended the same university—as one of the active senior officers and directors of the firm. Price impact is measured as the daily abnormal returns using the Daniel, Grinblatt, Titman, and Wermers (DGTW) characteristics-based benchmark returns. DGTW benchmark data is downloaded from Russ Wermer's website. CAR[0, +1] is the cumulative abnormal return from the recommendation date to one day after. CAR[+1, +30] is the cumulative abnormal return from one day after the recommendation date to 30 days after the recommendation date. *, **, *** denotes statistical significance of the difference at the 10%, 5%, and 1% levels based on two-tailed tests, respectively.

	Buy recommendations				Sell recommendations		
Panel A: CAR[0, +1]							
	Male	Female	Male - Female		Male	Female	Male - Female
Connected	1.58%	1.06%	0.51%	**	-2.55%	-2.34%	-0.22%
Non-connected	1.33%	1.03%	0.30%	***	-2.29%	-2.16%	-0.14%
Connected - non-connected	0.24%	0.03%			-0.26%	-0.18%	
	**				**		
Panel B: CAR[+1, +30]							
	Male	Female	Male - Female		Male	Female	Male - Female
Connected	0.78%	0.20%	0.58%		-0.52%	-0.54%	0.02%
Non-connected	0.68%	0.09%	0.59%	***	-0.86%	-0.85%	-0.02%
Connected - non-connected	0.10%	0.11%			0.34%	0.31%	
					*		

Table 8. Career Outcomes – Star Status By Investor Voting

This table reports probit regression results of analysts career outcomes. The dependent variables for the three models are prom1, prom2, and allstar, respectively. Prom1 is an indicator variable that equals 1 if an analyst was not a star the year before and is a star this year and 0 otherwise. Prom2 is an indicator variable that equals 1 if an analyst was a low-rank star (3rd-place or runner-up titles) in the year before and a high-rank star (1st or 2nd-place titles) this year and 0 otherwise. Allstar is an indicator variable that equals 1 if an analyst is a star analyst in a year. Star analyst ranking information is obtained from the October issues of the Institutional Investor magazine. Male is an indicator variable if the analyst is a man and 0 otherwise. Connection is the number of school ties an analyst has with the company he/she covers in a year, as a fraction of the number of firms he/she covers. A school tie means the analyst has attended the same university with one of the active senior officers and directors of the firm. an indicator variable that equals 1 if the analyst covering a firm has attended the same university as one of the active senior officer and directors of the firm and 0 otherwise. Ivy League is an indicator variable that equals 1 if the analyst has ever attended an Ivy League school and 0 otherwise. Experience–general is the number of years the analyst appears in the I/B/E/S database. Experience-firm specific is the number of years he/she provides EPS forecasts for the stock. Number of firms covered is the number of stocks the analyst provides EPS forecasts in the year. Number of industries covered is the number of Fama French industries represented by the firms the analyst covers in the year. Last year all star status is an indicator variable that equals 1 if the analyst was a star analyst the year before and 0 otherwise. *, **, *** denotes statistical significance of the difference at the 10%, 5%, and 1% levels based on two-tailed tests, respectively.

Panel A: Whole sample			
	prom1	prom2	allstar
Male	-0.173	-0.062	-0.191
	(-1.182)	(-0.379)	(-1.416)
Connection	0.12	0.085	0.06
	(0.730)	(0.419)	(0.393)
Male * Connection	0.02	0.062	0.066
	(0.112)	(0.291)	(0.408)
Ivy League	0.143	0.063	0.135
	(2.000)**	(0.754)	(2.103)**
Past forecast error	-1.339	-0.3	-1.876
	(-0.870)	(-0.174)	(-1.306)
Experience - general	0.014	-0.027	-0.011
	(0.782)	(-1.162)	(-0.736)
Experience - stock specific	0.016	0.149	0.098
	(0.501)	(3.953)***	(4.021)***
Number of industries covered	-0.049	-0.019	-0.034
	(-3.355)***	(-1.341)	(-2.905)***
Number of stocks covered	0.009	0.007	0.013
	(2.755)***	(2.022)**	(3.312)***
Last year all star status			2.811
			(36.882)***
Observations	8,989	8,989	8,987
Pseudo R-squared	0.0356	0.0598	0.582
Electionyear fixed effect	Y	Y	Y
Cluster at analyst level	Y	Y	Y

Panel B: Gender sub-samples						
	Male			Female		
	prom1	prom2	allstar	prom1	prom2	allstar
Connection	0.156	0.171	0.15	-0.058	-0.208	-0.146
	(2.159)**	(1.935)*	(2.300)**	(-0.338)	(-0.882)	(-0.857)
Ivy League	0.119	0.011	0.082	0.327	0.537	0.502
	(1.484)	(0.119)	(1.155)	(1.980)**	(2.279)**	(2.832)***
Past forecast error	-0.8	-0.049	-1.555	-12.406	-6.885	-5.416
	(-0.522)	(-0.028)	(-1.037)	(-2.690)***	(-1.728)*	(-1.624)
Experience - general	0.011	-0.03	-0.009	0.03	0.003	-0.027
	(0.548)	(-1.196)	(-0.582)	(0.653)	(0.049)	(-0.574)
Experience - firm specific	0.02	0.156	0.09	-0.018	0.076	0.147
	(0.550)	(3.803)***	(3.508)***	(-0.235)	(0.706)	(1.909)*
Number of industries covered	-0.053	-0.02	-0.04	-0.005	0.033	0.037
	(-3.273)***	(-1.393)	(-3.262)***	(-0.112)	(0.750)	-0.874
Number of stocks covered	0.009	0.006	0.013	0.02	0.038	0.03
	(2.435)**	-1.561	(3.217)***	(1.799)*	(2.746)***	(2.365)**
Last year all star status			2.851			2.638
			(34.584)***			(11.320)***
Observations	7,968	7,968	7,968	880	575	1,019
Psuedo R-squared	0.0384	0.0615	0.588	0.0798	0.124	0.574
Electionyear fixed effect	Y	Y	Y	Y	Y	Y
Cluster at analyst level	Y	Y	Y	Y	Y	Y

Table 9. A Placebo Test

This table examines the probability of being named one of the top analysts by the Wall Street Journal's "Best on the Street" column. Unlike the result from Institutional Investor magazine which is based on voting, this list is based on a computer algorithm that takes into account the analysts' forecast and recommendation performances. The dependent variable is 1 if an analyst is named by the Wall Street Journal as a member of "Best on the Street" and zero otherwise. All independent variables have the same definition as in Table 8. *, **, *** denotes statistical significance of the difference at the 10%, 5%, and 1% levels based on two-tailed tests, respectively.

VARIABLES	Male WSJ Result	Female WSJ Result
Connection	0.026	0.133
	-0.392	-0.843
Ivy League	-0.089	-0.054
	(-1.535)	(-0.354)
Past Forecast Error	-1.715	-2.238
	(-1.382)	(-0.785)
Experience - general	-0.032	-0.04
	(-2.577)***	(-1.280)
Experience - firm specific	0.057	0.02
	(1.881)*	-0.272
Number of industries covered	0.001	0.061
	-0.04	(1.774)*
Number of stocks covered	0.018	0.016
	(3.795)***	(2.105)**
Last Year WSJ List	0.1	0.107
	-1.043	-0.508
Constant	-1.404	-1.674
	(-7.433)***	(-3.072)***

Table 10. Young vs. Old

This table repeats the election outcome results of Table 8 Panel B for the young and old analyst sub-samples. All variables are similarly defined as in Table 8.

Panel A: Yound analysts						
	Male			Female		
	prom1	prom2	allstar	prom1	prom2	allstar
Connection	0.18	0.232	0.135	-0.215	-0.5	-0.337
	(2.359)**	(2.292)**	(1.54)	(-1.135)	(-1.610)	(-1.324)
Ivy League	0.047	0.004	0.172	0.357	0.72	0.851
	(1.484)	(0.119)	(1.155)	(1.969)**	(2.620)***	(3.576)***
Past forecast error	-2.214	-1.003	-1.191	-2.434	-5.981	-4.581
	(-1.661)*	(-0.498)	(-0.730)	(-0.629)	(-0.899)	(-1.207)
Experience - general	0.037	-0.022	0.05	0.087	0.323	0.065
	-0.932	(-0.372)	-0.93	-0.939	(1.738)*	-0.488
Experience - firm specific	0.129	0.279	0.28	-0.029	-0.192	0.477
	(2.167)**	(3.592)***	(4.291)***	(-0.188)	(-0.835)	(2.794)***
Number of industries covered	-0.04	-0.017	-0.046	0.041	0.032	0.1
	(-2.754)***	(-0.900)	(-2.816)***	-0.89	-0.6	(1.847)*
Number of stocks covered	0.011	0.004	0.012	0.031	0.047	0.028
	(3.047)***	-1.007	(2.588)***	(2.451)**	(2.983)***	(2.116)**
Last year all star status			2.917			2.747
			(23.188)***			(8.521)***
Observations	6,388	5,579	4,788	772	322	545
Psuedo R-squared	0.0766	0.0883	0.582	0.11	0.195	0.518
Electionyear fixed effect	Y	Y	Y	Y	Y	Y
Cluster at analyst level	Y	Y	Y	Y	Y	Y

Panel B: Old analysts						
	Male			Female		
	prom1	prom2	allstar	prom1	prom2	allstar
Connection	0.091	-0.011	0.151	0.19	0.546	0.041
	-0.799	(-0.081)	(1.842)*	-0.783	(1.673)*	-0.167
Ivy League	0.059	0.06	0.007	0.164	0.309	0.216
	-0.501	-0.4	-0.078	-0.62	-0.705	-0.825
Past forecast error	-0.839	1.145	-1.738	0.903	-8.051	-1.294
	(-0.329)	-0.409	(-0.708)	-0.229	(-0.439)	(-0.360)
Experience - general	-0.061	-0.064	-0.024	0.021	-0.071	-0.023
	(-2.270)**	(-1.514)	(-1.104)	-0.316	(-0.481)	(-0.427)
Experience - firm specific	0.058	0.135	0.061	0.08	0.271	0.075
	(1.656)*	(3.279)***	(2.382)**	-1.331	(1.680)*	-1.017
Number of industries covered	-0.03	-0.026	-0.031	-0.099	-0.046	-0.046
	(-1.585)	(-1.178)	(-2.249)**	(-1.617)	(-0.583)	(-0.741)
Number of stocks covered	0.013	0.005	0.012	0.025	0.001	0.036
	(2.958)***	-0.867	(2.491)**	(1.886)*	-0.043	(1.918)*
Last year all star status			2.804			2.791
			(24.420)***			(7.834)***
Observations	3,247	2,389	3,180	221	85	352
Psuedo R-squared	0.0565	0.0483	0.591	0.0967	0.173	0.61
Electionyear fixed effect	Y	Y	Y	Y	Y	Y
Cluster at analyst level	Y	Y	Y	Y	Y	Y