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EVIDENCE FROM WALL STREET

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ABSTRACT

We study the relation between gender and job performance among brokerage firm equity analysts. Women's representation in analyst positions drops from 16% in 1995 to 13% in 2005. We find women cover roughly 9 stocks on average compared to 10 for men. Women's earnings estimates tend to be less accurate. After controlling for forecast characteristics, the difference in accuracy is roughly equivalent to four years of experience. Despite reduced coverage and lower forecast accuracy, we find women are significantly more likely to be designated as All-Stars, which suggests they outperform at other aspects of the job such as client service.

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Despite the dramatic reduction in the gender income gap in recent decades, women remain underrepresented in many high-profile careers. Explanations for this phenomenon fall into two broad categories. One line of research emphasizes occupational self-selection due to preferences or differences in abilities (e.g. Polachek, 1981 and Pitts, 2003). Other researchers focus on discrimination in the workplace. Evidence of gender-based discrimination has been documented in certain fields (e.g. Neumark, 1996 and Goldin and Rouse, 2000), yet employers' attempts to offset bias through focused hiring strategies also raises concerns of reverse discrimination. Does the low representation of women in many high paying jobs reflect a lower "natural rate" due to preferences, or is it indicative of discrimination? Because of an emphasis on affirmative action, do employers reverse discriminate in order to attract more women for the job?

This study examines the gender composition of sell-side stock analysts in investment banks and brokerages, and investigates whether employers either systematically discriminate based on gender, or generally attempt to promote gender balance through affirmative action. Sell-side analyst positions are well paying jobs where the average annual salary in 2005 was about $168,000,[1] which is well above the per capita income in the U.S. As with many jobs on Wall Street, a vast majority of analysts are males, and it is often alleged that women face gender discrimination in such high profile, well paying jobs. For instance, a 1996 class action law suit against Merrill Lynch contained over 900 complaints, representing roughly one third of the female brokers who worked at the company during the previous five years.[2] Concerns about potential

[1] Source: CFA Institute survey.
[2] *USA Today* 9/15/2000. "Wall Street Battles Sexual Bias. Even as Brokerage Industry Fights Discrimination, women make accusations." Smith Barney (now owned by Citigroup) and Morgan Stanley

discrimination have led many investment banks and other employers to institute hiring programs to promote diversity. For example, a 2001 survey of investment banks reports that roughly one third of large investment banks tie their reward systems to diversity initiatives. An even greater proportion of these banks also specify numerical objectives for affirmative action recruiting.[3]

Although issues of gender discrimination and affirmative action have attracted considerable attention, we find that the proportion of female stock analysts has progressively declined over time. For instance, the proportion of female analysts declined from roughly 16% in 1995 to 13% in 2005. It is important to determine whether this decline indicates growing discrimination or whether it reflects a shift in women's career preferences. It is also important to understand whether employers' attempts to achieve gender balance in the workforce compromise the effectiveness of their workforce.

The essence of gender discrimination is that when faced with a choice between equally qualified men and women, employers prefer to hire men. As a result, gender discrimination leads to a higher hurdle being set for women, and hence women who are able to cross the hurdle would do a better job on average than their male counterparts. On the other hand, if affirmative action is an important factor in hiring decisions, then employers may set a lower hurdle for women to promote gender balance. If affirmative action based hiring is prevalent, women would on average perform worse than men.

Investment banks are traditionally known for their competitive locker room mentality and 90-hour work weeks, which women may find less attractive in a general

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also faced sex discrimination class action lawsuits in recent years that were backed by the U.S. Equal Employment Opportunity Commission.

[3] Securities Industry Association, 2003, "Report on Diversity Strategy, Development and Demographics: Key Findings."

sense but also for pragmatic family considerations. For example, Niederle and Vesterlund (2006) find experimental evidence that women dislike competitive environments whereas men tend to embrace them. If female equity analysts are relatively rare because women generally do not find that the job matches well with their preferences, then there would be no difference between the performance of women who do self-select into Wall Street careers and their male counterparts.

We analyze the relation between gender and job performance to investigate whether discrimination and affirmative action are prevalently practiced. Previous research on gender and job performance is limited to manufacturing workers or relies on survey data.[4] Our study is innovative in that we are able to able to quantify job performance for thousands of highly paid professionals. Sell side security analysts are unique in that a key aspect of their job performance can be objectively measured and evaluated. Analysts' earnings forecasts are an important component of their research reports that are emphasized by investors and form the basis for recognition in the media and among clients. Our analysis examines the role of gender on research output, forecast accuracy, and professional reputation as measured by the coveted All-American Research Team designation in *Institutional Investor* Magazine.

There are a number of behavioral characteristics that may lead to gender differences in forecast accuracy. Research from cognitive psychology shows that people in general are overconfident about their abilities and that men tend to be more overconfident than women (e.g. Barber and Odean, 2001). As a result, men may be more willing to deviate from the consensus with their predictions which could lead to less

[4] Hellerstein, Neumark, and Troske (1999) fit a production function to manufacturing data to estimate marginal productivity of labor by gender, and Holzer and Neumark (1999) rely on employer survey data to gauge job performance of affirmative action hires.

accurate forecasts on average. On the other hand, Gneezy, Niederle, and Rustichini (2003) find evidence that competition increases the performance of men but hinders the performance of women, which could provide men with an advantage in the competitive arena of investment banking. Moreover, Brown and Josephs (1999) show in experiments that the "mere suggestion of between-group differences can lead to a self-fulfilling prophecy in which the threat of failure promotes poor performance among the stigmatized." The net effect of these behavioral influences on forecast accuracy is unclear.

Our analysis of over 7900 investment bank security analysts reveals several striking findings. Women account for just 15.6% of analyst positions during our sample period, with a surprising downward trend from 16.1% in 1995 to 13.9% in 2005. Large brokerages are noticeably better at attracting women analysts. Women comprise 16.7% of analyst positions at the top decile of brokerages versus 13.7% at others. At the industry level, women's representation is highest among analysts who follow companies in consumer staples industry (22.5%) and lowest among analysts who cover material companies (12.2%). Differences in employment longevity across gender are relatively small. Women are 3.3% more likely to leave their positions within two years, and for analysts who begin work during 1995-2005, women hold their jobs on average one month less than men.

Women cover roughly one less company than men on average, nine stocks compared with ten covered by men. At the stock level, women and men analysts issue earnings forecasts with equal frequency. Previous research (e.g. Richardson, Teoh, and Wysocki 2003) shows that analysts initially make optimistic earnings forecasts and then gradually decrease their estimates to a level the firm can beat by the end of the fiscal period. We find this pattern holds for both women and men, yet women exhibit consistently smaller optimism bias than men throughout the forecast period. The difference in optimism across gender could indicate less overconfidence among women or a greater desire among men to please the management of the firms they cover.

Women's earnings forecasts tend to be less accurate than men's forecasts. After controlling for analysts' and stock characteristics and forecast timing, the magnitude of the difference in accuracy between men and women is roughly equivalent to the effect of four years of experience. Despite covering fewer firms and lower forecast accuracy, we find women are significantly more likely to be designated as All-Stars by *Institutional Investor* magazine. Membership on *II*'s All-American Research Team is based on thousands of institutional investor surveys and influences analysts' compensation at many investment banks. The fact that women cover fewer stocks and are less accurate at earnings forecasts but are more likely to be designated as All-Stars suggests they may perform better at non-quantifiable aspects of the job such as client service.

Taken together, our analysis of job performance supports the view that the low representation of women on Wall Street reflects differences in preferences or family considerations rather than discrimination by investment banks. While we do find significant differences in coverage, accuracy, and professional recognition across gender, the effects tend to be offsetting, which suggests neither gender-based discrimination nor affirmative action have a material impact on the quality of women analysts employed by brokerage firms.

The rest of the paper is organized as follows. Section 1 describes the data and provides summary statistics. Section 2 provides evidence on the role of gender on job performance. Section 3 describes professional recognition across gender, and Section 4 concludes.

1. Data and Descriptive Statistics

We compile the data from several sources. We obtain data on brokerage firm analysts' earnings forecasts for the period from 1995 to 2005 from I/B/E/S. The I/B/E/S detail files provide data on the security identity, the analyst's identity, the brokerage house the analyst belongs to, forecast period information, and the earnings forecast and forecast date. We focus on quarterly earnings forecasts. The name of the analyst in I/B/E/S Broker Translation File is listed by last name and first initial. We match the analyst's information from I/B/E/S with data from the corresponding annual edition (plus or minus one year) of *Nelson's Directory of Investment Research* which contains analysts' full name and contact information.

We determine gender using the database on baby names from the Social Security Administration.[5] Of the 10,996 unique analyst names in I/B/E/S during the 1995-2005 sample period, we are able to match 9,096 analysts with information from *Nelson's Directory*. We lose 247 observations due to duplicate last name and first initial (e.g. J. Smith in I/B/E/S could match with either Jennifer Smith or John Smith in *Nelson's*). We lose an additional 130 observations due to gender ambiguous first names such as Tracy.

[5] http://www.socialsecurity.gov/OACT/babynames. We examine the top 1000 baby names by gender each decade beginning in 1880 which results in 4,775 unique names. In order to increase the number of international names, we augment this list by adding additional data from www.behindthename.com, www.babynameindex.com, and www.wikipedia.org. With these additional sources, the number of unique names increase to 21,204.

Finally, for 773 observations we match names but are unable to determine gender because the names do not match the first names from any of our data sources.

Table 1 shows descriptive statistics for our resulting sample of 7,946 brokerage firm analysts. Analysts enter the sample in a given year if they make at least one quarterly earnings forecast in that year. The matching procedure is able to assign gender to over 70% of the full I/B/E/S sample. When data on first name is available from *Nelson's*, our success at assigning gender is over 90%.

In the full sample, women account for 15.6% of analyst positions, with an almost monotonic decrease from 16.1% in 1995 to 13.9% in 2005 as evident in Figure 1.[6] The downward trend is surprising since the general perception is that discrimination is on the decline and that employers now actively promote gender balance in their hiring policies. Perhaps representation was lower prior to 1995, but the finding suggests women's representation among sell side analysts has at best reached a plateau.

Table 1 also presents the gender composition of analysts in large and small brokerages. We rank brokerages based on the number of analysts affiliated with that brokerage in the I/B/E/S database each year and categorize the top 10% of the brokerages as "large" and the rest as "small." We find that women comprise 16.7% of analyst positions at large brokerages compared with 13.7% at other brokerages. Higher representation of women at large investment banks may reflect a greater emphasis on diversity as well as well as better working conditions. As noted earlier, large investment

[6] For the full sample we average the percentages for each year. Without controlling for year, women's representation in the full sample is 17.2%. This number is higher than the ratio in nine out of ten years, however, and it overstates women's representation at any particular point in time because women leave the analysts' position more often than men. To illustrate, in a balanced sample with two jobs if women work one year and men work two years, across two years there will be twice as many women as men in the sample.

banks are more likely to tie their reward systems to diversity initiatives. They may also be more likely to provide programs designed to address the needs of women. For example, *Working Mother* magazine currently lists several large investment banks on their list of best companies.[7] Evidence on job performance at top firms will help determine if the higher representation of women is due to their providing better working conditions or simply a result of quota based hiring.

Table 1 also presents the proportion of women among analysts covering different sectors. We use the Global Industry Classification Standards (GICS) to classify firms into ten sectors. At the industry level, women's representation is highest among analysts who follow companies in consumer staples (22.5%) and consumer discretionary (18.3%) industries. High representation in consumer oriented industries may be natural if these companies emphasize sales to women. Women analysts are least likely to cover companies in the materials (12.05%) and energy (12.1%) industries, which cater more to the industrial market than the consumer market.

2. Gender and Job Performance among Sell-Side Analysts

This section investigates whether on the job performance of sell-side analysts differs across gender. Sell-side analysts' job involves providing research and customer service to clients. We measure the performance of on the research side by examining the number of stocks that analysts follow, how frequently they revise their earnings forecasts and the accuracy of earnings forecasts for up to four quarters ahead. The number of stocks that analysts follow represents the workload that they carry. The frequency of

[7] Factors that *Working Mother* considers in its choice of best companies to work include flexible work arrangements and favorable maternity/childcare support.

forecast revisions provides a measure of how closely analysts follow the stocks that they cover.

Other aspects of customer service, such as keeping clients abreast of industry and firm-specific developments and arranging for meetings between investors and company management are highly valued by clients, but are hard to quantify. We capture theses aspects of performance using *Institutional Investor's* All-American Research rankings. *Institutional Investor* conducts a comprehensive survey of thousands of portfolio managers, who are the most important brokerage customers, about the quality of service provided by analysts, and publishes an annual list of All-Star analysts. We use the All-Star designation as a measure of analysts' performance of the non-quantifiable aspects of the job.

2.1 Analyst coverage and employment longevity

We begin with a look at number of stocks that each analyst covers. We calculate the number of stocks for which an analyst provides at least one one- to four-quarter ahead forecast in a particular calendar year as the workload carried by that analyst. Table 2 presents the average number of stocks that analysts cover each calendar year, categorized by gender. Women cover fewer stocks in each year in the sample, covering 9.1 stocks on average compared to 10.5 for men. Looking across years, the career average for women is 12.7 stocks for women versus 16.2 for men. Thus, women appear less likely to take on coverage of new stocks than men.

Table 2 shows that analysts at large brokerages tend to cover fewer stocks than analysts in smaller brokerages. In both large and small brokerages, women cover fewer stocks than men on average. Therefore, although women are more likely to work in larger brokerages, the differences in stock coverage across gender are not explained by differences in the size of the employer.

The finding that men cover more stocks indicates that men analysts carry a larger workload than women, which may reflect greater demands on women's time away from work. Traditionally women have carried a bigger share of family responsibilities and a reduction in number of firms covered may be a natural way for women to accommodate greater demands on their time away from work (e.g. Becker, 1985).

Table 2 also reports frequency of forecast revisions for one-quarter ahead forecasts within a fiscal quarter. Here the differences across gender are negligible. Each quarter for each stock, women issue 1.41 one-quarter ahead earnings forecasts on average whereas men issue 1.40 forecasts. Thus, at the stock level we observe no noticeable difference in forecast activity across gender.

We also examine the timing of forecasts. Analysts use a variety of information to update their earnings estimates. Ivkovic and Jegadeesh (2004) note that forecast revisions that are made immediately following earnings announcements tend to reflect analysts' interpretation of the firms' earnings and other financial information firms release, while forecasts revisions at other points in time reflect information about the company that analysts independently gather. The empirical evidence in Ivkovic and Jegadeesh suggests that the information analysts independently gather is more informative for financial market participants than analysts' interpretation of public information releases.

Figure 2 presents the distribution of forecasts revisions around earnings announcement dates. Consistent with the evidence in Stickel (1996) and Ivkovic and Jegadeesh (2004), we find forecasts revisions by both men and women are concentrated within the week after earnings announcements. However, figure 2 shows women are slightly more likely to issue forecasts in the weeks leading up to the announcement, which suggests women are more likely to rely on their independent research to revise their forecasts.

Another important aspect of job performance is employment longevity. Investment banks expend considerable effort to develop and support equity analysts and would prefer to amortize these costs over longer horizons. Table 3 presents measures of employment longevity for new analysts who begin forecasting in a given calendar year. The table reports likelihood of leaving their job (i.e. stop forecasting), within one, two, and three years. The differences in longevity are relatively small. Women are 1.5% more likely to leave work within one year, 3.3% more likely to leave within two years, and 2.8% more likely to leave within three years. Turning to average tenure, new women analysts hold their positions roughly one month less than men on average. We truncate the employment horizon to five years due to the relatively short sample period, which could underestimate differences in average tenure.[8]

2.2 Forecast accuracy

Forecast accuracy is an important measure of equity analysts' job performance. Earnings forecast is a key component of analyst research that is emphasized by investors and forecast accuracy forms an important basis for recognition in the media. Previous research (e.g. Richardson, Teoh, and Wysocki 2003) documents initially optimistic

[8] Hong and Kubik (2003) measure longevity differently and report that roughly 10% of analysts leave the sample within one year. They include all analysts in the I/B/E/S database and examine the number of years they remain in the database. We focus on analysts who newly enter the I/B/E/S data base in a given year and report the proportion of them who leave within a year. Our measure excludes analysts employed before 1995, and it results in higher exit rates since experienced analysts are less likely to leave their jobs than new hires. Focusing on new hires is more appropriate for the purposes of this paper.

earnings forecasts that are gradually "walked down" throughout the fiscal period to a level that the firm can beat. One possible explanation for the initial optimism bias is that analysts tend to be overconfident about the stocks that they follow and overestimate future earnings. Another explanation is analysts deliberately produce optimistic forecasts in order to generate interest in the stock which stimulates trading and leads to brokerage commissions.

Analysts tend to gradually reduce their optimistic forecasts as the earnings date approaches, resulting in mildly pessimistic forecasts on the date of the announcement. Previous research argues the phenomenon of beatable earnings targets is a result of guidance from firm management. Skinner and Sloan (2002) report that the stock price response to disappointing earnings is greater than the response to a similar positive surprise. They argue that this asymmetric stock price reaction gives managers an incentive to walk down their earnings guidance during the quarter and analysts follow managers' guidance. Cotter, Tuna, and Wysocki (2006) find empirical support that analysts follow management's earning guidance, and Hutton (2005) documents that analyst forecasts that are guided by management are more accurate but tend to be more frequently pessimistic.

We examine whether the optimism/pessimism bias are different across gender. We measure forecast error as $\left(\mathrm{Forecast}_{i,j,t} - \mathrm{EPS}_j\right) / \left|\mathrm{EPS}_j\right|$ where $\mathrm{Forecast}_{i,j,t}$ is the forecast from analyst *i* for stock *j* on day *t*, and EPS_j is the realized quarterly earnings per share. A positive forecast error indicates the forecast was optimistic and negative bias implies a pessimistic forecast. We exclude from the analysis observations where absolute value of EPS is less than 5 cents and Winsorize forecast errors at plus or minus 100%.

Table 4 presents the results for forecasts at different points in time around earnings announcements. The table shows that women's forecasts are significantly less optimistic than men's forecasts. Excluding forecasts following earnings announcements, when revisions may reflect a routine response to news, mean forecast errors are 0.9% for women compared with 1.7% for men. Both women and men exhibit optimism bias but women's forecasts contain significantly smaller optimism bias.

Partitioning the forecast sample by firm size using the NYSE median reveals that optimism bias is greater among small firms (2.2% for women versus 3.0% for men). For large firms the sign of the average bias differs across gender. Excluding announcement dates, women's forecasts for large firms are pessimistic on average (-0.34%) whereas men's forecasts tent to be optimistic (0.32%). Figure 3 plots the average forecast errors in event time around earnings announcements. The chart shows women's forecasts contain smaller optimism bias throughout the fiscal quarter. The difference in optimism bias across gender could indicate less overconfidence among women or a greater desire among men to please the management of the firms they cover.

The next set of tests examines the absolute forecast accuracy of women and men. Forecast accuracy depends on a number of stock specific factors as well as the timing of the forecast relative to earnings announcement date. For example, forecasts are typically less accurate for small firms because less information is available to the market. Also, firms with greater earnings volatility tend to be harder to forecast, and thus forecast accuracy is negatively related to volatility. Forecasts also become more accurate when they are made closer to earnings announcements (e.g. Clement, 1999). When we evaluate the relative forecast accuracy across analysts, we need to control for these factors that are exogenous to the analyst. Our first test of relative forecast accuracy controls for these factors by examining a matched sample where women and men issue earnings forecasts for the same stock on the same day.

Table 5 presents a comparison of the characteristics of the matched sample and the full sample. We include one- to four-quarter ahead earnings forecasts in the sample. The matched sample contains all observations where at least one male and one female analyst issued a forecast for the same stock and fiscal quarter, on the same day. The matched sample contains 147,458 forecasts made by 1,084 women, and 345,687 forecasts made by 4,454 men. The matched sample represents about 70% of the analysts and 17% of the earnings forecasts from the full sample.

Table 5 also presents the average size decile rank of the firms in the matched sample and the full sample. We assign a size decile ranks based on the size distribution of stocks listed on the New York Stock Exchange (NYSE). We assign a rank of 1 to firms in the smallest size decile, 2 to the next size decile and so on. The mean NYSE size decile is 4.98 for the matched sample versus 3.45 for the full sample. Since the matched sample requires forecasts from two analysts on the same day, stocks in this sample tend to be larger than the stocks in the full sample.

We measure relative forecast error as:

$$RFE_{j,t} = \frac{1}{F}\sum_{f=1}^{F}\left|\frac{\text{Forecast}_{f,j,t} - \text{EPS}_j}{\text{EPS}_j}\right| - \frac{1}{M}\sum_{m=1}^{M}\left|\frac{\text{Forecast}_{m,j,t} - \text{EPS}_j}{\text{EPS}_j}\right| \qquad (1)$$

where $\text{Forecast}_{f,j,t}$ is the quarterly earnings forecast made by female analyst *f* for stock *j* on day *t*, and EPS_j is the realized earnings per share for the stock. *F* is the number of forecasts by female analysts on day t and *M* is the number of forecasts by male analysts on day t. When there are forecasts made by either multiple female analysts or multiple male analysts, we consider each forecast as a separate observation. A positive relative forecast error indicates than women's earnings estimates are less accurate.

Table 6 reports average relative forecast errors for the matched sample.[9] Across forecasts horizons the relative error is 0.11%. As we discussed earlier, forecasts that analysts issue immediately after earnings announcement tend to present analysts' interpretation of financial data released by the company, while earnings forecasts made on other days tend to use information that analysts' privately gather. Table 6 also separately reports the relative accuracy of forecasts made on the earnings announcement day and the following day, and the accuracy of forecasts made on other days. The forecasts made immediately after earnings announcement are about equally accurate equal across gender, but women's forecasts on other days are about 0.19% less accurate. When partitioning the sample by forecast horizon, the results are only statistically significant for two and three quarters ahead forecasts.

Differences in forecast accuracy may be explained by differences in experience or other analyst characteristics. We examine the relation between gender and forecast accuracy while controlling for forecast characteristics using the regression approach similar to Clement (1999). We compute standardized proportional errors as:

$$PMAFE_{i,j,t} = \frac{AFE_{i,j,t} - \overline{AFE}_{j,t}}{\overline{AFE}_{j,t}} \tag{2}$$

where $AFE_{i,j,t}$ is the absolute forecast error for analyst *i*'s forecast of firm *j* for quarter *t*, and $\overline{AFE}_{j,t}$ is the mean absolute forecast error for firm *j* for period *t* across all analysts.

[9] Table 6 reports fewer observations than Table 5. Table 6 analyzes forecast days averaged across analysts whereas Table 5 reports the number of individual forecasts.

PMAFE represents analyst *i*'s proportional forecast error relative to the average of the analysts absolute forecast errors for firm *j* in quarter *t*. Positive values of *PMAFE* reflect worse than average performance and negative values reflect better than average performance. We Winsorize *PMAFE* at 100%.

PMAFE controls for firm and quarter effects by adjusting errors by their related firm-quarter means. Firm-quarter effects allow for the difficulty of predicting earnings to vary over time, which may occur due to corporate events such as mergers or acquisitions or more simply due to changes in managements' earning guidance.

We then regress the proportional forecast errors on analyst characteristics according to the following specification:

$$\begin{aligned} PMAFE_{i,j,t} = b_0 + b_1 AGE_{i,j,t} + b_2 GEXP_{i,t} + b_3 FEXP_{i,j,t} + b_4 NCOS_{i,t} + \ldots \\ b_5 NGIC_{i,t} + b_6 TOP10_{i,t} + b_7 ALLSTAR_{i,t} + b_8 GENDER_i + e_{i,j,t}. \end{aligned} \quad (3)$$

$AGE_{i,j,t}$ is the number of days between the forecast date and the earnings announcement date, and it measures forecast staleness. $GEXP_{i,t}$ measures the general experience of the analyst, and it equals the number of years analyst *i* has supplied at least one forecast on I/B/E/S up to quarter *t*. $FEXP_{i,j,t}$ is a firm-specific measure of the analyst's experience and it equals the number of years analyst *i* has made at least one forecast for firm *j* up to quarter *t*. $NCOS_{i,t}$ and $NGIC_{i,t}$ are the number of companies and industries (measured by two-digit GIC code) followed by the analyst, and they reflect the complexity of the analyst's portfolio. $TOP10_{i,t}$ is 1 if the analyst is employed by a Top decile brokerage firm (by number of analysts employed) and it captures differences access to brokerage firm resources. $ALLSTAR_{i,t}$ is 1 if the analyst is a member of *Institutional Investor's* All-

American Research Team in year *t*-1. Finally, $GENDER_i$ is 1 if the analyst is female and 0 if male. Similar to *PMAFE*, we adjust the independent variables by subtracting firm-quarter means. The resulting model takes the form $y_{i,j,t} - \overline{y_{j,t}} = \left(x_{i,j,t} - \overline{x_{j,t}}\right)b$.[10]

Table 7 reports the regression results. Across horizons, women produce proportional forecast errors that are 0.49% higher than men. Controlling for analyst characteristics produces larger differences in accuracy across gender than the univariate results in Table 6. For example, women are more likely to cover fewer stocks and work at top brokerage firms. These characteristics typically lead to more accurate forecasts and thus in the regression framework women are held to a higher standard.

The regression framework also provides a means to interpret the economic significance of the result. For example, the difference in accuracy across gender is on par with the incremental accuracy exhibited by All Star analysts (-0.41%) and is roughly equivalent to the effects of four years of firm specific experience (-0.52). The results are generally consistent when the sample is broken down by forecast quarter, and are stronger when examining the matched sample.

Taken together, the findings in this section indicate that women tend to produce less optimistic forecasts than men, and their forecasts tend to be less accurate than the forecasts of male analysts. The difference in accuracy is not large, but is similar in magnitude to the effects of other analyst characteristics examined in the literature such as experience and All-Star status.

3. Gender and Professional Recognition among Sell-Side Analysts

[10] The approach is similar to using firm-year dummies to control for firm-year effects. See Clement (1999) for more details.

The previous section documents differences across gender in stock coverage, employment longevity, and forecast accuracy. In this section we present an additional measure of job performance that captures non-quantifiable aspects of performance.

It is difficult to objectively measure qualitative aspects of job performance across employees from a number of different organizations. Fortunately, for brokerage firm analysts, *Institutional Investor* magazine (*II*) surveys roughly 2000 institutional investors each summer for their opinions on sell-side analysts. Based on the survey, *II* publishes a list of analysts that it designates as members of the All-American Research Team (All-Stars) each year in its October issue.

Institutional investors are the most important customers of sell-side analysts. Money management firms typically allocate their soft dollar commissions based on their internal surveys about the research services of various brokerages. The *II* survey represents the collective opinions of these brokerage clients, and in fact Stickel (1992) reports that brokerage houses base analysts' compensation on their All-Star status. Therefore, we use *II* All-Star designation by brokerages as our measure of analysts' overall job performance.

We examine whether the likelihood of All-Star status varies by gender, after controlling for other factors. We utilize a logistic regression to examine the determinants of All-Star status. In addition to the analyst characteristics in Equation (3), we include a measure of relative forecast accuracy similar to Hong and Kubik (2003). Each quarter for each stock analysts are ranked according to their absolute forecast errors using the following accuracy score:

$$Score_{i,j,t} = 100 - \left[\frac{Rank_{j,t} - 1}{Number\ of\ Analysts_{j,t} - 1} \right] \times 100, \tag{4}$$

where *Rank* equals 1 (2) for the analyst who produces the best (second best) quarterly forecast for firm *j* in quarter *t*, etc., and $Number\ of\ Analysts_{j,t}$ is the number of analysts who cover the firm in quarter *t*. An analyst with a rank of 1 receives a score of 100; the least accurate analyst receives a score of 0. We assign scores only when at least two analysts make earnings forecast for a particular fiscal quarter. Measuring accuracy in this way controls for differences in difficulty in forecasting earnings across firms. We average quarterly accuracy scores across stocks over the last three years as of March each year, and use this as our measure of accuracy $ACCURACY_{i,t}$ for analyst *i* in year *t*. The resulting logistic regression specification is:

$$\begin{aligned} ALLSTAR_{i,t} &= b_0 + b_1 GEXP_{i,t} + b_2 NCOS_{i,t} + b_3 NGIC_{i,t} + \ldots \\ &\quad + b_4 TOP10_{i,t} + b_5 ACCURACY_{i,t} + b_7 GENDER_i . \end{aligned} \tag{5}$$

In addition to a measure of forecast accuracy, we include the analyst characteristics from Equation (3). The link between employer status as a top decile brokerage firm and all-star membership is ambiguous. Analysts who work at large brokerage firms tend to be more visible which could help make them all-stars. On the other hand, large firms tend to attract better analysts in which case they could naturally become all-stars. Thus, Table 8 presents the results with and without *TOP10*.

Unconditionally, the likelihood of being an All-Star for women is 8.78% versus 7.99% for men. The logistic results in Table 8 confirm this disparity. After controlling for experience and accuracy, being a women analyst raises the marginal likelihood of All-Star status by 2.36%. Further controlling for employer status reduces the incremental probability to 1.04%. Expressed in terms of the unconditional likelihood, being a woman raises the chances of being designated as an All-Star by *Institutional Investor* magazine by more than 10 percent.

The fact that women cover fewer stocks and are less accurate at earnings forecasts but are more likely to be designated as All-Stars suggests they perform better at non-quantifiable aspects of performance such as client service. In addition to research reports, analyst attributes surveyed as important by institutional investors include industry knowledge, integrity, responsiveness, management access, communication skills, and management of conflicts of interest (see Johnson, 2005). Some criticize the rankings as having a popularity contest element to them (e.g. Emery and Li, 2005), and to the extent that women are relatively rare it may improve their visibility among clients. However, greater visibility among market participants may have real effects on job performance such as better access to firm management.

4. Conclusions

Women have historically been underrepresented in many high profile and lucrative careers. The reasons for such under representation range from differences in preferences and abilities to gender discrimination. Many employers have instituted affirmative action programs to encourage gender balance in hiring decisions.

This paper examines the gender composition and job performance of sell-side analysts. Our study investigates the relative abilities across gender on various aspects of a sell-side analysts' job and sheds light on whether gender discrimination or affirmative action are evident in on the job performance.

We find women cover roughly one less stock than men, and tend to forecast less accurately on average than their male counterparts. On the other hand, after controlling for experience and accuracy, we find women significantly are more likely to be designated by *Institutional Investor* magazine as members of the All-American Research Team which indicates women may be better at non-quantifiable aspects of job performance such as client service.

Taken together, our analysis supports the view that the low representation of women on Wall Street reflects differences in preferences rather than discrimination by investment banks. While we do find significant differences in performance across gender, the effects tend to be offsetting which indicates neither gender-based discrimination nor affirmative action have a material impact on the quality of women analysts employed by brokerage firms.

While critics often argue that affirmative action programs set lower standard for preferred groups, our findings do not support this view. However, we also find that any affirmative action programs for analysts that are currently in place are not effective in promoting gender balance since the proportion of female analysts have gradually declined over time. To the extent that lower female representation reflects greater demands on their time due to family obligation, improvements in working conditions, such as greater flexibility in work loads and enhanced childcare options, will open the door to greater participation by women. Also, greater emphasis on the qualitative factors of job performance emphasized in the All-Star surveys would enhance gender balance.

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Table 1
Financial Analysts Employed at Investment Brokerage Firms

	All Brokerage Firms			Top Decile Brokerage Firms			Other Firms		
		Percentage			Percentage			Percentage	
	Number	Women	Men	Number	Women	Men	Number	Women	Men
1995	1,857	16.10	83.90	1,013	18.46	81.54	1,012	13.93	86.07
1996	2,137	16.66	83.34	1,197	18.80	81.20	1,133	13.42	86.58
1997	2,560	17.15	82.85	1,463	18.87	81.13	1,357	13.71	86.29
1998	2,896	16.61	83.39	1,706	17.64	82.36	1,454	14.72	85.28
1999	3,107	16.06	83.94	1,853	17.05	82.95	1,593	14.63	85.37
2000	3,159	16.14	83.86	1,927	17.02	82.98	1,540	14.03	85.97
2001	3,350	16.09	83.91	2,075	16.87	83.13	1,607	13.88	86.12
2002	3,160	15.25	84.75	1,941	15.97	84.03	1,486	13.53	86.47
2003	3,154	14.39	85.61	1,898	14.96	85.04	1,468	12.87	87.13
2004	3,230	13.65	86.35	1,989	14.08	85.92	1,476	11.99	88.01
2005	3,289	13.86	86.14	2,029	13.85	86.15	1,488	13.44	86.56
Full Sample	7,946	15.63	84.37	5,051	16.69	83.31	5,136	13.65	86.35
Industry									
Energy	649	12.17	87.83	419	14.08	85.92	399	9.52	90.48
Materials	863	12.05	87.95	482	12.45	87.55	565	9.73	90.27
Industrials	2,018	12.74	87.26	1,170	13.93	86.07	1,177	10.54	89.46
Consumer Discretionary	2,364	18.32	81.68	1,416	19.70	80.30	1,419	15.72	84.28
Consumer Staples	786	22.52	77.48	441	24.94	75.06	446	19.51	80.49
Health Care	1,440	17.29	82.71	791	18.58	81.42	923	15.60	84.40
Financials	1,273	16.26	83.74	783	16.99	83.01	731	13.95	86.05
Information Technology	2,902	12.96	87.04	1,778	13.50	86.50	1,794	10.93	89.07
Telecommunication Services	617	12.48	87.52	409	11.98	88.02	324	10.80	89.20
Utilities	285	16.84	83.16	175	17.14	82.86	156	16.67	83.33

The table reports the average number of analysts and percentages by gender for analysts employed at investment brokerage firms. Number is the number of analysts for which we are able to assign gender. Unasgnd refers to the percentage of I/B/E/S analysts for which we are unable to assign gender. The data is obtained from I/B/E/S and *Nelson's Directory of Investment Research*. Industries are classified using Global Industry Classification Standards (GIGS). Top Decile Brokerage Firms refers to firms that employ the most analysts.

Table 2
Gender and Job Performance: Stock Coverage and Forecast Frequency

	Average Number of Stocks Followed by Analysts						Frequency of Forecast Revisions					
	All Brokers		Top Brokers		Other Brokers		All Brokers		Top Brokers		Other Brokers	
	Women	Men	Women	Men	Women	Men	Women	Men	Women	Men	Women	Men
1995	10.54	11.84	11.18	12.43	7.98	9.77	1.34	1.34	1.32	1.34	1.31	1.30
1996	9.80	11.50	10.27	12.33	8.03	9.00	1.33	1.33	1.33	1.35	1.30	1.26
1997	8.78	11.08	9.63	11.76	6.72	8.71	1.31	1.31	1.31	1.31	1.25	1.26
1998	9.10	10.60	10.05	11.36	6.57	8.10	1.37	1.38	1.38	1.40	1.30	1.31
1999	9.16	10.58	10.19	11.52	6.42	7.87	1.35	1.37	1.35	1.36	1.27	1.31
2000	9.08	9.90	9.98	10.76	6.82	7.38	1.34	1.36	1.35	1.34	1.27	1.33
2001	8.54	9.54	8.94	10.09	6.83	7.35	1.46	1.48	1.49	1.48	1.35	1.40
2002	8.44	9.74	8.98	10.48	6.70	7.42	1.43	1.42	1.45	1.41	1.35	1.36
2003	8.57	9.80	8.91	10.69	7.47	7.60	1.50	1.47	1.54	1.47	1.38	1.40
2004	8.85	10.20	9.56	11.32	7.02	7.42	1.56	1.49	1.60	1.50	1.43	1.42
2005	9.08	10.49	9.70	11.46	7.43	7.99	1.51	1.47	1.52	1.45	1.43	1.45
Yearly Average	9.09	10.48	9.76	11.29	7.09	8.06	1.41	1.40	1.42	1.40	1.33	1.34
Career Average	12.69	16.23	13.20	16.47	9.21	11.51	1.42	1.41	1.43	1.41	1.34	1.35

The table reports the average number of stocks covered by analysts and the frequency of forecast revisions by gender for analysts employed at investment brokerage firms. The data is obtained from I/B/E/S and *Nelson's Directory of Investment Research*. Industries are classified using Global Industry Classification Standards (GIGS). Top Brokers refers to the top decile brokerage firms that employ the most analysts. Yearly Average designates the average across years. Career Average is the average number of stocks an analyst follows throughout the sample period.

Table 3
Gender and Employment Longevity for Financial Analysts at Brokerage Firms

	Number of New Analysts		Percentage that Leave within 1 year		Percentage that Leave within 2 years		Percentage that Leave within 3 years		Average Tenure	
	Women	Men	Women	Men	Women	Men	Women	Men	Women	Men
1995	116	570	21.55	18.25	37.07	42.63	62.07	60.18	3.08	3.07
1996	132	717	23.48	19.11	49.24	46.44	71.21	64.30	2.76	2.95
1997	194	984	24.23	22.76	48.97	41.46	63.92	62.80	2.85	2.97
1998	212	1,090	25.00	25.96	56.13	48.72	70.75	67.98	2.63	2.79
1999	208	1,108	27.40	27.80	53.85	54.60	73.56	69.95	2.63	2.67
2000	195	1,082	23.08	26.71	54.87	53.14	70.77	68.58	2.73	2.73
2001	228	1,320	32.46	32.65	64.04	60.30	75.88	73.71	2.45	2.53
2002	189	1,046	33.33	29.73	57.67	54.21	69.31	68.83	.	.
2003	204	1,229	32.84	28.97	52.45	49.63	72.06	66.23	.	.
2004	162	1,146	25.31	21.29	57.41	49.39	.	.	.	.
2005	166	940	32.53	27.98	.	.	.	.	.	.
Full Sample	2,006	11,232	27.77	26.26	54.13	50.86	70.44	67.65	2.70	2.78

The table reports measures of employment longevity for brokerage firm equity analysts. The data is obtained from I/B/E/S and *Nelson's Directory of Investment Research*. Entry and exit into the employment position is measured by the starting and stopping of forecasting earnings. Average tenure is truncated at 5 years.

Table 4
Gender and Bias in Earnings Forecasts

	All Firms				Small Stocks				Large Stocks			
Days Relative	No. of	Forecast Bias			No. of	Forecast Bias			No. of	Forecast Bias		
to Earnings Date	Forecasts	Women	Men	p-value	Forecasts	Women	Men	p-value	Forecasts	Women	Men	p-value
-30 to -26	38,143	0.67	1.24	0.22	13,537	2.02	2.57	0.54	22,592	-0.44	0.16	0.25
-25 to -21	49,407	-0.07	0.92	0.01	16,736	0.23	2.27	0.01	30,247	-0.79	-0.09	0.09
-20 to -16	54,098	-0.93	-0.62	0.37	18,738	-0.59	0.52	0.12	32,427	-1.20	-1.58	0.32
-15 to -11	58,771	-1.66	-1.38	0.39	19,575	-1.74	-0.76	0.14	35,520	-2.26	-2.31	0.90
-10 to -6	59,563	-2.42	-2.07	0.23	19,228	-2.28	-1.73	0.38	36,289	-2.72	-2.83	0.72
-5 to -1	49,180	-2.05	-2.15	0.75	14,621	-2.42	-2.59	0.83	28,794	-3.08	-2.68	0.22
0	39,306	1.94	2.14	0.68	14,131	3.96	3.97	0.99	23,103	0.83	0.72	0.83
1	228,938	1.25	0.99	0.21	82,769	2.87	2.45	0.33	137,789	0.12	-0.15	0.21
2 to 6	191,202	2.89	3.39	0.04	82,867	4.11	4.45	0.45	98,217	1.19	1.96	0.01
7 to 11	49,727	2.75	3.83	0.03	21,815	4.83	5.08	0.79	24,515	0.45	2.01	0.00
12 to 6	41,282	2.60	4.23	0.00	16,973	4.53	5.95	0.13	21,576	1.21	2.32	0.06
17 to 21	40,954	2.90	3.60	0.19	16,345	5.56	5.29	0.78	21,943	1.27	1.91	0.29
22 to 26	42,913	2.46	3.29	0.10	16,530	4.95	4.25	0.47	23,602	0.50	2.20	0.00
27 to 32	56,324	1.76	3.03	0.00	20,940	2.45	4.55	0.01	31,741	0.96	1.69	0.13
All Except Day 0	960,502	1.00	1.51	<.0001	360,674	2.37	2.88	0.01	545,252	-0.23	0.20	<.0001
All Except Day 0, 1	731,564	0.92	1.68	<.0001	277,905	2.22	3.01	0.00	407,463	-0.34	0.32	<.0001

The table reports a measure of forecast optimism in the earnings forecasts of brokerage firm analysts. Forecast bias is measured as (Forecast – EPS)/EPS, where Forecast is the one-quarter ahead quarterly earnings forecast and EPS is the realized earnings per share. p-values reflect t-tests for difference in means and are rounded to two digits. Stocks are partitioned using the median size among NYSE stocks. The analyst data is from I/B/E/S and *Nelson's Directory of Investment Research*.

Table 5
Characteristics of Analyst Earnings Forecasts

	Matched Sample					Full Sample		
	Number of Analysts		Number of Forecasts		Stock	Number of Forecasts		Stock
	Women	Men	Women	Men	Size	Women	Men	Size
1995	230	787	3,306	4,296	6.81	20,832	132,662	3.97
1996	264	912	3,987	5,824	6.55	22,801	143,539	3.91
1997	323	1,076	5,118	8,085	6.39	24,884	167,550	3.76
1998	388	1,483	9,252	16,158	5.91	32,997	209,671	3.73
1999	397	1,689	11,666	22,335	6.17	33,520	224,909	4.05
2000	420	1,830	13,230	28,782	6.44	32,272	198,441	4.50
2001	459	1,965	19,733	45,412	6.00	41,798	263,947	4.20
2002	404	1,904	18,660	47,023	5.81	37,607	257,614	4.07
2003	358	1,834	18,534	47,872	5.77	39,973	281,775	4.04
2004	352	1,856	21,473	58,416	5.54	42,642	326,744	3.89
2005	363	1,813	22,499	61,484	5.36	45,715	349,322	3.73
Full Sample	1,084	4,454	147,458	345,687	4.97	375,041	2,556,174	3.43

The table reports characteristics of brokerage firm analyst earnings forecasts. In the Matched Sample, forecasts of quarterly earnings from women analysts are matched with forecasts from men analysts for the same stock on the same day. Stock size is the average size decile based on NYSE breakpoints. The analyst data is from I/B/E/S and *Nelson's Directory of Investment Research*.

Table 6
Gender and Earnings Forecast Errors

Panel A: All Horizons	All Days	Earnings Date	Not Earnings Date
Number of Observations	108,220	51,643	56,577
Relative Forecast Error	0.11	0.03	0.19
p-value	0.01	0.63	0.00
Panel B: Fiscal Quarters			
One quarter ahead			
Number of Observations	44,622	19,631	24,991
Relative Forecast Error	0.04	-0.05	0.11
p-value	0.51	0.57	0.22
Two quarters ahead			
Number of Observations	27,975	13,653	14,322
Relative Forecast Error	0.25	0.12	0.37
p-value	0.00	0.29	0.00
Three quarters ahead			
Number of Observations	20,909	10,628	10,281
Relative Forecast Error	0.18	0.03	0.33
p-value	0.07	0.80	0.03
Four quarters ahead			
Number of Observations	14,714	7,731	6,983
Relative Forecast Error	-0.04	0.05	-0.13
p-value	0.76	0.74	0.49

The table reports the difference between the earnings forecast errors for women and men brokerage analysts. Forecasts are matched across gender by stock and day and absolute errors are measured as |(Forecast – EPS)/EPS|, where EPS is the realized earnings per share. Earnings Date indicates days 0 and 1 following earnings announcement dates. Panel A reports the results for all quarterly forecast horizons, and Panel B partitions the results by forecast quarter. t-test p-values are rounded ton two digits. The analyst data is from I/B/E/S and *Nelson's Directory of Investment Research*, and covers 1995-2005.

Table 7
Characteristics of Earnings Forecast Errors

	All Horizons		1 quarter ahead		2 quarter ahead		3 quarter ahead		4 quarter ahead	
Variable	Estimate	p-value	Estimate	p-value	Estimate	p-value	Estimate	p-value	Estimate	p-value
Panel A: Full Sample										
Intercept	-3.34	0.00	-5.46	0.00	-2.62	0.00	-1.91	0.00	-1.60	0.00
AGE	0.55	0.00	0.89	0.00	0.45	0.00	0.30	0.00	0.23	0.00
GEXP	0.03	0.01	0.03	0.12	0.06	0.00	0.00	0.99	-0.02	0.28
FEXP	-0.13	0.00	-0.26	0.00	-0.09	0.00	-0.04	0.19	0.06	0.08
NCOS	0.05	0.00	0.09	0.00	0.03	0.01	0.02	0.03	0.03	0.02
NGIC	0.34	0.00	0.50	0.00	0.37	0.00	0.27	0.01	-0.02	0.84
TOP-BRK	-2.38	0.00	-3.73	0.00	-2.18	0.00	-1.67	0.00	-1.30	0.00
ALL-STAR	-0.41	0.00	-0.49	0.01	-0.51	0.02	0.12	0.60	-0.57	0.03
GENDER	0.49	0.00	0.23	0.24	0.93	0.00	0.52	0.02	0.49	0.04
N	2,669,152		970,980		696,114		561,348		440,710	
Adj R-Sq	0.04		0.08		0.03		0.01		0.01	
Panel B: Matched Sample										
Intercept	-10.43	0.00	-16.22	0.00	-7.10	0.00	-4.59	0.00	-3.86	0.00
AGE	1.03	0.00	1.55	0.00	0.74	0.00	0.48	0.00	0.37	0.00
GEXP	0.02	0.29	0.01	0.72	0.07	0.08	0.02	0.68	-0.02	0.73
FEXP	-0.05	0.15	-0.12	0.03	-0.06	0.31	0.07	0.32	0.08	0.33
NCOS	0.06	0.00	0.08	0.00	0.04	0.08	0.02	0.44	0.05	0.14
NGIC	0.11	0.41	0.19	0.36	-0.06	0.80	0.27	0.31	-0.10	0.74
TOP-BRK	-2.25	0.00	-3.44	0.00	-2.00	0.00	-1.20	0.00	-1.10	0.01
ALL-STAR	-0.74	0.00	-0.81	0.04	-1.42	0.00	-0.43	0.40	-0.26	0.67
GENDER	1.45	0.00	1.81	0.00	1.77	0.00	0.81	0.02	0.43	0.29
N	460,598		192,467		118,937		87,069		62,125	
Adj R-Sq	0.08		0.16		0.05		0.02		0.01	

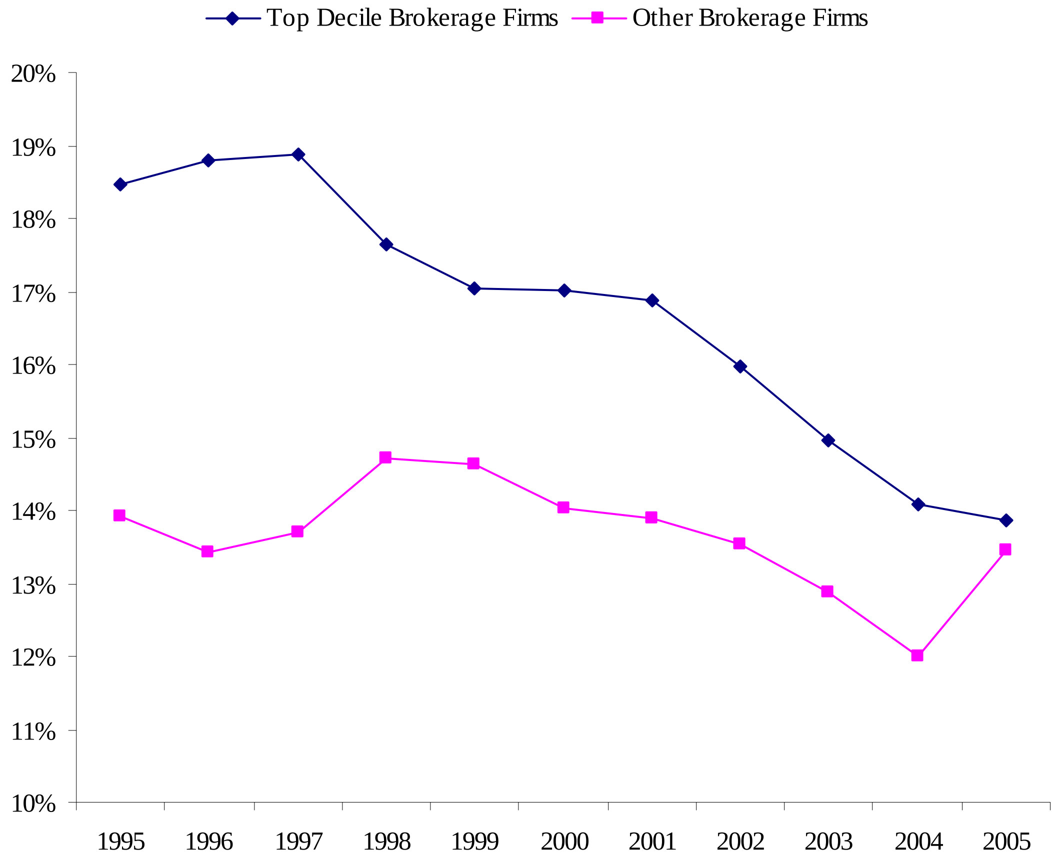
Absolute forecast errors, measured as |(Forecast – EPS)/EPS|, are regressed on forecast characteristics. In the Matched Sample forecasts are matched across gender by stock and day. AGE is a measure of staleness for the forecast, GEXP and FEXP is the number of years the analyst has issued forecasts (forecasts for the stock in question), NCOS and NGICS are the number of companies and industries followed by the analyst. TOP-BRK is 1 if the analyst works at a top decile brokerage firm by number of analysts, and ALL-STAR is 1 if the analyst is designated as an All-Star by *Institutional Investor* magazine, and GENDER is 1 if the analyst is a woman. p-values are rounded to two digits. The analyst forecast data is from I/B/E/S and *Nelson's Directory of Investment Research*, and covers 1995-2005.

Table 8
Gender and All-Star Designation Among Brokerage Analysts

Variable	Estimate	p-value	Marginal Effects (%)	Estimate	p-value	Marginal Effects (%)
Intercept	-4.34	0.00		-6.66	0.00	
GEXP	0.11	0.00	0.82	0.11	0.00	0.47
NCOS	0.06	0.00	0.46	0.06	0.00	0.24
NGIC	-0.29	0.00	-2.12	-0.17	0.00	-0.72
ACCURACY	0.02	0.00	0.13	0.01	0.00	0.06
GENDER	0.29	0.02	2.36	0.23	0.05	1.04
TOP-BRK	.	.	.	2.85	0.00	11.79
N	28,157			25,211		
Pseudo R2	0.095			0.193		

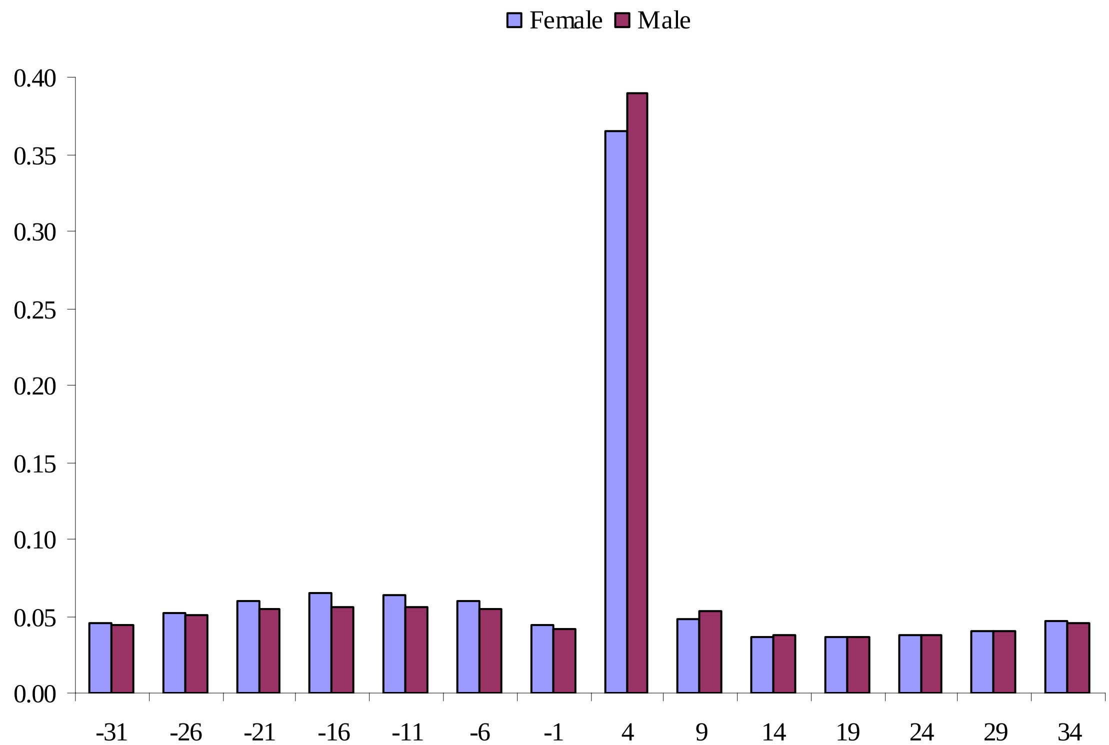
The table reports the results of logistic regressions of All-Star status on analyst characteristics. All-Star status reflects membership in *Institutional Investor* magazine's All-American Research Team. GEXP is the number of years experience the analyst has at issuing forecasts. NCOS and NGICS are the number of companies and industries followed by the analyst. TOP-BRK is 1 if the analyst works at a top decile brokerage firm by number of analysts. ACCURACY is the average forecast accuracy rank across analysts for the stocks the analyst covers. GENDER is 1 if the analyst is a woman. Standard errors are clustered by analysts and the resulting p-values are reported next to each coefficient. The analyst data is from I/B/E/S and *Nelson's Directory of Investment Research*. The sample period covers 1995-2005.

Figure 1
Evolution of Women's Employment as Financial Analysts at Investment Brokerage Firms



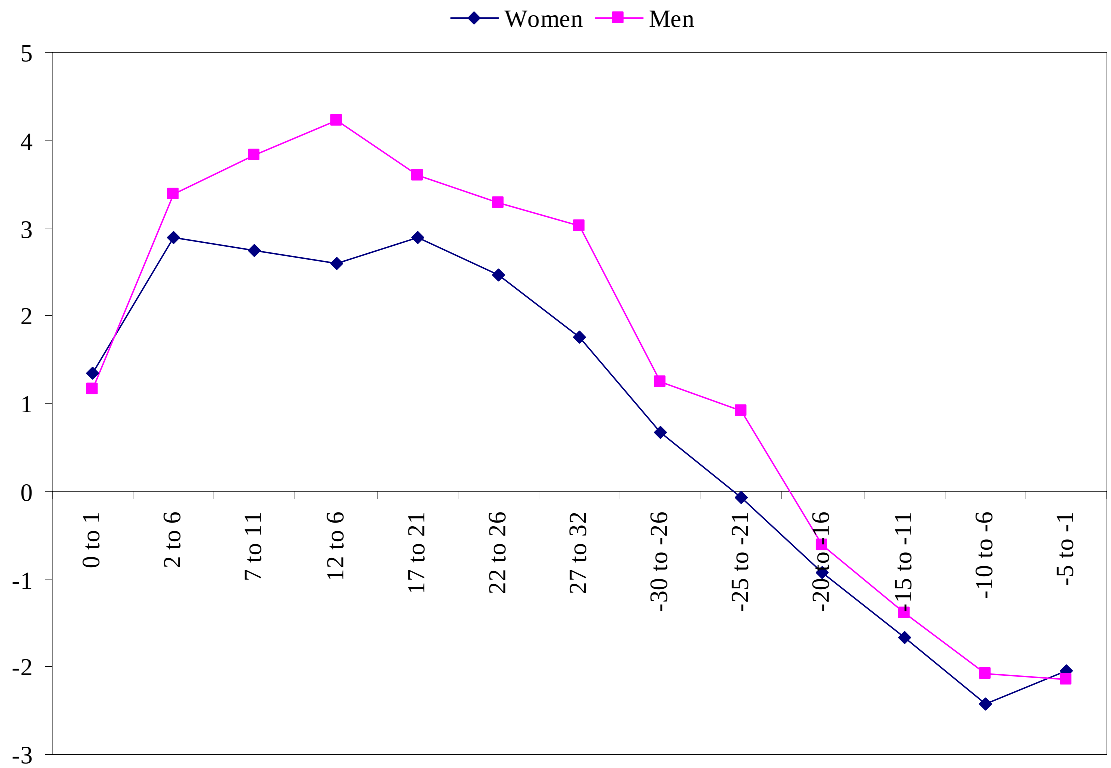
The chart plots the average percentage of women employed as financial analysts at investment brokerage firms. The data is obtained from I/B/E/S and *Nelson's Directory of Investment Research*. Top Decile Brokerage Firms refers to firms which employ the most analysts.

Figure 2
Distribution of Earnings Forecasts by Gender Relative to the Announcement Date



The chart plots the distribution of earnings forecasts around announcement dates (day 0). The data is from I/B/E/S and the sample period covers 1995 through 2005.

Figure 3
Gender and Forecast Error throughout the Fiscal Quarter



The chart shows optimism in the earnings forecasts of brokerage firm analysts. Forecast bias is measured as (Forecast – EPS)/EPS, where Forecast is the one-quarter ahead quarterly earnings forecast and EPS is the realized earnings per share. The analyst data is from I/B/E/S and *Nelson's Directory of Investment Research* and covers 1995-2005.