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Gender and Job Performance: Evidence from Wall Street

Clifton Green, Narasimhan Jegadeesh, and Yue Tang

This study concerns the relationship between gender and job performance among brokerage firm equity analysts. Women's representation in analyst positions dropped from 16 percent in 1995 to 14 percent in 2005. The study found significant gender-based differences in performance on various dimensions. For example, women cover roughly 9 stocks, on average, as compared with 10 for men, and women's earnings estimates tend to be less accurate than men's estimates. But the study also found that women are significantly more likely than men to be designated as All-Stars, which indicates that they outperform men in other aspects of job performance.

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 has emphasized occupational self-selection attributable to preferences or differences in abilities (Polachek 1981; Pitts 2003). Other researchers have focused on discrimination in the workplace. Although evidence of gender-based discrimination has been documented in certain fields (Ashenfelter and Hannan 1986; Neumark 1996; Goldin and Rouse 2000), employers' attempts to offset bias through targeted hiring strategies raise concerns about reverse discrimination. Does the low representation of women in many high-paying jobs reflect a lower "natural rate" attributable to preferences, or is it indicative of discrimination? Given the prevalence of affirmative action, do some employers practice reverse discrimination to attract more female applicants?

Sell-side analyst positions pay well: A 2005 survey found that the median compensation for security analysts was more than $182,000, well above the annual U.S. per capita income.[1] As with many jobs on Wall Street, a vast majority of analysts are men, and women are often alleged to face gender discrimination in such high-profile, well-paying jobs. For instance, a 1996 class-action lawsuit against Merrill Lynch contained more than 900 complaints, which represented roughly one-third of the female brokers who worked at the firm during the previous five years (Knox 2000).[2] Concerns about potential discrimination have led many investment banks and other employers to institute hiring programs that promote diversity. For example, a 2001 survey of investment banks reported that about one-third of large investment banks tie their reward systems to diversity initiatives. An even greater proportion of such banks also specify numerical objectives for affirmative action recruiting.[3]

Perhaps surprisingly, as issues of gender discrimination and affirmative action have attracted considerable attention over time, the proportion of female stock analysts has declined, from around 16 percent in 1995 to 14 percent in 2005. In our study, we set out to determine whether growing discrimination contributed to this decline. We also attempted to determine whether employers' efforts to achieve gender balance in the workforce compromise the effectiveness of that workforce.

Gender discrimination means that when faced with a choice between equally qualified women and men, employers prefer to hire men. On the one hand, if gender discrimination affects hiring decisions, one would expect that a higher hurdle is set for women than for men (Olson and Becker 1983; Jones and Makepeace 1996; Winter-Ebmer and Zweimuller 1997) and thus that women who are able to clear that hurdle would, on average, do a better job 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 in order to promote gender balance (Glazer 1975; Epstein 1992; Coate and Loury 1993); if affirmative-action-based hiring is prevalent, women would, on average, perform worse than men.

Clifton Green is associate professor of finance, Narasimhan Jegadeesh is Dean's Distinguished Professor of Finance, and Yue Tang is a doctoral candidate at Emory University, Atlanta.

In our study, we analyzed the relationship between gender and job performance of sell-side analysts and looked for prima facie evidence of gender discrimination or evidence that employers lower their hiring standards to promote affirmative action. Other researchers (see, e.g., Leonard 1984; Hellerstein, Neumark, and Troske 1999; Holzer and Neumark 1999) have investigated productivity differences among various groups of employees. Our sample and methodology, however, differ from those of earlier researchers. To estimate productivity, Leonard (1984) used aggregate data for manufacturing workers. As Holzer and Neumark (1999) pointed out, "The usefulness of this approach is limited by the highly aggregated nature of the data and its focus only on manufacturing." In subsequent studies, Hellerstein et al. (1999) and Holzer and Neumark (1999) used data from their surveys of persons responsible for hiring noncollege workers in four metropolitan areas.

We examined relative gender-based performance in a comprehensive sample of highly paid sell-side analysts who are unique in that key aspects of their job performance can be publicly observed and evaluated. We used the following measures of job performance: number of stocks that analysts follow, accuracy of analysts' earnings forecasts, frequency of forecast revisions, and professional reputation (as measured by the coveted All-America Research Team designation in *Institutional Investor* magazine).[4]

Data and Descriptive Statistics

We compiled our data from several sources. We obtained data on sell-side analysts' earnings forecasts for 1995–2005 from I/B/E/S. The I/B/E/S files provide data on the security's identity, the analyst's identity, the analyst's brokerage house, the earnings forecast, the forecast period, and the forecast date. We focused on quarterly earnings forecasts. The names of analysts in the I/B/E/S Broker Translation File are listed by last name and first initial. We matched the analyst 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 names and contact information.

We determined gender by using the U.S. Social Security Administration's database on baby names.[5] Of the 10,996 unique analyst names in the I/B/E/S database for the 1995–2005 sample period, we were able to match 9,096 analysts with information from *Nelson's Directory of Investment Research*. We lost 247 observations because of duplicate last names and first initials (e.g., J. Smith in I/B/E/S could be matched with either Jennifer Smith or John Smith in *Nelson's Directory*). We lost an additional 130 observations because of such gender-ambiguous first names as Tracy. Finally, for 773 observations, we matched names but were unable to determine gender because the first names did not match any of the first names from our data sources.

Table 1 presents descriptive statistics for our resulting sample of 7,946 brokerage firm analysts. Analysts entered the sample in a given year if they made at least one quarterly earnings forecast in that year. Using our matching procedure, we were able to assign gender to more than 70 percent of the full I/B/E/S sample. When data on first names were available from *Nelson's Directory*, we were able to assign gender to more than 90 percent of the full sample.

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

Table 1 also presents the gender composition of analysts in the top 10 and other brokerages. We ranked brokerages on the basis of the number of analysts affiliated with each brokerage in the I/B/E/S database each year, and the top 10 brokerages have the most analysts. We found that women compose 19.8 percent of analyst positions at top 10 brokerages, as compared with 14.02 percent at other brokerages. The higher representation of women at large investment banks may reflect a greater emphasis on diversity.[7] As noted earlier, large investment banks are more likely than small firms to tie their reward systems to diversity initiatives. Large firms may also provide better working conditions. For example, several large investment banks currently appear on *Working Mother* magazine's list of best companies on the basis of such criteria as flexible work arrangements and parent/childcare support. Evidence on job performance at top firms can help determine whether the higher representation of women is attributable to the firms' providing better working conditions or is simply a result of affirmative action hiring.

Table 1 also shows the proportion of women among analysts who cover various sectors. We used the first two digits of the Global Industry Classification Standard (GICS) codes to classify

Table 1. Financial Analysts Employed by Investment Brokerage Firms, 1995–2005

	All Brokerages			Top 10 Brokerages			Other Brokerages		
	Number	Women (%)	Men (%)	Number	Women (%)	Men (%)	Number	Women (%)	Men (%)
1995	1,857	16.10	83.90	566	20.67	79.33	1,419	14.45	85.55
1996	2,137	16.66	83.34	650	21.54	78.46	1,652	14.53	85.47
1997	2,560	17.15	82.85	755	22.25	77.75	1,987	15.05	84.95
1998	2,896	16.61	83.39	821	20.83	79.17	2,302	15.03	84.97
1999	3,107	16.06	83.94	968	19.52	80.48	2,467	14.96	85.04
2000	3,159	16.14	83.86	1,065	19.72	80.28	2,434	14.59	85.42
2001	3,350	16.09	83.91	1,149	20.97	79.03	2,517	13.83	86.17
2002	3,160	15.25	84.75	984	20.02	79.98	2,464	13.51	86.49
2003	3,154	14.39	85.61	916	17.58	82.42	2,522	13.05	86.95
2004	3,230	13.65	86.35	793	17.91	82.09	2,652	12.37	87.63
2005	3,289	13.86	86.14	778	16.84	83.16	2,729	12.86	87.14
Full sample	7,946	15.63	84.37	2,715	19.80	80.20	6,966	14.02	85.98
Industry									
Energy	729	12.89	87.11	279	15.77	84.23	610	10.82	89.18
Materials	920	11.63	88.37	318	13.84	86.16	778	10.54	89.46
Industrials	2,141	12.75	87.25	640	18.13	81.88	1,786	11.03	88.97
Consumer discretionary	2,564	18.02	81.98	844	22.63	77.37	2,134	16.64	83.36
Consumer staples	830	22.65	77.35	271	29.89	70.11	678	20.35	79.65
Health care	1,564	16.94	83.06	418	19.38	80.62	1,361	15.94	84.06
Financials	1,381	15.71	84.29	424	21.46	78.54	1,157	14.26	85.74
Information technology	2,989	13.08	86.92	865	16.76	83.24	2,577	11.84	88.16
Telecommunication services	702	10.83	89.17	257	12.84	87.16	554	10.29	89.71
Utilities	315	16.83	83.17	113	19.47	80.53	257	13.62	86.38

Notes: This table reports the average number of analysts and percentages by gender for analysts employed by investment brokerage firms. "Number" is the number of analysts for whom we were able to assign gender; we excluded analysts for whom we were unable to assign gender on the basis of their first names. Because some analysts move from one category of brokerage to another within any given year, the number of analysts in "All Brokerages" is not the sum of the numbers in other categories.

firms into 10 economic sectors. At the industry level, women's representation is highest among analysts who follow companies in consumer staples (22.65 percent) and consumer discretionary (18.02 percent). A high representation in consumer-oriented industries may be expected if those industries emphasize sales to women. Female analysts are less likely than their male counterparts to cover companies in the materials (11.63 percent) and energy (12.89 percent) industries, which cater more to the industrial market than to the consumer market. Differences in gender representation among industry groups may reflect differences in preferences, or they may be a manifestation of stereotypes that women have more expertise in some industries than in others.

Gender and Job Performance among Sell-Side Analysts

Sell-side analysts provide research and professional advice to clients. We measured performance on the research side by examining the number of stocks that analysts follow, how frequently they revise their earnings forecasts, and the accuracy of those forecasts up to four quarters ahead. The number of stocks that analysts follow represents their workload. The frequency of forecast revisions measures how closely analysts follow the stocks that they cover.

Other aspects of the analyst's job (e.g., keeping clients informed of industry- and company-specific developments and arranging meetings between investors and company management) are highly valued by clients but are hard to quantify. We captured these aspects of analyst performance by using *Institutional Investor*'s All-America Research Team rankings. *Institutional Investor* conducts an annual comprehensive survey of thousands of portfolio managers, who are the most important brokerage customers, about the quality of service that analysts provide and publishes an annual list of All-Star analysts. We used the All-Star designation as a composite measure of analyst performance regarding the hard-to-quantify but important aspects of the job.

Analyst Coverage and Employment Longevity. We began by looking at the number of stocks each analyst covers. We calculated the number of stocks for which an analyst provides at least one one-to-four-quarters-ahead forecast in a particular calendar year as the analyst's workload. **Table 2** reports, by gender, the average number of stocks that analysts cover each calendar year. Women cover fewer stocks than do men in each year—8.65, on average, as compared with 9.92 for men. Over time, analysts sometimes change the stocks they cover. The average number of stocks that women cover over their careers is 11.70, as compared with 14.75 for men. Thus, women appear less likely than men to cover new stocks.

Table 2 shows that analysts at top 10 brokerages tend to cover more stocks than do analysts at smaller brokerages. At both large and small brokerages, women cover fewer stocks than men do, on average. Therefore, although women are more likely than men to work at large brokerages, the gender-based differences in stock coverage are not explained by differences in employer size. Perhaps women voluntarily choose a lighter workload, which Becker (1985) argued is rational if women face greater demands on their time away from work. These aspects of job performance indicate that employers do not discriminate against women by overloading them with work.

Table 2 also reports frequency of revisions for one-quarter-ahead forecasts within fiscal quarters. Here, the gender-based differences 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 gender-based differences in forecast activity.

We also examined the timing of forecasts. Analysts use a variety of information to update their earnings estimates. Ivković and Jegadeesh (2004) noted that forecast revisions made immediately after earnings announcements tend to reflect analysts' interpretations of the earnings and other financial information that companies release, whereas forecast revisions at other times reflect information about companies that analysts gather independently. The empirical evidence in Ivković and Jegadeesh (2004) indicates that the information that analysts gather on their own is more useful to market participants than analysts' interpretations of publicly available information.

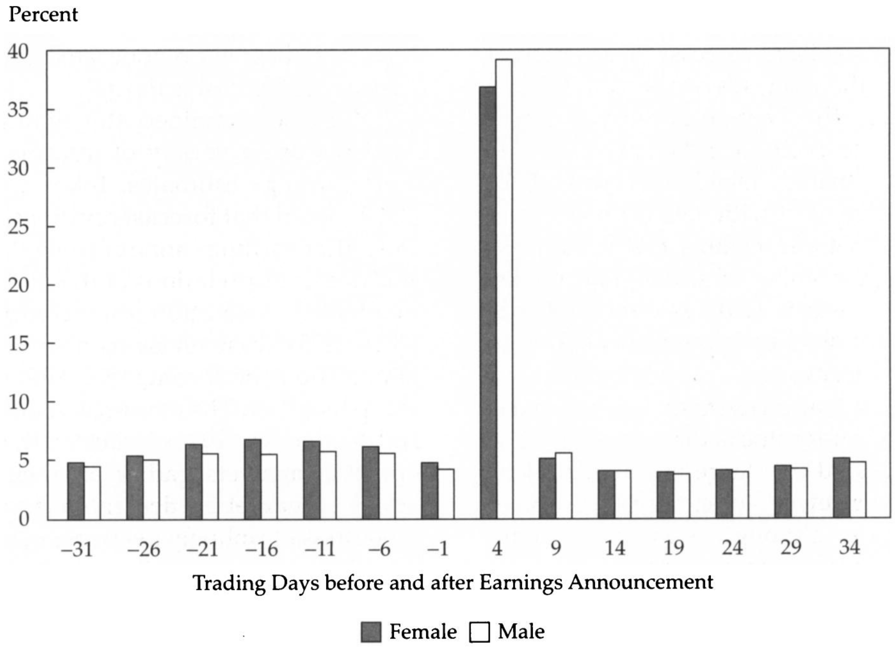
Figure 1 presents the distribution of forecast revisions around earnings announcement dates. Consistent with Stickel (1992) and Ivković and Jegadeesh (2004), we found that forecast revisions by both women and men are concentrated in the week after the earnings announcement. Figure 1, however, shows that women are slightly more likely than men to issue forecasts in the weeks leading up to the announcement, which suggests that women are more likely than men to rely on their independent research in revising their forecasts.

Table 2. Gender and Job Performance: Stock Coverage and Forecast Frequency, 1995–2005

	Average Number of Stocks Followed by Analysts						Frequency of Forecast Revisions					
	All Brokerages		Top 10 Brokerages		Other Brokerages		All Brokerages		Top 10 Brokerages		Other Brokerages	
	Women	Men	Women	Men	Women	Men	Women	Men	Women	Men	Women	Men
1995	10.00	11.28	11.64	12.25	9.06	10.92	1.34	1.34	1.28	1.32	1.33	1.32
1996	9.43	10.89	10.61	12.10	8.74	10.45	1.33	1.33	1.29	1.33	1.30	1.30
1997	8.50	10.55	9.92	11.79	7.71	10.12	1.31	1.31	1.28	1.29	1.27	1.29
1998	8.76	10.08	9.91	11.36	8.20	9.66	1.37	1.38	1.34	1.37	1.34	1.35
1999	8.66	10.04	9.74	11.01	8.11	9.67	1.35	1.37	1.34	1.34	1.29	1.33
2000	8.59	9.27	9.42	10.04	8.10	8.96	1.34	1.36	1.35	1.35	1.28	1.31
2001	7.97	8.95	8.41	9.92	7.66	8.54	1.46	1.48	1.45	1.45	1.41	1.44
2002	7.83	9.13	8.52	9.76	7.41	8.89	1.43	1.42	1.39	1.37	1.41	1.40
2003	8.14	9.22	8.78	10.22	7.83	8.88	1.50	1.47	1.44	1.43	1.48	1.43
2004	8.53	9.74	9.34	10.57	8.18	9.51	1.56	1.49	1.50	1.46	1.55	1.47
2005	8.72	10.01	9.30	10.22	8.50	9.95	1.51	1.47	1.48	1.42	1.49	1.45
Yearly average	8.65	9.92	9.60	10.84	8.14	9.60	1.41	1.40	1.38	1.38	1.38	1.37
Career average	11.70	14.75	12.48	14.68	11.31	14.78	1.42	1.41	1.38	1.38	1.39	1.38

Notes: This table reports, by gender, the average number of stocks that analysts cover and the frequency of forecast revisions for analysts employed at investment brokerage firms. The yearly average is the average calculated across the 11 years (i.e., at a given point in time); the career average is the mean of the total number of stocks covered by analysts throughout their careers.

Figure 1. Distribution, by Gender, of Earnings Forecasts around Announcement Dates, 1995–2005



Note: This figure depicts the distribution of earnings forecasts around announcement dates (Day 0).

Another important aspect of job performance is employment longevity. Investment banks expend considerable resources to develop and support equity analysts and would prefer to amortize those costs over long horizons. **Table 3** reports measures of employment longevity for new analysts who begin forecasting in a given calendar year. The table shows the likelihood of analysts' leaving their jobs (i.e., stopping forecasting) within one, two, and three years. The differences in longevity are relatively small. Women are 1.5 percentage points more likely than men to leave work within one year, 3.3 percentage points more likely to leave within two years, and 2.8 percentage points more likely to leave within three years. With respect to average tenure, new female analysts stay in their jobs about one month less than their male counterparts. We truncated the employment horizon at five years because of the relatively short sample period, which could underestimate differences in average tenure.[8]

Table 3. Gender and Employment Longevity: Financial Analysts at Brokerage Firms, 1995–2005

	Number of New Analysts		Percentage Who Leave within 1 Year		Percentage Who Leave within 2 Years		Percentage Who Leave within 3 Years		Average Tenure (years)	
	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

Notes: This table reports measures of employment longevity for brokerage firm equity analysts. Entry into and exit from the analyst position is measured by the starting and stopping of forecasting earnings.

Forecast Accuracy. Forecast accuracy is an important measure of equity analysts' job performance. Investors value earnings forecasts, which are a key component of analyst research, and forecast accuracy is an important basis for media recognition. Previous research (see, e.g., Richardson, Teoh, and Wysocki 2004) has documented initially optimistic earnings forecasts that were gradually "walked down" throughout the fiscal period to a level that the company could beat. One explanation for this initial optimism bias is that analysts tend to be overconfident about the stocks they follow and thus overestimate future earnings. Another explanation is that analysts deliberately produce optimistic forecasts to generate interest in the stock, which stimulates trading and leads to brokerage commissions.

As the earnings announcement date approaches, analysts tend to moderate their optimistic forecasts gradually, which results in mildly pessimistic forecasts on the date of the announcement. Previous research has argued that the phenomenon of beatable earnings targets is a result of guidance from company management. Skinner and Sloan (2002) reported that the stock price response to disappointing earnings is greater than the response to a positive earnings surprise. They argued that this asymmetric stock price reaction gives company managers an incentive to walk down their earnings guidance during the quarter—guidance that analysts typically follow. Cotter, Tuna, and Wysocki (2006) found empirical evidence that analysts follow management's earnings guidance, and Hutton (2005) showed that analyst forecasts that are guided by company management are more accurate but tend to be more frequently pessimistic than other forecasts.

We examined whether the optimism/pessimism bias has gender-based differences. We measured forecast error as follows:

$$Forecast\ error_{i,j,t} = \frac{\left(Forecast_{i,j,t} - EPS_{j,t}\right)}{\left|EPS_{j,t}\right|}, \quad (1)$$

where $Forecast_{i,j,t}$ is the forecast from analyst i for stock j on day t and $EPS_{j,t}$ is the corresponding realized quarterly earnings per share. A positive forecast error indicates that the forecast was optimistic, and a negative bias implies a pessimistic forecast. We excluded from our analysis observations whose absolute EPS value is less than five cents, and we winsorized forecast errors at plus or minus 100 percent.

Table 4 presents the results for forecasts at various times around earnings announcement dates. 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 percent for women and 1.7 percent for men. Both women and men exhibit optimism bias, but women's forecasts contain significantly smaller optimism bias than do men's forecasts.

Figure 2 plots the average forecast errors in event time around earnings announcement dates. It shows that women's forecasts contain smaller optimism bias than do men's forecasts throughout each fiscal quarter. These gender-based differences in optimism bias could indicate less overconfidence among women or a greater desire among men to please the management of the companies they cover.

To examine optimism bias further, we partitioned the sample into pre- and post-Global Settlement Agreement (GSA) periods. Reached during the fourth quarter of 2002, the GSA stipulated the separation of research and investment banking divisions at 10 leading brokerages. Because analysts did not play a significant role in attracting investment banking business in the post-GSA period, they had less of an incentive to please company managers and thus less of an incentive for an optimism bias.

In unreported results, we found no optimism bias in earnings forecasts from 2003 to 2005. Moreover, we found no difference in the average forecast bias between genders. These findings indicate that the observed difference in forecast bias between genders is largely a result of differences in the pre-GSA period, which suggests that men strategically biased their forecasts during that period.

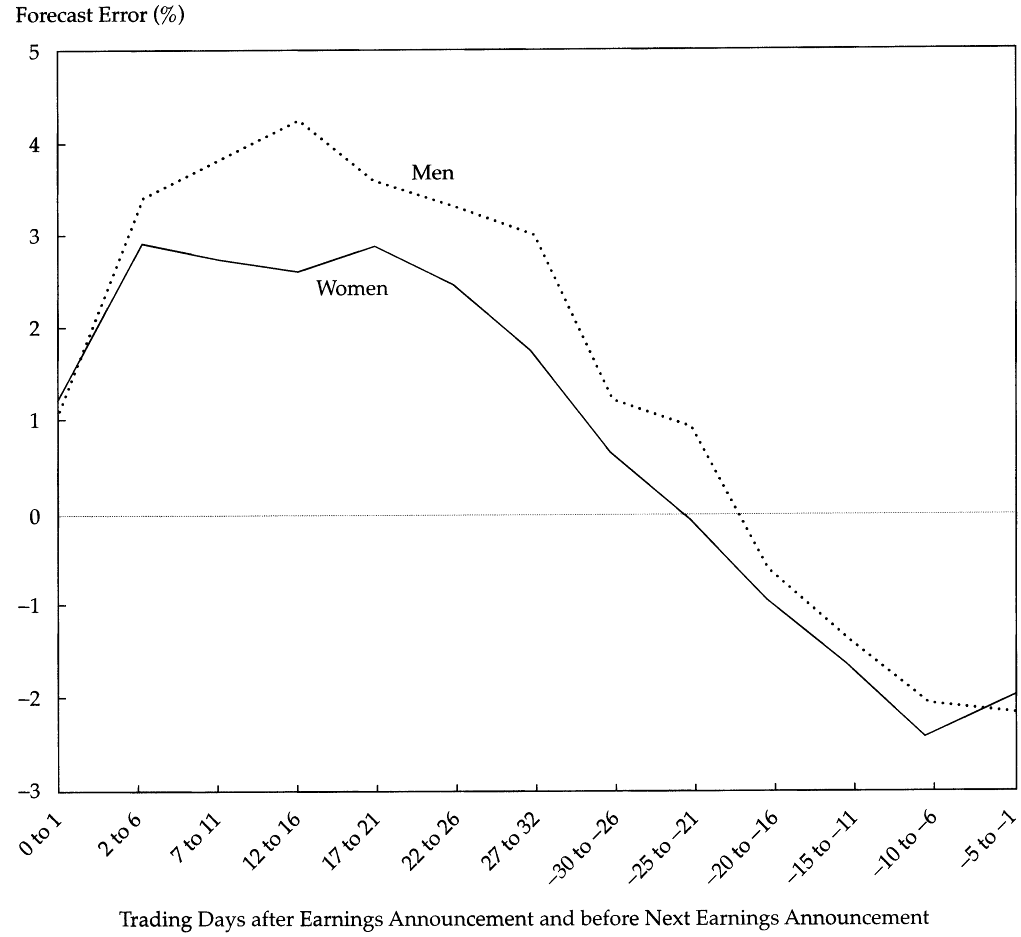
We conducted the next set of tests to examine the absolute forecast accuracy of women and men. Forecast accuracy depends on a number of stock-specific factors, as well as the timing of the forecast relative to the earnings announcement date. For example, forecasts are typically less accurate for small companies because less information is available to the market. In addition, the future earnings of companies with great earnings volatility tend to be hard to forecast, and thus, forecast accuracy is negatively related to volatility. The closer to earnings announcement dates that forecasts are made, the more accurate they are (see, e.g., Clement 1999). When one evaluates the relative forecast accuracy of an analyst, one needs to control for those factors that are exogenous to the analyst.

Table 4. Gender and Bias in Earnings Forecasts, 1995–2005

Days Relative to Earnings Data	Number of Forecasts	All-Firms Forecast Bias		p-Value	Number of Forecasts	Small-Stocks Forecast Bias		p-Value	Number of Forecasts	Large-Stocks Forecast Bias		p-Value
		Women	Men			Women	Men			Women	Men	
–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 16	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	<0.0001	360,674	2.37	2.88	0.01	545,252	–0.23	0.20	<0.0001
All except Days 0, 1	731,564	0.92	1.68	<0.0001	277,905	2.22	3.01	0.00	407,463	–0.34	0.32	<0.0001

Notes: This table reports a measure of forecast optimism bias in the earnings forecasts of brokerage firm analysts. Forecast bias is measured as $(Forecast - EPS)/EPS$, where *Forecast* is the one-quarter-ahead earnings forecast and *EPS* is the realized earnings per share; p-values are based on t-tests for differences in means and are rounded to two digits. We partitioned the stocks by using the median size among NYSE stocks.

Figure 2. Gender and Forecast Error for Each Fiscal Quarter, 1995–2005



Notes: This figure plots optimism bias in the earnings forecasts of sell-side analysts. Forecast bias is measured as (*Forecast* – *EPS*)/*EPS*, where *Forecast* is the one-quarter-ahead earnings forecast and *EPS* is the actual earnings per share.

To account for inherent differences in forecast accuracy among stocks and across time, we followed Clement (1999) by using absolute standardized proportional forecast error (ASPFE) as our measure of forecast accuracy:

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

where $AFE_{i,j,t}$ is the absolute forecast error $|Forecast_{i,j,t} - EPS_{j,t}|$ for analyst i's forecast of company j for quarter t and $\overline{AFE}_{j,t}$ is the mean absolute forecast error for company j for quarter t among all analysts. *ASPFE* represents analyst i's proportional forecast error relative to the average of all analysts' absolute forecast errors for company j for quarter t. Positive values of *ASPFE* reflect worse-than-average performance, and negative values reflect better-than-average performance. We winsorized *ASPFE* at 100 percent.

ASPFE controls for company and quarter effects by adjusting errors by their related company-quarter means. Company-quarter effects allow for the difficulty of predicting earnings to vary over time, which may occur because of such corporate events as mergers or acquisitions or simply because of changes in managers' earnings guidance.

Because forecast accuracy critically depends on the timeliness of forecasts, we looked at the relative forecast accuracy of earnings forecasts made for the same stock on the same date by women and men. This matched sample contains 147,458 forecasts made by 1,084 women and 345,687 forecasts made by 4,454 men. The sample includes forecasts made by 70 percent of the analysts and 17 percent of all earnings forecasts in the full sample.

Using these matched forecasts, we examined relative forecast accuracy by gender, after controlling for other factors related to accuracy, by using the following regression:

$$\begin{aligned} ASPFE_{i,j,t} = & b_0 + b_1 AGE_{i,j,t} + b_2 GEXP_{i,t} \\ & + b_3 FEXP_{i,j,t} + b_4 NCOS_{i,t} \\ & + b_5 NGIC_{i,t} + b_6 TOP10_{i,t} \\ & + b_7 ALLSTAR_{i,t} + b_8 GENDER_i \\ & + \sum_{k=1}^{9} c_k GIC\ dummy_{i,k} + e_{i,j,t}, \end{aligned} \tag{3}$$

where

$AGE_{i,j,t}$ = the number of days between the forecast date and the earnings announcement date (a measure of forecast staleness)

$GEXP_{i,t}$ = the number of years analyst i has supplied at least one forecast on I/B/E/S up to quarter t (a measure of the analyst's general experience)

$FEXP_{i,j,t}$ = the number of years analyst i has made at least one forecast for company j up to quarter t (a company-specific measure of the analyst's experience)

$NCOS_{i,t}$ = the number of companies analyst i follows at the time of the quarter t forecast

$NGIC_{i,t}$ = the number of industries (measured by the two-digit GICS codes) followed by the analyst (included to reflect the complexity of the analyst's portfolio)

$TOP10_{i,t}$ = 1 if the analyst is employed by a top 10 brokerage firm (this captures differences in access to brokerage firm resources)

$ALLSTAR_{i,t}$ = 1 if the analyst is a member of *Institutional Investor*'s All-America Research Team in year $t - 1$

$GENDER_i$ = 1 if the analyst is female and 0 if male

$GIC\ dummy_{i,k}$ = 1 if forecast i is for a company that belongs to economic sector k as identified by the company's two-digit GICS code[9]

As with *ASPFE*, we adjusted the independent variables (except for the dummy variables) by subtracting company-quarter means. The resulting model takes the form $y_{i,j,t} - \bar{y}_{j,t} = (x_{i,j,t} - \bar{x}_{j,t})b$.[10]

Table 5 presents our regression estimates. We included one-to-four-quarters-ahead earnings forecasts in the sample. We found that forecasts are more accurate when forecast dates are closer to the next earnings announcement date and when forecasts are made by All-Star analysts. Moreover, forecast accuracy is negatively related to the number of companies and industries that an analyst follows; these results are consistent with Stickel (1992) and Clement (1999). For our matched sample, however, forecast accuracy is not related to analyst experience.

We found that analysts' gender is significantly related to forecast accuracy. The positive coefficients indicate that the absolute forecast errors are 1.46 percent smaller for men than for women across all forecast horizons. The difference in forecast accuracy declines as we move from one-quarter-ahead forecasts to four-quarters-ahead

Table 5. Gender and Earnings Forecast Errors, 1995–2005

	All Horizons		1 Quarter Ahead		2 Quarters Ahead		3 Quarters Ahead		4 Quarters Ahead	
Variable	Estimate	*p*-Value	Estimate	*p*-Value	Estimate	*p*-Value	Estimate	*p*-Value	Estimate	*p*-Value
Intercept	–11.64%	0.00	–17.52%	0.00	–5.61%	0.00	–5.64%	0.01	–5.39%	0.06
AGE	1.03	0.00	1.56	0.00	0.73	0.00	0.47	0.00	0.37	0.00
GEXP	0.02	0.31	0.01	0.86	0.07	0.10	0.03	0.53	–0.02	0.75
FEXP	–0.04	0.25	–0.11	0.05	–0.05	0.41	0.07	0.32	0.09	0.27
NCOS	0.03	0.01	0.05	0.02	0.02	0.43	0.01	0.78	0.03	0.29
NGIC	0.24	0.05	0.43	0.03	0.05	0.82	0.33	0.19	–0.03	0.92
TOP10	–1.34	0.00	–2.04	0.00	–1.30	0.00	–0.88	0.02	–0.69	0.12
ALLSTAR	–0.68	0.01	–0.76	0.06	–1.31	0.01	–0.32	0.55	–0.19	0.77
GENDER	1.46	0.00	1.89	0.00	1.74	0.00	0.74	0.04	0.38	0.35
Adjusted R^2	0.09		0.17		0.05		0.02		0.01	
N	456,194		190,574		117,874		86,262		61,484	

Notes: In this table, absolute standardized forecast errors (see Equation 2) are regressed on forecast characteristics. Forecasts by women and men are matched by stock and date. For definitions of variables, see Equation 3.

forecasts. Our findings suggest that an analyst's gender is more strongly related to forecast accuracy than is an analyst's All-Star status on the *Institutional Investor* survey.

As discussed earlier, forecasts issued immediately after an earnings announcement tend to present analysts' interpretations of financial data released by the company, whereas earnings forecasts made on other days tend to use information that analysts gather privately. Therefore, to understand the source of gender-based differences in accuracy, we examined whether those differences are related to the timing of earnings forecasts.

Table 6 reports the accuracy of forecasts made on the earnings announcement date and the following day, as well as the accuracy of forecasts made on other dates. The most notable finding is that the gender-based difference in forecast accuracy is smaller for revisions made immediately after earnings announcements than for other revisions. The coefficient on gender is 0.43 right after earnings announcements and 2.54 for other dates. As Ivković and Jegadeesh (2004) noted, forecast revisions following earnings announcements reflect analysts' interpretations of public information and forecast revisions on other dates tend to be driven by private information. Our findings indicate that gender-based differences in forecast accuracy are larger when analysts revise their forecasts on the basis of private information.[11]

Table 6. Earnings Forecast Errors: Revisions following Earnings Announcements and on Other Dates, 1995–2005

	Earnings Date		Nonearnings Date	
Variable	Estimate	*p*-Value	Estimate	*p*-Value
Intercept	–2.01%	0.12	–11.37%	0.00
AGE	4.21	0.00	1.13	0.00
GEXP	0.03	0.34	0.05	0.18
FEXP	–0.04	0.41	–0.01	0.81
NCOS	0.04	0.03	0.04	0.04
NGIC	0.16	0.31	0.36	0.05
TOP10	–0.68	0.00	–1.72	0.00
ALLSTAR	–0.89	0.00	–1.01	0.01
GENDER	0.43	0.05	2.54	0.00
Adjusted R^2	0.0005		0.0916	
N	260,398		200,497	

Notes: In this table, absolute standardized forecast errors (see Equation 2) are regressed on forecast characteristics. The earnings date indicates Days 0 and 1 following earnings announcement dates. Forecasts by women and men are matched by stock and date. For definitions of variables, see Equation 3.

Taken together, these findings suggest 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 similar in magnitude to the effects of other analyst characteristics examined in the literature, such as All-Star status.[12] These results indicate that brokerages do not discriminate against women by setting a higher hurdle for forecasting skills.

Gender and Professional Recognition among Sell-Side Analysts

To objectively measure qualitative aspects of job performance among employees from a number of different organizations is difficult. Fortunately, *Institutional Investor* magazine (*II*) surveys around 2,000 institutional investors each summer for their opinions on sell-side analysts. According to survey respondents, the four most important factors are industry knowledge, accessibility/responsiveness, integrity/professionalism, and management access (see Johnson 2005). These qualitative perceptions of institutional clients can be quantified only through a detailed survey. From its extensive survey, *II* publishes a list of analysts whom it designates members of the All-America Research Team (All-Stars) in every October issue.

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

After controlling for other factors, we examined whether the likelihood of All-Star status varies by gender. We used a logistic regression to study the determinants of All-Star status. In addition to the analyst characteristics in Equation 2, we included a measure of relative forecast accuracy similar to that in Hong and Kubik (2003). Each quarter for each stock, analysts are ranked according to their absolute forecast errors by using the following accuracy score:

$$Score_{i,j,t} = 100 - \left(\frac{Rank_{j,t} - 1}{Number\ of\ analysts_{j,t} - 1} \right) \times 100, \quad (4)$$

where $Rank_{j,t}$ equals 1 for the analyst who produces the best quarterly forecast for company *j* in quarter *t*, 2 for the next-best analyst, and so on;

Number of analysts$_{j,t}$ is the number of analysts who cover the company 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 assigned scores only when at least two analysts made earnings forecasts for a particular fiscal quarter. Measuring accuracy in this way controls for differences in difficulty in forecasting earnings among companies. We averaged quarterly accuracy scores among stocks over the last three years as of March each year and used this number as our measure of accuracy ($ACCURACY_{i,t}$ for analyst i in year t). The resulting logistic regression is as follows:

$$\begin{aligned} ALLSTAR_{i,t} = b_0 &+ b_1 GEXP_{i,t} + b_2 NCOS_{i,t} \\ &+ b_3 NGIC_{i,t} + b_4 TOP10_{i,t} \\ &+ b_5 ACCURACY_{i,t} + b_7 GENDER_i \\ &+ \sum_{k=1}^{9} c_k GIC\ dummy_{i,k} + e_{i,t}. \end{aligned} \quad (5)$$

In addition to a measure of forecast accuracy, we included the same control variables as in Equation 3.

Table 7 presents the results for the full sample and for the top 10 and other brokerages. Unconditionally, the likelihood of being an All-Star is 8.78 percent for women versus 7.99 percent for men. The logistic results in Table 7 confirm this disparity. After controlling for various characteristics, we found that being a female analyst increases the likelihood of being an *II* All-Star analyst. Interestingly, the likelihood of being an All-Star analyst is not related to gender for the top 10 brokerages. For the other brokerages, which, in aggregate, employ twice as many analysts as the top 10 brokerages, women are significantly more likely than men to be All-Star analysts.

That women cover fewer stocks and are less accurate at forecasting earnings but are more likely to be designated as All-Stars suggests that they perform better than men at other aspects valued by clients, including industry knowledge, integrity, responsiveness, and management access. This finding—coupled with our findings that women, on average, cover fewer stocks than men and are less accurate in their earnings forecasts—suggests that men and women perform differently in different dimensions of the job. Therefore, our results indicate that brokerages are not systematically discriminating against women by setting higher hurdles for them, nor are they diluting their standards to achieve gender balance through affirmative action plans.

Some researchers have criticized the rankings as being something of a popularity contest (see, e.g., Emery and Li 2005); and to the extent that female analysts are relatively rare, the rankings may improve their visibility among clients. Greater visibility among market participants, however, may have real effects on job performance (e.g., better access to company management). Moreover, because an All-Star designation often directly affects an analyst's compensation and career prospects, this designation is an important measure of job performance.

Table 7. Gender and All-Star Designations among Brokerage Analysts, 1995–2005

	All Brokerages		Top 10 Brokerages		Other Brokerages	
Variable	Estimate	p-Value	Estimate	p-Value	Estimate	p-Value
Intercept	–5.98%	0.00	–3.99%	0.00	–5.99%	0.00
GEXP	0.07	0.00	0.06	0.00	0.05	0.00
NCOS	0.05	0.00	0.06	0.00	0.04	0.00
NGIC	–0.72	0.01	–0.72	0.03	–0.61	0.13
ACCURACY	0.07	0.00	0.04	0.00	0.06	0.00
GENDER	0.28	0.03	–0.16	0.25	0.44	0.02
Pseudo R^2	0.0650		0.0567		0.0528	
N	16,019		5,022		10,997	

Notes: This 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-America Research Team. *ACCURACY* is an analyst's average forecast accuracy rank among analysts for the stocks the analyst covers. For definitions of other variables, see Equation 3. Standard errors are clustered by analysts, and the resulting p-values are reported next to each coefficient.

Conclusion

Women have historically been underrepresented in many high-profile and lucrative careers. Explanations for the low representation of women range from gender discrimination to differences in preferences and abilities. Many employers have instituted affirmative action programs to encourage gender balance in hiring decisions. We examined the gender composition and job performance of sell-side analysts. We investigated the relative performance of women and men on various aspects of a sell-side analyst's job and shed light on whether gender discrimination or affirmative action is evident in job performance. We also examined the accuracy of earnings forecasts by women and men.

On the one hand, we found that women cover roughly one fewer stock than men do and tend to forecast less accurately, on average, than their male counterparts. On the other hand, we found that women are significantly more likely than men to be designated by *Institutional Investor* magazine as members of the All-America Research Team, which indicates that women outperform men from their clients' perspective. Overall, neither women nor men exhibit dominant performance relative to the other gender. Therefore, our results do not support the view that employers engage in pervasive gender discrimination in hiring decisions by setting higher standards for women.

Some of the women in our sample were likely helped by the affirmative action plans that some brokerages have implemented to achieve gender balance. Although critics of affirmative action argue that such programs set lower standards for underrepresented groups, our findings on the likelihood of obtaining All-Star status do not support this view. Holzer and Neumark (1999) found that in their sample of blue-collar workers, women hired under affirmative action plans were not, on average, less productive than men, which is consistent with our findings for sell-side analysts.

Our findings also have important implications for employers. To the extent that the lower representation of women reflects greater demands on their time away from work, improvements in working conditions (e.g., greater flexibility in workloads and enhanced childcare options) would open the door to increased participation by women. In addition, greater emphasis on aspects of job performance that are important to clients, as highlighted in the *Institutional Investor* surveys (industry knowledge, responsiveness, integrity/professionalism, and management access), would also enhance gender balance.

Longevity on the job is an important consideration in recruitment decisions. We found that women are more likely than men to leave their analyst positions within the first two years after being hired. This statistical relationship between gender and attrition may deter brokerages from hiring women. If women who aspire to be analysts intend to stay on the job longer than indicated by the statistical evidence, they would be well advised to credibly convey their intention to potential employers.

Finally, our findings also provide guidance for aspiring analysts and junior analysts of either gender. Our analysis shows that All-Star status is more likely for analysts who cover more stocks and who issue more-accurate forecasts than do other analysts. Our results indicate that analysts would benefit from covering at least as many companies as their industry peers do. This finding should be particularly helpful for women, who on average cover fewer stocks than men do.

This article qualifies for 1 CE credit.

Notes

1. This information is from a 2005 CFA Institute survey on investment professionals' annual compensation.
2. In recent years, Smith Barney and Morgan Stanley have also faced sex discrimination class-action lawsuits that were supported by the U.S. Equal Employment Opportunity Commission.
3. Specifically, 44 percent of large security firms (with 8,000 or more employees) responded that they had numerical recruiting objectives for improving diversity (Securities Industry and Financial Markets Association 2003).
4. Kumar (2007) studied the effects of analyst gender on the market's response to analysts' research reports. Whereas our emphasis is on understanding the net effect of gender discrimination and affirmative action on the performance of male and female analysts, Kumar focused on the effects of social biases on the market's response to new information.
5. See www.socialsecurity.gov/OACT/babynames. We examined the top 1,000 baby names by gender for each decade beginning in 1880, which resulted in 4,775 unique names. To increase the number of international names, we augmented that list with data from http://new.babynameindex.com and www.wikipedia.org. The total number of unique names in our sample is 21,204.
6. For the full sample, we averaged the percentages for each year. Without our controlling for year, women's representation is 17.2 percent. This number is higher than the ratio in 9 out of 10 years, however, and it overstates women's representation at any particular point in time because

women leave analyst positions more often than men do. To illustrate, in a balanced sample with two jobs, if women work one year and men work two years, the sample will have twice as many women as men over two years.

7. Large firms may also face a higher risk of discrimination lawsuits (Bradford 2005).
8. Hong and Kubik (2003) measured longevity differently than we did; they reported that roughly 10 percent of analysts leave the sample within one year. They included all analysts in the I/B/E/S database and examined the number of years they remained in the database. Focusing on analysts who enter the I/B/E/S database in a given year, we report the proportion of them who leave within a year. Our measure excludes analysts employed before 1995, and it results in higher exit rates because experienced analysts are less likely than new hires to leave their jobs. Focusing on new hires is more appropriate for the purposes of our study.
9. The two-digit GICS codes identify 10 economic sectors. Because we included an intercept in the regression, we did not assign a dummy variable for one economic sector in order to avoid multicollinearity.
10. This approach is similar to using company-year dummies to control for company-year effects. See Clement (1999) for more details.
11. We found similar results for the pre- and post-GSA subperiods.
12. Although our performance findings generally agree with Kumar (2007), we found the opposite relationship between gender and forecast accuracy. The difference in results is likely a result of differences in methodology or sample period. Our matched-sample tests compare forecasts of women and men for the same stock on the same date so that we can effectively control for forecast timing and differences in stock characteristics. The difference between our findings and those of Kumar indicates that Kumar's results may be sensitive to the choice of controls or to the functional form of the relationship between forecast accuracy and the controls. In our regressions, however, we found that women are less accurate than men not only in the matched sample but also in the full sample. For brevity, we do not present the full-sample results.

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