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Sell-Side Analysts and Gender: A Comparison of Performance, Behavior, and Career Outcomes

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Using a comprehensive sample of investment recommendations, the authors investigated differences in the performance, behavior, and career outcomes of male and female sell-side analysts. They found that the recommendations of female analysts, compared with those of their male counterparts, produce similar abnormal returns but with lower idiosyncratic risks. Further, gender does not seem to negatively affect female analysts' career outcomes as defined by their "star" rankings and job mobility among brokerage firms.

Sell-side analysts are prominent figures in the investment arena. Investors make enormous efforts to identify those analysts with the most reliable earnings forecasts and investment recommendations and are willing to pay considerable sums for access to "star" analyst research (excellent examples include Kothari 2001 and Lee 2001; see also Boni and Womack 2006; Green 2006; Loh and Mian 2006; Sorescu and Subrahmanyam 2006; Emery and Li 2009).

Using a large sample of investment recommendations from January 1994 through December 2005, we examined whether female sell-side analysts perform and behave differently from their male counterparts.[1] We also examined whether the career outcomes of female analysts differ from those of male analysts after controlling for analyst performance and behavior.

Specifically, we compared male and female analysts in terms of their (1) performance, as measured by the excess return (alpha) of investment recommendations, (2) risk taking, measured as the portfolio residual risk implied by investment recommendations, (3) bias, measured as the percentage of sell recommendations, and (4) career outcomes, measured as the probability of moving among brokerage firms of different sizes and by the probability of their being *Institutional Investor* (*I.I.*) or *Wall Street Journal* (*WSJ*) "stars."[2]

Discussion of findings. We found that the investment recommendations of female analysts as compared with those of male analysts produce similar abnormal returns but with lower idiosyncratic risks. Taken together, our results imply that the recommendations of female analysts may generate slightly higher information ratios than the recommendations of male analysts, a finding consistent with prior research on individual investors (see, e.g., Sunden and Surette 1998; Barber and Odean 2001). Further, we detected no evidence of discrimination against female analysts regarding their career outcomes. In fact, female analysts seem to have a better chance of being recognized as star analysts in both the *Institutional Investor* and the *Wall Street Journal* rankings, influential components of analysts' compensation (see, e.g., Stickel 1992; Womack 1996).

Our study is related to prior research on the determinants of analyst performance (see, e.g., Lys and Sohn 1990; Stickel 1995; Clement 1999; Jacob, Lys, and Neale 1999), analyst bias and analyst risk-taking behavior (see, e.g., Lin and McNichols 1998; Michaely and Womack 1999; Dollar, Fisman, and Gatti 2001; Clement and Tse 2005; Li and Masulis 2007), and career outcomes (see, e.g., Hong and Kubik 2003; Emery and Li 2009). Our study complements prior research by exploring previously unexamined gender effects after controlling for various analyst-related characteristics.

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Our study also relates to the literature on gender differences. On the relation between gender and performance, researchers have found that women may be less effective than men in competitive environments (Gneezy, Niederle, and Rustichini 2003) and that women tend to shy away from competition whereas men embrace it (Niederle and Vesterlund 2007). On the relation between gender and risk taking, researchers have found that women tend to take less risk than men across a variety of settings (for a review, see Byrnes, Miller, and Schafer 1999). In financial markets, research has shown that among individual investors, females tend to be more risk averse and less overconfident than males and to underperform males on a risk-adjusted basis (see, e.g., Sunden and Surette 1998; Barber and Odean 2001). Research has also shown that women are more effective in promoting fairness and honesty—important attributes in the finance industry. For example, as compared with men, women base their votes more on social issues (Goertzel 1983), score higher on integrity tests (Ones and Viswesvaran 1998), and take stronger stances on unethical behavior (Reiss and Mitra 1998). Also, female members of Parliament are associated with lower levels of corruption (Dollar et al. 2001).

Previous studies have suggested that women may face a glass ceiling whereby they are underrepresented among the ranks of senior level (and higher-paid) personnel within their firms because of workplace discrimination against women (Wenneras and Wold 1997; Goldin and Rouse 2000; Black and Strahan 2001) and because women are less effective in competitive environments (Gneezy et al. 2003). Our study complements and extends prior research by determining the existence of any gender effect for sell-side analysts through the objective measuring of performance and behavior with respect to investment recommendations while controlling for other important characteristics. In addition, objectivity was provided by the market response to analysts' research reports. This approach works because market participants can react to analysts' research reports anonymously and quickly and should thus be more likely to reveal their true attitude toward such research.

The studies closest in spirit to ours are Kumar (2010) and Green, Jegadeesh, and Tang (2009). Using earnings forecasts, Kumar provided a careful and detailed analysis of the performance, risk-taking behavior, and career outcomes of female and minority analysts. He found that female analysts provide more accurate earnings forecasts than male analysts and that stock market prices reflect this finding. He also found that female analysts issue bolder forecasts by way of upward revisions and that female analysts are more likely to move to larger brokerage firms. After controlling for various characteristics, Green et al. showed that although the earnings forecasts of female analysts are less accurate than those of male analysts, women are significantly more likely to be designated *I.I.* stars. They found that an analyst's gender is a better predictor of forecast accuracy than *I.I.* star status, suggesting that brokerages do not discriminate against women in assessing forecasting skills.

Our study extends the literature in several important ways. Using investment recommendations (including revisions to recommendations) instead of earnings forecasts, we examined the impact of gender on both performance and risk-taking behavior. Making recommendations and issuing forecasts are the two most important aspects of a sell-side analyst's job. These two aspects are separate though intimately related. Many consider recommendations to be more important to investors than earnings forecasts (Womack 1996; Francis and Soffer 1997) because recommendations offer a direct way to compare the risk and return performance of the analyst against that of the market. Stocks added to the buy list are expected to outperform, and stocks added to the sell list are expected to underperform.

The importance of studying analyst recommendations is well illustrated by the $1.4 billion Global Settlement of 2003. The Global Settlement between regulators and investment banks concerned biased analyst recommendations related to the business of investment banking (Smith, Craig, and Solomon 2003). Moreover, studying investment recommendations is particularly important because bias in recommendations is more severe than it is in forecasts (Lin and McNichols 1998), as evidenced by the focus on bias in stock recommendations in the Global Settlement. On this point, our results indicate that female analysts tend to issue fewer sell recommendations than male analysts. This finding may be related to our additional finding that female analysts take less risk than their male counterparts.

Further, we studied both *I.I.* and *WSJ* star rankings as well as analyst job mobility among brokerage firms of different sizes. Being an *I.I.* or *WSJ* star can lead to an analyst's earning millions of dollars in additional annual compensation. In fact, being an *I.I.* star is reportedly among the three most important determinants of analyst compensation (Stickel 1992; Michaely and Womack 1999; Hong and Kubik 2003; Li 2005). We controlled for analyst performance and behavior in our analysis of career outcomes.

Data and Analyst Characteristics

In this section, we report the particulars of the data we used and our measures of performance, risk taking, bias, and other analyst characteristics, as well as summary statistics of those characteristics.

Data. We obtained our primary data from the Institutional Brokers' Estimate System (I/B/E/S). The I/B/E/S database provides the last name, first-name initial, brokerage affiliation, and investment recommendations for each analyst, as well as a unique code for each analyst that allows one to track analysts should they change affiliations.[3] The I/B/E/S investment recommendation database starts in October 1993; our sample begins in 1994. I/B/E/S provides standardized recommendations with integer ratings from 1 through 5, corresponding to "strong buy," "buy," "hold," "underperform," and "sell," respectively.

Following Clement (1999) and Jacob et al. (1999), we excluded analysts with pre-1984 forecasts in the I/B/E/S database to avoid a left-censored bias in the experience measure. We also excluded those analysts who issued only "hold" recommendations. This procedure yielded a sample of 33,399 analysts and 828,355 analyst-year observations. Because the I/B/E/S database sometimes assigns multiple codes to a single analyst, merging the data for those analysts reduced the sample to 27,514 analysts. Requiring CRSP stock returns for creating a three-month recommendation portfolio within each year for estimation purposes further reduced the sample to 6,195 analysts and 35,992 analyst-year observations. (Later in the article, we will describe the process that we used in creating the recommendation portfolio.) Finally, excluding analysts whose gender could not be determined left us with a sample of 5,189 analysts and 25,512 analyst-year observations.

To obtain gender information, we first conducted a search on the first name of each analyst. The I/B/E/S database provides only the last name and first initial of each analyst. Therefore, we had to search news articles in such databases as LexisNexis and ProQuest to find the first name of each analyst. In addition, the *I.I.* and *WSJ* star rankings include the full names of all ranked analysts. If our search resulted in multiple analysts with the same first and last names, we matched information on brokerage firm affiliation with the I/B/E/S database to ensure the proper identification of each analyst.

Identifying first names determined the gender of about two-thirds of our analysts. We were able to determine the gender of additional analysts by searching news articles in such databases as LexisNexis and ProQuest to see whether analysts were referred to as he or she, his or her, or Mr. or Ms./Mrs. The photos of star analysts provided by *I.I.* and the *WSJ* further helped us determine gender.

Panel A of **Table 1** reports the proportion of analysts by gender. Of the 5,189 sample analysts, we determined that 796 analysts, or about 15%, were female. In untabulated results, we found that the proportion of male analysts has increased slowly but steadily—from 82.9% in 1994 to 84.7% in 2005.

Table 1. Summary Statistics, January 1994–December 2005

A. Gender composition			
Female	796	15.34%	
Male	4,393	84.66%	
Total	5,189	100.00%	
	Full Sample	Male	Female
B. Analyst performance and characteristics			
ALPHA (bps)	2.10	2.17	1.69
RESIRISK (%)	1.90	1.90	1.91
PCTSELL (%)	4.89	4.92	4.80***
IISTAR (%)	8.58	8.28	10.42***
WSJSTAR (%)	5.11	5.07	5.28***
EXPERIENCE	8.07	8.21	7.28***
COVERAGE	7.37	7.35	7.44***
NREPORT	11.51	11.76	10.11***
NCOMPANY	7.91	8.07	7.04***
BROKERSIZE	427	418	477***
COMPANYSIZE ($ billions)	6.82	6.76	7.11***
N	25,512	21,783	3,729

***Significant at the 1% level.

Measures of Performance, Risk Taking, and Bias. With respect to the measures of performance and risk-taking behavior in investment recommendations, we first created a recommendation portfolio for each analyst in our sample, following Emery and Li (2009). This portfolio consisted of long positions in those stocks with an analyst rating of 1 or 2 and short positions in those stocks with an analyst rating of 4 or 5. Stocks were added to the portfolio on the recommendation date and removed from the portfolio on the date when the rating was revised to 3. A stock's classification changed when a superseding recommendation altered the stock's classification as a buy or a sell. For example, we considered a change from 1 or 2 to 4 or 5 a revision. We did not consider an upgrade from 2 to 1 a revision because the stock had already been classified as a long position. Reiteration of a previous recommendation did not change a stock's classification. Returns within each year accumulated from the recommendation date until either (1) the date of revision or (2) the end of the year if there was no revision during the remainder of the year. In determining the portfolio return for each analyst, we used equally weighted CRSP daily returns for each recommendation. For estimation purposes, we required a minimum period of three months for the overall recommendation portfolio within each year.

We then estimated the Fama–French (1993) three-factor model:

$$R_{it} = \alpha_i + \Sigma_{j=1}^{3} \beta_j R_{jt} + \varepsilon_{it}, \tag{1}$$

where

R_{it} = the return on the recommendation portfolio of analyst *i* in excess of the three-month T-bill return on day *t*

α_i = the multifactor model Jensen's alpha, which measures the average daily abnormal return on the portfolio of analyst *i*

β_j = the regression coefficient for factor *j*

R_{jt} = the return of factor *j* on day *t*

ε_{it} = an error term for the portfolio of analyst *i* on day *t*

The factors (*j*) are the return on the CRSP value-weighted NYSE/Amex/NASDAQ market index in excess of the three-month T-bill return and the size and book-to-market factors of Fama and French (1993). Prior research has identified these factors as being related to systematic return patterns. We included them in our analysis to avoid rewarding analysts for simply exploiting these well-known return factors.

We used *ALPHA*, the intercept of the Fama–French three-factor model regression, to measure analyst recommendation performance. Following Chevalier and Ellison (1999) in their examination of the risk-taking behavior of fund managers, we measured analyst risk taking in recommendations with *RESIRISK*, the residual return standard deviation in the three-factor model regression.[4]

One objective of the recent efforts to reduce analyst bias, following the $1.4 billion Global Settlement, is to increase the proportion of negative recommendations (Opdyke 2002). Therefore, we used the percentage of negative recommendations among analysts' recommendations (*PCTSELL*), including both underperformance and sells, to measure any bias in investment recommendations.

Other Analyst Characteristics. We included several control variables (see **Exhibit 1** for definitions of variables). Following Stickel (1992), among others, we measured analyst reputation by using *IISTAR* and *WSJSTAR*, dummy variables that equaled 1 if the analyst was an *Institutional Investor* or *Wall Street Journal* star analyst, respectively, and 0 otherwise.[5] We followed Jacob et al. (1999) in using the number of research reports issued (*NREPORT*) to measure the timeliness of reports, which should proxy for the willingness of analysts to exert effort. Clement (1999) and Jacob et al. (1999) argued that an increase in the number of companies covered (i.e., broader coverage) increases task complexity. Jacob et al. also argued that broader coverage broadens industry knowledge. Accordingly, we included *NCOMPANY* to measure analyst breadth of coverage. Like Stickel (1995) and Hong and Kubik (2003), we used brokerage firm size (*BROKERSIZE*) as a proxy for marketing ability and the reputation of analysts' firms. We used *COMPANYSIZE* as a proxy for the information environment of the companies covered. Prior research has shown that smaller companies have a more opaque information environment owing to less information disclosure and less news and research coverage (Stickel 1995). Finally, we used *COVERAGE*, the average number of analysts who cover the same company as a particular analyst, as another measure of the information environment (see, e.g., Piotroski and Roulstone 2004).

We included *EXPERIENCE*, the number of years that an analyst has been submitting reports to I/B/E/S, to measure the impact of learning by doing (see, e.g., Clement 1999; Jacob et al. 1999).

Summary Statistics of Analyst Characteristics. Panel B of Table 1 reports summary statistics for our measures of analyst performance, behavior, and other characteristics. Analyst performance is summarized in the first three rows of variables, followed by results for our additional variables concerning analyst characteristics. Female

Exhibit 1. Definitions of Variables

FEMALE	Dummy variable that equals 1 for female analysts and 0 otherwise.
ALPHA	The intercept of the Fama–French (1993) model regression (in basis points).
RESIRISK	Residual return standard deviation of the Fama–French (1993) model regression (in basis points).
CARs	Return effects are measured by market-adjusted cumulative abnormal returns (*CARs*), which are measured with an interval of $t-1$ to $t+1$ days around analyst recommendation announcement dates. The market model estimation period used to calculate *CARs* is $t-210$ to $t-60$ days prior to the recommendation announcement.
PCTSELL	Percentage of "sells" and "underperforms" among the analyst's recommendations.
IISTAR and *WSJSTAR*	Dummy variable that equals 1 if the analyst is an *Institutional Investor* or *Wall Street Journal* star analyst, respectively, and 0 otherwise.
EXPERIENCE	Number of years that an analyst has been submitting reports to I/B/E/S.
COVERAGE	Logarithm of the average number of analysts who cover the same company that a particular analyst covers at the end of the prior calendar year.
NREPORT	Logarithm of the number of research reports that an analyst issues.
NCOMPANY	Logarithm of the number of companies that an analyst covers.
BROKERSIZE	Logarithm of the number of analysts employed by the analyst's house. For analysts who switch houses within a given year, we used the time-weighted average of the two houses.
COMPANYSIZE	Logarithm of the mean market capitalization of the companies that an analyst covers at the end of the prior calendar year.

Note: All variables are calculated within a calendar year.

analysts are significantly different from male analysts in several respects. Female analysts have statistically significantly lower *PCTSELL*, higher *IISTAR* and *WSJSTAR*, lower *EXPERIENCE*, higher *COVERAGE*, lower *NREPORT*, lower *NCOMPANY*, and higher *BROKERSIZE*. Thus, our findings suggest that female analysts are more likely than their male counterparts to be recognized as star performers in both the *I.I.* and the *WSJ* analyst rankings. They also tend to issue fewer sell recommendations, have fewer years of work experience, select stocks to cover that are most often followed by other analysts, issue fewer reports, cover a smaller number of companies, and cover larger companies.

Test Methodologies and Empirical Results

In this section, we report our test methodologies and empirical results with respect to various analyst characteristics and career outcomes and describe our sensitivity tests.

Performance, Risk Taking, and Bias. We examined whether gender affects analyst performance and behavior. One approach we could use to examine the effects of gender is the simple regression

$$\text{Dependent variable}_t = a_0 + a_1 FEMALE + \text{Year effects} + \varepsilon_t, \tag{2}$$

where the dependent variables include our measures of analyst performance (*ALPHA*), risk-taking behavior (*RESIRISK*), and bias behavior (*PCTSELL*). We could also include yearly dummies (Year effects) to control for time variation in performance. However, this simple specification is incomplete because male and female analysts are different across several characteristics. Our selected characteristics might affect analyst performance and behavior. Therefore, we would need to control for each characteristic separately in order to properly account for any gender differences. In this way, our model would yield unbiased parameter estimates. Specifically, we estimated the following model:

$$\begin{aligned}\text{Dependent variable}_t = {} & a_0 + a_1 FEMALE + a_2 IISTAR_t \\ & + a_3 WSJSTAR_t + a_4 EXPERIENCE_t \\ & + a_5 COVERAGE_t + a_6 NREPORT_t \\ & + a_7 NCOMPANY_t + a_8 BROKERSIZE_t \\ & + a_9 COMPANYSIZE_t + \text{Year effects} + \varepsilon_t.\end{aligned} \tag{3}$$

Table 2 reports the regression results, with select measures of analyst performance and behavior included as dependent variables. Columns 1–5 report the results of gender effects on analyst performance, risk-taking behavior, recommendation bias, and cumulative abnormal returns (*CARs*) around upgrade and downgrade recommendation

Table 2. Gender vis-à-vis Performance and Behavior, January 1994–December 2005 (*t*-statistics in parentheses)

	Performance $ALPHA_t$ (1)	Risk Taking $RESIRISK_t$ (2)	Bias $PCTSELL_t$ (3)	*CARs*(–1, 1) Upgrades (4)	*CARs*(–1, 1) Downgrades (5)
FEMALE	–0.29	–0.08***	–0.08***	–0.33***	–0.14
	(–0.92)	(–4.31)	(–2.87)	(–2.04)	(–0.67)
IISTAR	–0.15	–0.21***	–0.15***	0.52***	–0.33
	(–0.45)	(–10.99)	(–4.69)	(2.75)	(–1.30)
WSJSTAR	–0.64	–0.09***	–0.05	0.62***	–0.39
	(–1.69)	(–4.19)	(–1.35)	(2.49)	(–1.28)
EXPERIENCE	0.07***	–0.04***	0.02***	0.00	–0.04**
	(2.57)	(–27.80)	(9.09)	(0.47)	(–2.01)
COVERAGE	0.87***	0.97***	0.78***	0.14	–0.77***
	(3.55)	(62.05)	(30.44)	(1.19)	(–4.38)
NREPORT	–1.22***	0.07***	–0.23***	0.30	–0.70***
	(–2.73)	(–2.55)	(–5.93)	(1.51)	(–2.53)
NCOMPANY	1.46***	–0.41***	–0.09**	0.13	0.64**
	(2.78)	(–13.02)	(–1.99)	(–0.57)	(2.02)
BROKERSIZE	0.01	0.12***	0.27***	0.27***	–0.29***
	(0.14)	(20.52)	(27.86)	(6.42)	(–5.01)
COMPANYSIZE	–0.63***	–0.35***	–0.18***	–0.20***	0.37***
	(–6.28)	(–55.41)	(–18.57)	(–4.18)	(5.34)
R^2	0.01	0.23	0.08	0.02	0.02
N	25,512	25,512	25,512	17,463	16,925

Notes: Table 2 reports the estimated results from Equation 3, a model that uses ordinary least-squares regression. The coefficient estimates are in basis points for the regressions when *ALPHA* and *CARs* are the dependent variables. A recommendation is considered an upgrade if the numerical change in two consecutive recommendations is negative and a downgrade otherwise. The observation is deleted if the recommendation date coincides with the quarterly or annual earnings announcement date. The coefficient estimates are in percentages for the regressions when *RESIRISK* and *PCTSELL* are the dependent variables.

**Significant at the 5% level.
***Significant at the 1% level.

announcements. In conducting our cumulative abnormal returns analysis, we excluded analyst recommendations that might conflict with corporate earnings releases—that is, so as not to confuse market reactions to corporate earnings releases with market reactions to analyst recommendation announcements, we excluded all those recommendations that occurred immediately after corporate earnings announcements. Our results show that the *FEMALE* indicator is negative, but insignificant, for *ALPHA*, suggesting that the recommendations of female analysts produce abnormal returns similar to those of their male counterparts. The *FEMALE* indicator is statistically significantly negative for *RESIRISK*, which suggests that the recommendations of female analysts concern stocks with slightly lower idiosyncratic volatility. Taken together, these results imply that the recommendations of female analysts, on average, generate slightly higher information ratios than those of male analysts.

Next, we reviewed the relative performance of men and women by separating their recommendations into upgrades and downgrades and then calculating the associated cumulative abnormal returns within each category. The return effects, or *CARs* model, results shown in columns 4 and 5 indicate that women underperform with respect to their upgrade recommendations and demonstrate some outperformance with respect to their downgrades (although this outperformance is statistically insignificant). The *CARs* results may be consistent with our other findings regarding female behavior whereby women tend to take less risk in recommending upgrades. That women may take less risk (column 2)[6] could be an underlying reason for their relatively poor performance vis-à-vis men overall and also with respect to upgrades—that is, less willingness to take risk may translate into a reduced willingness to recommend changes in recommendations, leading to underperformance. In this way, the evidence shown in columns 4 and 5 aligns in a consistent manner.

Column 3 reports the results of gender effects on analyst bias behavior. The coefficient estimate on *FEMALE* is negative and significant for *PCTSELL*. These results suggest that female analysts are less willing to issue sell recommendations and so may be more cautious than men in their sell recommendations. Curiously, this finding is inconsistent with the prior findings that women are less biased than men (see, e.g., Goertzel 1983; Ones and Viswesvaran 1998; Reiss and Mitra 1998; Dollar et al. 2001). More research is needed to address these findings.

With respect to the various control variables used in each of our regression models in columns 1–5, we point the interested reader to prior research that offers a review and rationale for each variable included in our analysis.

Career Outcomes. The relation between gender and career outcomes is particularly interesting in the finance industry. For example, Cari Dominguez, a former U.S. Equal Employment Opportunity Commission (EEOC) chairwoman, has suggested that "an increasing number of women are pursuing Wall Street careers, but the brokerage industry remains plagued by a 'longstanding, endemic problem' of discrimination."[7] According to CFA Institute, although the compensation gap between female and male Chartered Financial Analysts (CFA charterholders) is narrowing, female CFA charterholders earn somewhat less, after adjusting for experience. As we reported earlier, only about 16% of our sample sell-side analysts were female, with the proportion of male analysts increasing steadily over our sample period.

Our study extends prior research that examined such career outcomes as job mobility among brokerage firms (Hong and Kubik 2003) and being an *I.I.* or *WSJ* star (Emery and Li 2009) by investigating whether gender meaningfully affects career outcomes.

Until now, the relation between gender and job mobility (i.e., analysts improving their careers by changing firms) has remained ambiguous. Prior research has argued that moving to a larger brokerage firm represents a positive career outcome because high-status brokerage firms are likely to offer higher compensation. However, there may be both implicit and explicit career discrimination against female analysts seeking to move to larger, higher-status brokerage firms given that allegations of gender discrimination constantly plague the larger firms and given that so many more analysts are male. Even so, larger brokerage firms may be more likely to have greater resources, allowing adoption of formal policies to encourage recruitment and retention of female analysts. For instance, Kumar (2010) found that female analysts have an increased likelihood of moving up to high-status firms and a smaller chance of moving down to low-status firms as compared with their male counterparts—evidence that job mobility among brokerage firms is perhaps more favorable toward female analysts.

How gender affects *I.I.* star rankings is difficult to ascertain. On the one hand, *Institutional Investor* asserts that "because of ratings by this magazine and others, research is the most closely monitored Wall Street field of all, making it eminently clear who the outstanding analysts are, male or female" (Galant 1996, p. 143). On the other hand, the nature of the *I.I.* survey exposes it to potential charges of gender discrimination. In March, April, or May of each year, *I.I.* sends surveys globally to such people as directors of research and investment fund managers. In its October issue, *I.I.* publishes its lists of first, second, third, and runners-up teams of its rankings based on the returned scores weighted by the size of each respondent's institution. However, the respondents may be influenced by gender discrimination. For example, because the survey respondents of buy-side fund managers are predominantly male, they may be subconsciously vulnerable to stereotypical gender prejudices.

Compared with the *I.I.* rankings, the *WSJ* rankings seem less likely to be influenced by gender prejudices. The annual *WSJ* rankings name the top five performers in each industry on the basis of industry-adjusted returns on portfolios created from analyst investment recommendations. The *WSJ* rankings have several explicit eligibility requirements that eliminate most analysts from the highly competitive listing. Although Emery and Li (2009) showed that these explicit requirements are likely dominated by recognition—similar to the implicit requirements of the *I.I.* rankings—it is unlikely that these requirements introduce implicit gender discrimination. Owing to potential implicit gender discrimination among the respondents for the *I.I.* rankings, we examined the *WSJ* rankings purely as a robustness comparison in order to verify any significant gender effects that we found with the *I.I.* rankings.

In analyzing gender as it relates to *I.I.* and *WSJ* star status and job mobility, we followed Hong and Kubik (2003) and Emery and Li (2009). We used probit models in which *IISTAR* (*WSJSTAR*) equals 1 if the analyst was an *I.I.* (*WSJ*) star in year *t* and 0 otherwise. We expressed the probit models in the following equation:

$$\Pr\begin{pmatrix} Job\ mobility—Up_t/ \\ Job\ mobility—Down_t/ \\ IISTAR_t = 1/ \\ WSJSTAR_t = 1 \end{pmatrix} = \Phi\begin{Bmatrix} a_0 + a_1FEMALE + a_2IISTAR_{t-1} \\ + a_3WSJSTAR_{t-1} + a_4ALPHA_{t-1} \\ + a_5EXPERIENCE_{t-1} + a_6COVERAGE \\ + a_7NREPORT_{t-1} + a_8NCOMPANY_{t-1} \\ + a_9COMPANYSIZE_{t-1} + a_{10}RESIRISK_{t-1} \\ + a_{11}PCTSELL_{t-1} + \text{Yearly dummy variables} \end{Bmatrix}, \tag{4}$$

where

Job mobility—Up = 1 if an analyst works for a low-status brokerage firm in year *t* – 1 and moves to a high-status firm in year *t* and 0 otherwise

Job mobility—Down = 1 if an analyst works for a high-status brokerage firm in year *t* – 1 and moves to a low-status firm in year *t* and 0 otherwise[8]

We defined high-status brokerage firms as those firms in the top 20% of all brokerage firms and low-status firms as the bottom 20% of all brokerage firms. Green et al. (2009) found that female analysts are more likely than males to leave within the first two years of initial hiring. In order to isolate the effects of gender, we controlled for all other analyst characteristics.

Table 3 reports the results of estimating Equation 4. The coefficient estimate for *FEMALE* is statistically insignificant after controlling for other analyst characteristics and for all career outcomes, except for *IISTAR*. This finding implies that being a female analyst increases the chance of becoming an *I.I.* star—that is, our results show no evidence of discrimination against female analysts in their career outcomes.

The control variable results largely reinforce findings from the prior literature. However, we included a few control variables for job mobility that were unexamined in previous research. The coefficient estimate of *ALPHA* is insignificant for all four models. The coefficient estimate of *PCTSELL* is positive and significant at the 1% level for the probability of moving up, suggesting that the likelihood of moving up may offer an incentive for analysts to be optimistic in their investment recommendations. Neither *WSJ* star status nor analyst risk-taking behavior in investment recommendations appears to have any effect on job mobility.

Following Emery and Li (2009), we also examined whether gender affects the probability of nonstars becoming stars and whether existing stars tend to repeat across years. We did so by estimating Equation 4 for nonstars and stars in the prior year. We further studied the probability that stars' rankings will change across years by estimating Equation 4 for the subset of analysts who are stars in the prior year, where the dependent variable is a binary (0, 1) variable that indicates the direction of movement (DOM) in the analyst's ranking from the prior year. The lowest ranking corresponds to those stars who do not repeat in the following year. For an increase in the ranking probability, the dependent variable equals 1 for stars whose rank increases by at least one level or who repeat at rank 1. For a decline in probability, the dependent variable equals 1 for stars whose rank decreases by at least one level. In untabulated results, we did not find a significant gender effect on these career outcomes. Altogether, our results suggest that gender does not significantly affect the career outcomes of sell-side analysts.

Sensitivity Tests. To determine the robustness of our results, we performed a number of sensitivity tests. First, we tested a variety of additional performance measures. We used alternative methodologies to measure recommendation performance and risk-taking behavior, including the value-weighted analyst portfolio, the market model, and the Carhart (1997) four-factor model. Because analysts cover related industries, we created an analyst-specific index by matching the stocks in individual analyst portfolios with industry indices on the basis of two-digit SIC codes. We replaced the market index with the analyst-specific industry indices in the factor models to control for industry momentum. To address the potential effect of bias on analyst performance, we excluded IPO research coverage in cases where the brokerage house of an analyst was the lead underwriter. None of the performance measurements qualitatively affected our results.

Table 3. Gender and Career Outcomes, January 1994–December 2005

	Job Mobility—Up$_t$		*Job Mobility—Down$_t$*		*IISTAR$_t$*		*WSJSTAR$_t$*	
	Coefficient	*t*-Statistic	Coefficient	*t*-Statistic	Coefficient	*t*-Statistic	Coefficient	*t*-Statistic
FEMALE	0.03	0.63	–0.08	–1.49	0.15***	3.25	0.06	1.30
IISTAR	0.27***	5.73	–1.08***	–7.80	2.53***	60.58	0.43***	10.50
WSJSTAR	0.03	0.47	–0.04	–0.53	0.28***	4.71	0.62***	13.04
ALPHA	–0.09	–0.96	–0.15	–1.44	0.03	0.22	–0.04	–0.40
EXPERIENCE	0.00	0.25	0.00	0.59	0.03***	6.00	0.03***	6.64
COVERAGE	0.14***	3.93	–0.10***	–2.71	0.12***	2.66	0.00	–0.11
NREPORT	–0.33***	–5.23	0.31***	4.90	–0.10	–1.47	–0.04	–0.62
NCOMPANY	0.23***	3.25	–0.22***	–3.00	0.18**	2.18	0.27***	3.69
COMPANYSIZE	0.07***	5.47	0.02	1.20	0.15***	9.51	0.05***	4.18
RESIRISK	–4.02***	–2.39	4.62***	2.88	–12.19***	–5.46	–5.52***	–2.93
PCTSELL	0.31**	2.19	–0.29*	–1.75	0.26	1.50	–0.02	–0.10
INTERCEPT	–1.93***	–18.31	–1.92***	–17.68	–2.70***	–21.13	–2.27***	–21.59
Pseudo-R^2	0.05		0.03		0.51		0.08	
N	23,329		22,465		21,203		22,020	

Note: Table 3 reports the results of estimating probit models for both the mobility of analysts among brokerage firms and their being an *I.I.* or *WSJ* star, as expressed in Equation 4.

*Significant at the 10% level.
**Significant at the 5% level.
***Significant at the 1% level.

We also tested different model specifications. Because some of the dependent variables are fractions (e.g., *PCTSELL*), we also performed logistic regressions for these variables. Moreover, in addition to panel regressions, we used Fama–MacBeth (1973) regressions to examine performance and behavior. Again, these different specifications did not modify our conclusions.

It is possible that individual analysts' forecasts and recommendations are not independent across companies or over time. For example, Stickel (1990) and Welch (2000) found evidence of herding in analysts' forecasts and recommendations, respectively. Dependence across recommendations is likely to introduce cross-sectional correlation in performance measures and, in turn, inflate test statistics. To address this potential problem, we excluded recommendations whose time spans between the recommendation and revision dates overlapped with any prior recommendation for the same stock. Although the resulting sample was only a subset of the original sample, our results were similar to those we presented earlier.

Because financial analysts are also industry specialists, we further measured analyst performance and behavior against industry benchmarks. Following Boni and Womack (2006), we used the 62 industries of the Standard & Poor's/MSCI Barra Global Industry Classification System (GICS) to classify industries. Boni and Womack showed that industry groups constructed with the 62 GICS industries are very good proxies for Wall Street industry groups. They also showed that the number of companies an analyst covers in her most covered GICS industry (the industry with the largest number of companies the analyst covers) is more than 80% of the total number of companies the analyst covers. They found that the value of analyst recommendations lies in analysts' ability to pick stocks within industries. We conducted a sensitivity analysis by using only the investment recommendations in the analyst's most covered GICS industries. Our results are similar to these industry benchmarks.

For job mobility, we also defined top brokerage firms differently, using the number of analysts employed or the annual IPO deal volume. Again, we found similar results.

Conclusion

Using a comprehensive sample of sell-side analyst investment recommendations, we investigated differences in the performance, risk-taking and bias behavior, and career outcomes of male and female sell-side analysts over time.

We found that the recommendations of female analysts as compared with those of their male counterparts produce similar abnormal returns but with slightly lower idiosyncratic risks. Our results suggest that female analysts underperform with respect to their upgrade recommendations and have little or no outperformance with their downgrades. This finding may be consistent with our finding that female analysts tend to take less risk in their recommendations than their male counterparts. Finally, our examination of the relation between gender and career outcomes with respect to job mobility among brokerage firms and star status based on *Institutional Investor* and *Wall Street Journal* rankings found no evidence of discrimination against female analysts. In fact, female analysts seem to have a better chance of being recognized as stars in both the *Institutional Investor* and the *Wall Street Journal* analyst rankings.

We are grateful to Alok Kumar for providing gender data for 2001–2005.

This article qualifies for 1 CE credit.

Notes

1. Unfortunately, owing to data availability constraints, we were unable to extend our analysis beyond 2005.
2. Each year, *Institutional Investor* publishes its All-America Research Team and the *Wall Street Journal* publishes its "Best on the Street" analyst rankings. Here, we refer to the (sell-side) analysts in both groups as "stars."
3. First Call does not identify individual analysts, which precludes tracking analysts and merging the earnings forecast and investment recommendation databases. Zacks Investment Research does not include such large firms as Merrill Lynch, Goldman Sachs, and Donaldson, Lufkin & Jenrette, which make up about 10% of all I/B/E/S recommendations. I/B/E/S includes all the major houses plus a larger number of smaller houses.
4. Chevalier and Ellison (1999) used two measures to examine the risk-taking behavior of mutual fund managers, namely, (1) residual return standard deviations in the market model regression in which the mutual fund returns are the dependent variables and (2) absolute deviations of market betas and residual return standard deviations of individual managers from the means of these two variables across all managers within a year. We similarly examined the same measures for analysts. Because the results are similar, we report only those for the residual return standard deviations in this article.
5. Formerly, the *WSJ* published two sets of rankings, one based on investment recommendations and the other on earnings forecasts. The *WSJ* stopped providing the rankings based on earnings forecasts in 2002. For brevity, we present only the results based on the *WSJ*'s investment recommendation rankings. We found similar results for the *WSJ*'s rankings based on earnings forecasts.

6. This finding is consistent with Sunden and Surette (1998) and Barber and Odean (2001), who found that females are more risk averse and less overconfident than males among individual investors. We also note that our results are generally consistent with Kumar (2010), who found that female analysts have greater forecast accuracy than male analysts.
7. The EEOC filed a class action lawsuit in 2001 on behalf of about 100 women in Morgan Stanley's institutional stock department, alleging that the firm discriminated against these employees "in promotion, compensation, terms, conditions, and privileges of employment"; Morgan Stanley settled the case for $54 million in 2004 and agreed to implement "far-reaching" measures to enhance the role of women in its work force (see http://online.wsj.com/article/0,,SB1000141174603082808.djm,00.html).
8. We also estimated Equation 4 by adding analyst and brokerage firm fixed effects and found similar results. Because the coefficient estimates of fixed-effect probit models are inconsistent (see, e.g., Greene 2011), the results are not tabulated but are available from the authors upon request.

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