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Self-Selection and the Forecasting Abilities of Female Equity Analysts

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ABSTRACT

This paper investigates whether there are systematic differences between the forecasting style and abilities of female and male analysts, and whether market participants recognize these differences. My key conjecture is that only female analysts with superior forecasting abilities enter the profession due to a perception of discrimination in the analyst labor market. Consistent with this conjecture, I find that female analysts issue bolder and more accurate forecasts and their accuracy is higher in market segments in which their concentration is lower. Further, the stock market participants are aware of the male–female skill

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differences. They respond more strongly to the forecast revisions by female analysts even though those analysts get less media coverage. The short-term market reaction is incomplete, however, because it is followed by a strong post-revision drift. The perception of abilities is similar in the analyst labor market, where female analysts are more likely to move up to high-status brokerage firms, while their downward career mobility is lower. Collectively, these results indicate that female analysts have better-than-average skill due to self-selection and market participants are at least partially able to recognize their superior abilities.

1. *Introduction*

An emerging literature in accounting and finance focuses on the role of gender in financial markets and corporate decisions. For example, Atkinson, Baird, and Frye [2003] show that female mutual fund managers receive lower inflows into their funds, especially during the early years of their career. Wolfers [2006] examines the strength of stock market reaction following appointment of female CEOs to search for evidence of discrimination. Huang and Kisgen [2009] study the corporate policies of firms with female CFOs and find that, relative to male CFOs, female CFOs exhibit a greater propensity to make decisions that maximize shareholder value. In this paper, I extend this literature and study the behavior of female equity analysts. Specifically, I investigate whether female analysts have better forecasting abilities than male analysts and whether market participants are able to identify the male–female skill differences.

My conjecture is that female equity analysts are unlikely to be representative of the female population that is known to exhibit higher risk aversion (e.g., Jianakoplos and Bernasek [1998], Byrnes, Miller, and Schafer [1999], Dwyer, Gilkeson, and List [2002], Sapienza, Zingales, and Maestripieri [2009]) and lower levels of competitiveness (e.g., Niederle and Vesterlund [2007]). They are more likely to represent a special group of competitive women who choose to pursue a career in the male-dominated financial services industry. Female analysts are also likely to possess superior forecasting abilities that could allow them to compete more effectively with male analysts. Overall, due to a self-selection process, only women with above average abilities would choose the analyst profession and, consequently, on average, female analysts are likely to be more skillful than male analysts.[1]

I test this self-selection hypothesis using a large sample of analysts' earnings forecasts. First, I investigate whether forecast characteristics and forecasting abilities vary with analysts' personal attributes such as gender. To directly test the self-selection hypothesis, I examine analysts' forecast accuracy and task assignments during the first few years following their initial

[1] An alternative to the self-selection hypothesis is that affirmative action and a growing push toward workplace diversity would favor female analysts and, as a result, female analysts are likely to be less skillful than male analysts. This alternative hypothesis is not supported by the data.

employment. If female analysts with superior abilities enter the profession, they would have greater forecast accuracy at the time of entry and would also cover more influential stocks (e.g., large-cap stocks or stocks with high institutional ownership). In addition, I identify whether the average forecast accuracy of female analysts is higher in market segments in which their concentration is lower.

Next, in two separate market settings, I determine whether perceptions of analysts' abilities differ from their actual abilities and whether this difference varies systematically with analysts' personal attributes. In the first setting, I examine whether the stock market's short-term and long-term reactions to forecast revisions are influenced by analysts' gender. In the second setting, I consider the analyst labor market and investigate whether gender influences the upward and downward career mobility of analysts across brokerage firms.

If the stock market's perception of analysts' forecasting abilities is unbiased, the strength of the market's reaction to changes in analysts' opinions would mainly depend upon the news content of the forecast revision (i.e., the surprise) and the forecast accuracy of the analyst. After accounting for the news content, forecasting accuracy, and other known determinants of market reaction, qualitative features associated with the news, such as analyst gender, would not influence the market's response. Similarly, in the analyst labor market, assessment of forecasting abilities would not be colored by analysts' personal attributes. After accounting for forecasting style (e.g., forecast boldness, frequency of forecasts, etc.), accuracy, and other known determinants of career mobility, the upward and downward career mobility rates of analysts would not depend upon their personal attributes.

In contrast, if the stock market's perception of analysts' abilities is influenced by various social biases (e.g., discrimination, stereotyping, prejudice, etc.), the perception of abilities might be systematically distorted. In this scenario, the strength of the market's reaction following forecast revisions would depend not only on the news content of the revision and analysts' abilities, but also upon their personal attributes. Depending upon the nature of the social bias, analysts' personal attributes could either amplify or weaken the strength of the stock market's reaction. Similarly, in the analyst labor market, the upward and downward career mobility rates of analysts across brokerage houses could be affected incrementally by their personal attributes.

The empirical evidence indicates that forecasting style and accuracy vary systematically with analysts' gender. Female analysts are more likely to issue bolder forecasts and, irrespective of the forecasting style, their forecasts are more accurate. Consistent with the self-selection hypothesis, I find that female analysts are relatively more accurate and cover larger stocks with high institutional ownership, even when they are less experienced.

Examining the stock market's reaction to analysts' forecast revisions, I find that the market assigns greater importance to the opinions of female analysts. After controlling for forecast accuracy and other known determinants of market reaction, the short-term market reaction is stronger following forecast revisions by female analysts. Consistent with the self-selection hypothesis, I also find that the forecast accuracy is higher and the market's reaction to forecast revision is stronger when a revision is made by a female analyst at a small brokerage firm or when a female analyst covers a stock that is mostly covered by male analysts.

Although the market responds strongly to the revisions of female analysts, the reaction is incomplete. In the long run, the post-revision drift is strong following forecast revisions by female analysts. In contrast, the market impounds the information faster when an all-star analyst revises the earnings forecast. The long-term market reaction estimates indicate that the market does not fully uncover the information contained in the forecast revisions of female analysts.

One potential alternative explanation for the stronger market reaction to forecast revisions by female analysts could be that it reflects greater media coverage to female analysts. To examine whether greater media coverage influences markets' perceptions of abilities, I follow Bonner, Hugon, and Walther [2007] and use the Factiva database to obtain annual media coverage estimates (the number of news articles that mention the analyst's name) for each analyst. I find that the media does not provide greater coverage to female analysts. In fact, after accounting for skill and accuracy, there are relatively fewer news stories about female analysts. This evidence points to the intriguing possibility that perhaps the media exhibits a bias against female analysts.

To reinforce the evidence on perception of abilities obtained from the stock market setting, I examine whether analysts' personal characteristics also influence evaluation of abilities in the analyst labor market. In this economic setting, the effects of gender can be quantified more precisely because analysts' personal attributes such as gender are directly observable by the market participants. Consistent with the evidence from the stock market setting, I find that female analysts have a higher probability of moving to a high-status brokerage firm and a lower probability of being demoted to a low-status brokerage firm. This evidence further supports the hypothesis that markets have more favorable opinions about the abilities of female analysts. Taken together, these empirical findings support the self-selection hypothesis, which posits that due to a perception of discrimination in the analyst labor market, only female analysts with high abilities self-select into the profession.

The rest of the paper is organized as follows. In the next section, I examine the forecasting style of female analysts, including their forecast boldness. In section 3, I use multiple methods to compare the forecasting abilities of male and female analysts. In section 4, I examine the stock market's perception of analysts' abilities, conditional upon their personal attributes. In section 5, I examine whether analysts' personal attributes influence their career mobility. I conclude in section 6 with a summary of the paper.

2. *Forecasting Style of Female Analysts*

In this section, I investigate whether the forecasting style of female analysts differs from the style of male analysts. While I consider several forecast characteristics to capture style, I focus on forecast boldness and determine whether female analysts are more likely to issue bold or herding forecasts. I also examine the distribution of analysts across market segments and determine whether female analysts are concentrated among certain subsets of stocks, industries, or brokerage houses.

2.1 DATA SOURCES AND SAMPLE SELECTION

I use data from several sources. The main data set used in the study is the analysts' earnings forecasts available from Thomson Reuters' Institutional Brokers Estimate System (I/B/E/S). Like the recent empirical literature on analyst forecasts (e.g., Gleason and Lee [2003], Clement and Tse [2005]), I primarily focus on one year ahead annual earnings forecasts. For robustness, I also consider their quarterly forecasts.

The annual earnings forecasts data cover the period from May 1983 to June 2006 and contain a total of 2,856,198 forecasts issued by 18,292 analysts who cover 21,107 stocks. I merge the I/B/E/S data with the Center for Research on Security Prices (CRSP) data set to identify stocks for which daily and monthly stock returns are available. This matching reduces the number of forecasts to 2,232,457 and the stock coverage to 13,672 stocks. Several forecasts have a missing analyst code, and, after excluding those records, there are 2,200,758 valid forecasts made by 17,240 analysts who cover a total of 13,636 stocks.

I identify the gender of analysts using their full names. Unfortunately, the I/B/E/S database does not provide analysts' full names. It only provides the last name and the first initial of each analyst, which is clearly not sufficient for identifying analysts' gender. Thus, I hand-collect analysts' full names using multiple directories.

I obtain the full names of all-star analysts from the *Institutional Investor* magazine. The October issue of the magazine provides a list of all-star analysts with their full names and some biographical information. To obtain the full names of other non–all-star analysts, I use analyst registers from the 1995 to 2005 versions of Nelson's directory of investment research and analyst directories available at Yahoo Finance and other financial Web sites. In some instances, I also conduct searches of news articles on Factiva and Google to identify analysts' full names. The search is performed using the analyst's last name and the name of the brokerage firm. In instances where the search yields a first name that does not identify the gender unambiguously, I read the article and try to identify the gender.

After identifying the gender of all analysts, I merge the list with the I/B/E/S analyst translation file to assign an analyst code to each analyst. Following these data merges, I identify a set of forecasts for which I can identify the I/B/E/S analyst code, and gender of associated analysts. The final sample consists of 1,953,481 forecasts (about 88% of total), 13,020 stocks (about 95% of total), and 12,812 analysts. Overall, I am able to identify the gender for 93.46% of all valid analysts.[2]

In addition to the analyst data, I use the Thomson Reuters' Institutional (13F) holdings data to obtain a quarterly measure of institutional ownership for each firm. For each analyst, I also search the Factiva database for three separate years (1997, 2000, and 2003) to identify the number of news articles that mention the analyst's name and obtain annual measures of media coverage. To identify affiliated analysts, I use Thomson Financial's New Issues (SDC) database. An analyst is classified as affiliated if she works at a brokerage firm that was either a lead underwriter or a co-underwriter of an initial public offering (IPO) of the covered stock during the previous five years, a secondary equity offering (SEO) during the past two years, or a lead bond underwriter during the past one year. Last, for each stock in the sample, I obtain the daily and monthly prices, returns, and market capitalization data from Center for Research on Security Prices (CRSP), quarterly book value of common equity from Compustat, and the monthly time series of the three Fama–French factors and the momentum factor from Kenneth French's data library.[3]

2.2 ANALYST DISTRIBUTION ACROSS MARKET SEGMENTS

Table 1 presents the summary statistics for the analyst data. The proportion of female analysts has increased almost monotonically during the sample period. The proportion of female analysts peaked in 2001 when about 20% of all analysts were female. Over the entire 1983 to 2005 sample period, there are about 16% female analysts and they also issue about 16% of all forecasts. Overall, female analysts represent a significant segment of the total analyst population.

To examine whether female analysts are concentrated in certain industries, I use two related measures. For each of the 48 Fama and French [1997] industries, I compute the average proportion of analysts that are female and the average proportion of forecasts that are issued by female analysts. The results reported in table 2 indicate that female analysts have a greater

[2] The number of valid analysts appears low for several reasons. First, about 2,565 analysts in the I/B/E/S database have multiple analyst codes. In these instances, I correct the error and assign a new analyst code to each set of multiple analyst codes and treat all analysts within the set as one analyst. Second, a significant number of forecasts are made by an analyst team. I exclude 1,808 cases in which all analysts in the team do not have the same gender and a gender cannot be assigned to the team. Third, in some instances, the name field contains information other than the analyst's name (e.g., the name of the industry). Fourth, there are instances where the full name and the gender of the analyst are available, but since the matching with the I/B/E/S data is performed using the analyst's last name, the first initial, and the brokerage name, I cannot assign an I/B/E/S analyst code because there are multiple analysts with the same last name and the same first initial in the I/B/E/S database.

[3] The data library is available at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/.

TABLE 1

Sample Statistics

Time Period	NumForecasts (1)	NumStocks (2)	NumAnalysts (3)	FemAnalysts (4)	FemAnForecasts (5)
1983–85	172,268	2,879	3,471	8.56%	7.50%
1986–90	344,873	4,317	4,478	13.61%	13.12%
1991–95	387,948	5,239	4,092	15.84%	14.43%
1996–00	538,031	7,879	6,831	17.62%	16.67%
2001–05	510,361	5,832	7,519	16.45%	16.12%
1983–2005	1,953,481	13,020	12,812	16.03%	15.66%

This table reports the sample statistics for one-year-ahead earnings forecast revisions for the 1983 to 2005 period. Only forecasts for stocks that are available in the CRSP database are included in the sample. *NumForecasts* is the total number of forecasts, *NumStocks* is the total number of stocks, and *NumAnalysts* is the total number of analysts present during the chosen time period. I also report the percentages of all analysts that are female (*FemAnalysts*) and the percentages of all forecasts that are issued by female analysts (*FemAnForecasts*).

TABLE 2

Analyst Characteristics and Industry Concentration

Fama–French Industry	PercTotFore (1)	NumAnalysts (2)	FemAnalysts (3)	FemAnForecasts (4)
Agriculture	0.424	498	11.044	9.102
Aircraft	0.854	493	13.590	8.641
Alcoholic Beverages	0.381	397	17.380	15.185
Apparel/Clothing	1.157	708	20.904	39.814
Automobiles	2.277	1,275	10.196	9.132
Banking	6.558	1,658	13.329	12.209
Business Services	11.424	4,995	12.973	11.192
Business Supplies	2.223	1,003	13.958	13.371
Candy and Soda	0.554	383	14.621	15.253
Chemicals	2.903	1,548	12.597	12.644
Coal	0.248	274	9.489	4.668
Computers	6.002	2,944	11.990	10.171
Construction	1.099	1,170	11.026	14.093
Construction Materials	2.770	1,851	13.344	13.495
Consumer Goods	2.453	2,038	16.143	24.332
Defense	0.217	327	10.398	8.292
Electrical Equipment	3.260	2,436	11.535	8.785
Electronic Equipment	7.994	3,285	11.842	7.408
Entertainment	1.278	838	15.155	11.243
Fabricated Products	0.329	504	12.698	11.326
Financial Trading	10.638	3,890	14.010	12.839
Food Products	1.984	884	16.176	15.794
Healthcare	2.029	1,115	14.260	16.371
Insurance	4.146	1,210	13.636	16.918
Machinery	3.666	2,056	12.354	10.193
Measurement Equipment	2.298	1,897	11.914	9.153
Medical Equipment	2.289	1,399	13.939	11.085
Miscellaneous	0.249	450	10.889	9.924
Nonmetallic Mining	1.125	694	12.680	9.409
Personal Services	0.861	1,068	15.169	14.755
Petroleum	8.567	1,783	11.049	7.322
Pharmaceutical	4.536	1,696	15.212	13.669
Precious Metals	1.264	400	7.750	10.970

(*Continued*)

TABLE 2—*Continued*

Fama–French Industry	PercTotFore (1)	NumAnalysts (2)	FemAnalysts (3)	FemAnForecasts (4)
Printing and Publishing	1.496	830	17.229	17.441
Real Estate	0.485	761	12.352	13.852
Recreational Products	0.803	978	13.497	13.632
Restaurants	2.226	989	14.459	11.720
Retail	8.148	2,507	15.796	24.005
Rubber and Plastic	0.659	865	15.029	14.606
Shipbuilding/Railroad	0.219	279	10.753	10.312
Shipping Containers	1.484	864	14.005	13.523
Steel Works	2.228	1,273	10.919	7.465
Telecommunications	3.759	1,992	12.952	10.782
Textiles	0.555	434	19.585	25.568
Tobacco Products	0.130	169	15.385	19.222
Transportation	3.125	1,478	13.667	10.245
Utilities	3.658	1,366	13.397	11.878
Wholesale	4.413	3,599	14.421	17.036

For each of the 48 Fama and French [1997] industries, the table reports the percentage of all forecasts that belong to the industry (*PercTotFore*), the number of unique analysts that covered the industry during the 1983 to 2005 sample period (*NumAnalysts*), the proportion of analysts who are female (*FemAnalysts*), and the percentage of all forecasts issued by female analysts (*FemAnForecasts*).

concentration in retail, clothing, textiles, tobacco, and consumer industry categories, while they are under-represented in metals, coal, petroleum, steel, and other mining-related industries. This evidence indicates that although female analysts are not randomly assigned to industries and have greater concentration in certain market segments, they are broadly distributed across all industries.

I also examine the distribution of analysts across individual stocks. I find that 95.83% of stocks are covered by both male and female analysts, which indicates that although female analysts have greater concentration in certain industries, they are reasonably well represented in most segments of the market. This broad distribution allows me to accurately compare analysts' actual forecasting abilities and markets' perceptions of their abilities, conditional upon analysts' personal attributes.

2.3 ANALYST GENDER AND FORECAST CHARACTERISTICS

To better identify the characteristics of stocks and brokerages that have greater concentrations of female analysts, I examine the relation between analyst characteristics and a set of stock and brokerage characteristics using Fama–MacBeth logit regressions. In these regressions, I use either a gender dummy or an all-star dummy as the dependent variable.[4] The *Female Dummy*

[4] Due to an implicit causal interpretation of a regression model, it is uncommon but certainly not inappropriate to have a personal attribute as the *dependent variable*. For instance, Case and Paxson [2008] estimate a regression model with height as the dependent variable to identify the correlates of height. In a similar spirit, I attempt to identify the correlates of gender using the female dummy as a dependent variable.

is set to one if an analyst is female, while the *All-Star Dummy* is set to one for an analyst who is identified as an "all-star" in the October issue of the *Institutional Investor* magazine in the previous year.[5]

The set of independent variables in the specification includes *Affiliated Analyst Dummy*, which is set to one if the brokerage house that employs the analyst has an underwriting relation with the stock covered by the analyst. *Brokerage Size* is defined as the number of analysts that work for the brokerage firm. The set of firm characteristics includes *Firm Size*, *Book-To-Market*, *12-Month Return*, and *Institutional Ownership*, which are defined as the stock's market capitalization, the book-to-market ratio, the past 12-month return, and the level of institutional ownership, respectively. All firm characteristics are measured with a lag of one month.

The logit regression estimates are presented in table 3, panel A. The *t*-statistics are based on standard errors corrected for potential higher order serial correlation using the Pontiff [1996] method.[6] The results indicate that female analysts work at relatively larger brokerage houses and are more likely to be affiliated analysts. This evidence supports the conjecture that there is a greater push at larger brokerage firms toward affirmative action and increased workplace diversity. Examining the relation between stock characteristics and analyst characteristics, I find that, like the all-star analysts, female analysts cover relatively larger stocks and stocks with high institutional ownership. Given this heterogeneity in the distribution of analysts across stocks, industries, and brokerage firms, I control for these differences in the subsequent empirical investigation.

To identify the set of forecast characteristics that are more likely to be associated with analysts' gender, I extend the logit regression model and include a set of forecast characteristics as additional independent variables. This set mainly contains the determinants of forecasting behavior identified in Clement and Tse [2005]. Specifically, *Affiliated Analyst Dummy* is set to one if an analyst works at a brokerage house with an underwriting relation with the firm; *Forecast Accuracy* is the negative value of the price-scaled absolute difference between the earnings forecast and the actual earnings; *Brokerage Size* is the number of analysts at the brokerage firm; *Firm Experience* is the number of years the analyst covered the stock; *General Experience* is the

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[5] The focus of this study is on female analysts. The all-star dummy is included in the analysis because those results can provide an appropriate benchmark for interpreting the evidence associated with gender.

[6] The independent variables (except the dummy variables) are standardized so that each variable has a mean of zero and a standard deviation of one. To ensure that extreme values are not affecting the estimates, I winsorize all variables at their 0.5 and 99.5 percentile levels. Last, because all observations in a given month are not independent, the standard errors in each of the monthly cross-sectional regressions could be downward biased. However, the coefficient estimates in the monthly regressions are not affected by the potential cross-sectional correlation. Since I use the time series of the monthly coefficient estimates to obtain their statistical significance, my results are not sensitive to the potential cross-sectional dependence among observations within a month.

TABLE 3

Correlates of Analyst Gender and Reputation: Fama–MacBeth Logit Regression Estimates

	Dependent Variable	
Variable	Female Dummy (1)	All-Star Dummy (2)
Panel A: The baseline model		
Intercept	−1.365	−1.592
	(−11.68)	(−10.04)
Female Dummy		0.060
		(9.27)
All-Star Dummy	0.068	
	(5.27)	
Affiliated Analyst Dummy	0.038	0.140
	(3.32)	(8.26)
Brokerage Size	0.200	0.593
	(10.72)	(9.25)
Firm Size	0.065	0.054
	(5.72)	(6.55)
Book-To-Market	−0.017	−0.082
	(−3.74)	(−8.62)
12-Month Return	0.024	−0.033
	(4.31)	(−5.82)
Institutional Ownership	0.031	0.140
	(5.99)	(12.97)
Average Number of Obs	4,089	4,089
Average Pseudo R^2	0.060	0.107
Panel B: An extended model		
Intercept	−1.586	−1.761
	(−10.75)	(−10.33)
Female Dummy		0.043
		(3.49)
All-Star Dummy	0.036	
	(4.59)	
Affiliated Analyst Dummy	0.023	0.112
	(2.43)	(9.42)
Forecast Accuracy	0.028	0.001
	(8.77)	(0.07)
Brokerage Size	0.159	0.181
	(13.17)	(20.19)
Firm Experience	−0.005	0.152
	(−1.55)	(12.74)
General Experience	−0.116	0.513
	(−12.68)	(12.22)
Number of Firms Covered	−0.037	0.208
	(−5.87)	(13.31)
Number of Industries Covered	0.122	−0.244
	(11.46)	(−12.37)
Days Since Last Forecast	0.009	−0.009
	(3.03)	(−2.11)
Forecast Horizon	0.005	0.003
	(1.71)	(1.05)

(*Continued*)

TABLE 3—*Continued*

	Dependent Variable	
	Female Dummy	All-Star Dummy
Variable	(1)	(2)
Forecast Frequency	−0.032	0.182
	(−7.88)	(8.87)
Firm Size	0.016	0.072
	(3.37)	(10.92)
Book-To-Market	−0.027	−0.054
	(−6.69)	(−8.07)
12-Month Return	0.022	−0.013
	(6.95)	(−2.61)
Institutional Ownership	0.034	0.127
	(8.74)	(14.58)
Average Number of Obs	4,089	4,089
Average Pseudo R^2	0.132	0.184

This table reports the estimates from monthly Fama–MacBeth logit regressions, where the dependent variable is either a *Female Dummy* that is set to one for female analysts or an *All-Star Dummy* that is set to one for analysts who are identified as an "all-star" in the October issue of the *Institutional Investor* magazine in the previous year. Panel A reports the estimates for the baseline model that contains only brokerage and stock characteristics. Panel B reports estimates from an extended specification that also includes the main determinants of forecasting behavior identified in Clement and Tse [2005]. The set of independent variables includes: *Affiliated Analyst Dummy,* which is set to one if the brokerage firm that employs the analyst was either a lead underwriter or a co-underwriter of an IPO of the covered stock during the previous five years, a secondary equity offering during the past two years, or the lead bond underwriter during the past one year; *Forecast Accuracy*, which is defined as the negative value of price-scaled absolute forecast error ((Earnings Forecast − Actual Earnings)/Price); *Brokerage Size,* measured as the number of analysts that work for the firm; *Firm Experience* is the number of years the analyst covered the stock; *General Experience* is the number of years since the analyst first appeared in the I/B/E/S database; *Number of Firms (Industries) Covered* is the total number of unique stocks (industries) covered by the analyst during the year; *Days Since Last Forecast* is the number of days elapsed since the most recent forecast for the stock; *Forecast Horizon* is the number of days between the forecast date and fiscal period end date; *Forecast Frequency* is the number of forecasts for the stock issued by the analyst during the previous fiscal year. For all these independent variables, I compute peer group adjusted measures, where the peer group consists of all other analysts who revise the forecast for the same stock in the same month. Other independent variables include the following four stock characteristics: *Firm Size*, *Book-To-Market*, *12-Month Return*, and *Institutional Ownership*, which are defined as the stock's market capitalization, the book-to-market ratio, the past 12-month return, and the level of institutional ownership, respectively. The Pontiff [1996] method is used to correct the Fama–MacBeth standard errors for potential serial correlation. The *t*-statistics for the coefficient estimates are shown in parentheses below the estimates. All variables are winsorized at their 0.5 and 99.5 percentile levels. The independent variables (except the dummy variables) have been standardized. The sample period spans from 1983 to 2005.

number of years since the analyst first appeared in the I/B/E/S database; *Number of Firms (Industries) Covered* is the total number of unique stocks (industries) covered by the analyst during the year; *Days Since Last Forecast* is the number of days elapsed since the most recent forecast for the stock by any analyst; *Forecast Horizon* is the number of days between the forecast date and fiscal period end date; and *Forecast Frequency* is the number of forecasts for the stock issued by the analyst during the previous year.

I compute peer group adjusted measures of all forecast characteristics using the Clement and Tse [2005] method. The peer group consists of all other analysts who revise the forecast for the same stock in the same month.[7]

[7] The peer group adjusted measure (x_{adj}) for variable x lies between zero and one and is defined as $x_{adj} = (x - x_{min})/(x_{max} - x_{min})$, where x_{min} and x_{max} are the minimum and the

This adjustment provides a simple but an effective method to account for month and firm effects in the regression specification.[8]

The Fama–MacBeth logit regression estimates are presented in table 3, panel B. I find that the coefficient estimates of analyst, stock, and brokerage characteristics are similar to their estimates in the baseline model presented in table 3, panel A. In addition, the results indicate that female analysts issue relatively fewer forecasts and they are less likely to update their forecasts following a revision by another analyst. I also find that female analysts are more accurate. I also find that female analysts are more likely to be chosen as all-star analysts, which is consistent with the evidence in Green, Jegadeesh, and Tang [2009].[9] The accuracy results are also consistent with the self-selection hypothesis, which posits that women with better-than-average abilities enter the profession.

2.4 DO FEMALE ANALYSTS ISSUE BOLDER FORECASTS?

To better characterize the forecasting style of female analysts, I use monthly Fama and MacBeth [1973] logit regressions and examine whether female analysts exhibit a greater propensity to issue certain types of forecasts.[10] I focus on the following five forecast type indicators: bold, bold-positive, bold-negative, herding-positive, and herding-negative. The analysis on bold versus herding forecasts is partially motivated by the findings in Clement and Tse [2005], who show that bold forecasts are more likely to be induced by new private information. In light of the extant psychological evidence that associates males with optimism and overconfidence (e.g., Barber and Odean [2001]), I expect that male analysts will exhibit a greater propensity to issue upward revised bold forecasts.

I estimate logit regressions, where one of the five forecast types is the dependent variable. Using the classification method adopted in the analyst herding literature, I classify forecasts that are both above the prevailing consensus and above the most recent forecast issued by the analyst as bold-positive forecasts. Similarly, forecasts that are both below the prevailing consensus and below the most recent forecast issued by the analyst are classified as bold-negative forecasts. Together, bold-positive and bold-negative forecasts are classified as bold forecasts, and the remaining forecasts are classified as herding forecasts. Herding forecasts are further classified as herding-positive and herding-negative, depending upon the position (above

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maximum values of x within the peer group. The results are similar when the peer group adjusted measure is the standardized measure defined as $(x - \mu)/\sigma$, where μ is the mean and σ is the standard deviation of the peer group.

[8] In the robustness checks section, I also report estimates from a panel regression specification with stock, month, and brokerage fixed effects.

[9] About 17% of all-star analysts are female, and this proportion is slightly higher than the proportion of female analysts in the entire analyst population ($\approx$16%).

[10] I find similar results when I estimate a panel regression specification and use firm-clustered standard errors to account for potential cross-sectional dependence in errors (Petersen [2009]).

or below, respectively) of the revised forecast relative to the most recent analyst forecast.

The primary set of independent variables includes a gender dummy and an all-star dummy. To examine the incremental effects of the two analyst attributes, I include the determinants of forecast type identified in Clement and Tse [2005] as additional independent variables. This set contains analyst attributes, brokerage characteristics, and several stock characteristics.[11] I report the monthly Fama–MacBeth logit regression estimates in table 4, where I compute the *t*-statistics using standard errors that have been corrected for serial correlation.

In the first specification, the dependent variable is the bold forecast dummy. I find that the coefficient estimates of female and all-star dummy variables are positive and statistically significant. Specifically, the female dummy has a strong positive estimate (estimate = 0.059, *t*-statistic = 4.01), which indicates that female analysts are $0.059 \times 25 = 1.47\%$ more likely to issue bold forecasts (see column [1]).[12]

When I separate bold forecasts into bold-positive and bold-negative, a clearer picture of analysts' forecasting style emerges (see columns [2]–[5]). I find that female analysts are more likely to issue bold (herding) forecast when they revise their forecasts upward (downward). Specifically, female analysts are $0.135 \times 25 = 3.38\%$ more likely to issue a bold-positive forecast and $0.122 \times 25 = 3.05\%$ less likely to issue a bold-negative forecast (see columns (2) and (3)). Further, female analysts' propensity to issue herding negative forecasts is marginally positive but statistically insignificant (see column (5)). In comparison, the all-star analysts exhibit a marginally higher (lower) propensity to issue bold negative (positive) forecasts and a lower overall propensity to issue herding forecasts.[13]

These logit regression estimates indicate that female analysts are relatively more optimistic in their forecasts. They are more bullish when they revise their forecasts higher and less bearish when they revise their forecasts lower. Female analysts' greater propensity to issue bold positive forecasts is somewhat surprising and might appear inconsistent with the extant psychological evidence that associates optimism with males. However, the evidence is consistent with the self-selection hypothesis, which posits that only skillful and "male-like" female analysts would choose to enter the profession. In this scenario, female analysts are likely to have more similarities to rather than differences from their male counterparts. Further, in light of the findings in Hong and Kubik [2003] and Clarke and Subramanian [2006], who show

[11] Clement and Tse [2005] do not use *Affiliated Analyst Dummy, Institutional Ownership*, and firm-specific measures, but I include them in the set of independent variables for additional robustness.

[12] I use a factor of 25% to interpret the coefficient estimates in logit regression specifications (Wooldridge [2002]).

[13] The results are very similar when I exclude stocks with low analyst coverage (bottom decile), which are likely to have noisy consensus estimates.

TABLE 4

Analyst Characteristics and Forecasting Style: Fama–MacBeth Logit Regression Estimates

	Dependent Variable				
	Bold	Bold Pos	Bold Neg	Herd Pos	Herd Neg
Variable	(1)	(2)	(3)	(4)	(5)
Intercept	3.588	1.871	1.717	0.572	0.817
	(15.52)	(12.28)	(10.95)	(13.68)	(16.06)
Female Dummy	0.059	0.135	−0.122	−0.121	0.083
	(4.01)	(3.59)	(−2.55)	(−3.81)	(1.27)
All-Star Dummy	0.067	−0.036	0.095	−0.028	−0.015
	(2.84)	(−2.01)	(3.52)	(−3.47)	(−1.19)
Female × All-Star	0.002	0.003	−0.002	−0.001	0.001
	(1.53)	(1.35)	(−1.30)	(−0.52)	(0.46)
Control variables					
Affiliated Analyst Dummy	−0.003	0.001	−0.001	0.013	−0.004
	(−0.12)	(0.18)	(−0.24)	(2.53)	(−0.75)
Lagged Forecast Accuracy	−0.004	0.105	−0.108	−0.104	0.121
	(−1.01)	(10.89)	(−10.58)	(−9.79)	(11.95)
Brokerage Size	0.043	−0.008	0.050	−0.077	−0.011
	(7.78)	(−1.78)	(7.77)	(−8.75)	(−1.92)
Firm Experience	0.011	−0.009	0.002	−0.004	−0.024
	(2.53)	(−1.54)	(0.34)	(−0.68)	(−3.49)
General Experience	0.014	0.011	0.022	−0.012	−0.008
	(2.38)	(1.97)	(3.69)	(−1.84)	(−1.19)
Number of Firms Covered	−0.030	0.005	−0.035	0.031	0.065
	(−5.38)	(0.72)	(−5.05)	(3.67)	(6.79)
Number of Industries Covered	0.022	0.011	0.010	0.023	−0.021
	(4.29)	(1.55)	(1.43)	(3.22)	(−2.79)
Days Since Last Forecast	−0.039	0.058	−0.052	0.109	0.131
	(−5.66)	(8.33)	(−5.16)	(8.50)	(4.53)
Forecast Horizon	0.080	0.067	−0.037	−0.024	−0.091
	(5.32)	(6.66)	(−5.15)	(−5.25)	(−6.57)
Forecast Frequency	−0.009	−0.063	0.054	0.044	−0.018
	(−1.98)	(−7.71)	(7.01)	(6.01)	(−2.59)
Firm Size	−0.007	0.048	−0.055	−0.011	0.020
	(−1.71)	(4.43)	(−3.52)	(−2.60)	(2.49)
Book-To-Market	−0.006	−0.029	0.024	0.029	−0.028
	(−1.52)	(−3.73)	(2.49)	(4.43)	(−4.21)
12-Month Return	−0.060	0.109	−0.089	−0.022	0.082
	(−5.96)	(6.93)	(−6.95)	(−3.90)	(5.95)
Institutional Ownership	0.071	0.091	−0.031	−0.050	−0.001
	(5.37)	(4.73)	(−2.52)	(−4.46)	(−0.11)
Average Number of Obs	4,089	4,089	4,089	4,089	4,089
Average Pseudo R^2	0.125	0.185	0.189	0.138	0.127

This table reports the estimates from monthly Fama–MacBeth logit regression estimates, where the dependent variable is a forecast type indicator. In columns (1) to (5), the dependent variable is either a bold forecast dummy, a bold-positive forecast dummy, a bold-negative forecast dummy, a herding-positive forecast dummy, or a herding-negative forecast dummy, respectively. Forecasts that are both above the prevailing consensus and above the most recent forecast issued by the analyst are classified as bold-positive forecasts. Similarly, forecasts that are both below the prevailing consensus and below the most recent forecast issued by the analyst are classified as bold-negative forecasts. Together, bold-positive and bold-negative forecasts are defined as bold forecasts, while other remaining forecasts are classified as herding forecasts. Herding forecasts are also classified as herding-positive and herding-negative, depending upon the position of the revised forecast relative to the most recent analyst forecast. All independent variables have been previously defined in table 3. The Pontiff [1996] method is used to correct the Fama–MacBeth standard errors for potential serial correlation. The t-statistics for the coefficient estimates are shown in parentheses below the estimates. All variables are winsorized at their 0.5 and 99.5 percentile levels. The independent variables (except the dummy variables) have been standardized. The sample period spans from 1983 to 2005.

that analysts with greater employment risk issue conservative forecasts, this evidence points to the possibility that female analysts issue bolder forecasts because they perceive lower employment risk.

3. *Are Female Analysts More Accurate?*

In this section, I use multiple methods to evaluate the forecast accuracy of female analysts. One of the main objectives is to determine whether female analysts' bold forecasting style translates into greater forecast accuracy. If better-than-average female analysts self-select into the profession, they would have higher forecast accuracy, especially at the time of entry and in market segments in which their concentration is low.

3.1 FORECAST ACCURACY DIFFERENCES ACROSS TIME

To begin, I compute the peer group adjusted measure of forecast accuracy (the negative value of price-scaled absolute forecast error), where the peer group consists of the group of other analysts who revise the forecast for the same stock in the same month. Figure 1 shows the 12-month

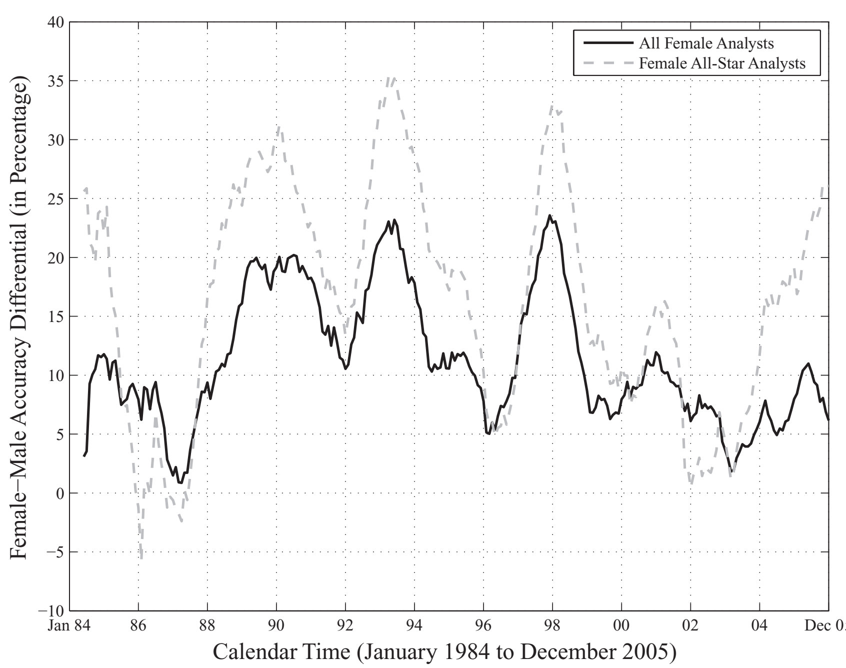

FIG. 1.—Female–male forecast accuracy differential over time. This figure shows the 12-month backward moving average of the mean peer group adjusted forecast accuracy of female analysts relative to male analysts. The female–male forecast accuracy differential for an industry is defined as 100 × (Average female accuracy − Average male accuracy)/(Average male accuracy). Forecast accuracy is defined as the negative value of price-scaled absolute forecast error ((Earnings Forecast − Actual Earnings)/Price). The peer group consists of all other analysts who revise the forecast for the same stock in the same month.

backward moving average time series of monthly forecast accuracy of all female and all-star female analysts relative to male analysts. The time-series plot indicates that, in the absence of control variables, throughout the sample period, female analysts have higher forecast accuracy than male analysts. In unreported results, we find that their average forecast accuracy is often even higher than the all-star analysts. Further, as expected, the plot shows that the forecast accuracy of female all-star analysts is even higher.[14]

3.2 STOCK- AND INDUSTRY-LEVEL ACCURACY COMPARISONS

For an alternative perspective on the relation between analyst characteristics and forecast accuracy, I compare the forecast accuracy levels of analyst groups within each of the 48 Fama–French industries and within individual stocks. The stock-level forecast accuracy for an analyst group is the average forecast accuracy of all stock forecasts made by the analysts who belong to the group. The industry-level accuracy for a group is computed in an analogous manner by averaging the accuracy levels of all stock forecasts within the industry that are made by the analysts from the group.

The graphical evidence in figure 2 indicates that the mean female–male forecast accuracy differential is 7.35% (median is 4.58%). In more than two-thirds of the industries, female analysts have greater forecast accuracy. Not surprisingly, the all-star analysts have the highest accuracy levels. They are 5.03% more accurate than female analysts and 10.98% more accurate than male analysts. When I compare the mean accuracy levels of analyst groups for individual stocks, I find similar results. The average female–male forecast accuracy differential is 62.11% and the median is 10.81%. The average accuracy level of female analysts is higher than the male analysts in 59.62% of stocks.[15] Similarly, the all-star analysts have the highest average stock-level accuracy.

3.3 FORECAST ACCURACY REGRESSION ESTIMATES

The time-series and industry plots illustrate that there is a strong relation between forecast accuracy and analyst attributes. However, these plots portray only a partial picture, because I cannot control for other determinants of forecast accuracy, such as the timing of a forecast relative to other forecasts. To account for those additional factors that are known to influence forecast accuracy, I estimate Fama–MacBeth regressions and examine the relation between analyst attributes and forecast accuracy separately for each type of forecast. If female analysts have superior forecasting skill, they would have high average forecast accuracy, irrespective of the type of forecast. Moreover, analyst gender would be strongly associated with forecast accuracy, even after accounting for the known determinants of accuracy.

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[14] I find that female analysts are more accurate than male analysts across time even when I use analysts' quarterly earnings forecasts.

[15] To obtain reliable accuracy estimates, I exclude stocks with fewer than five male and female forecasts during the sample period. The results are similar when I use other cutoffs.

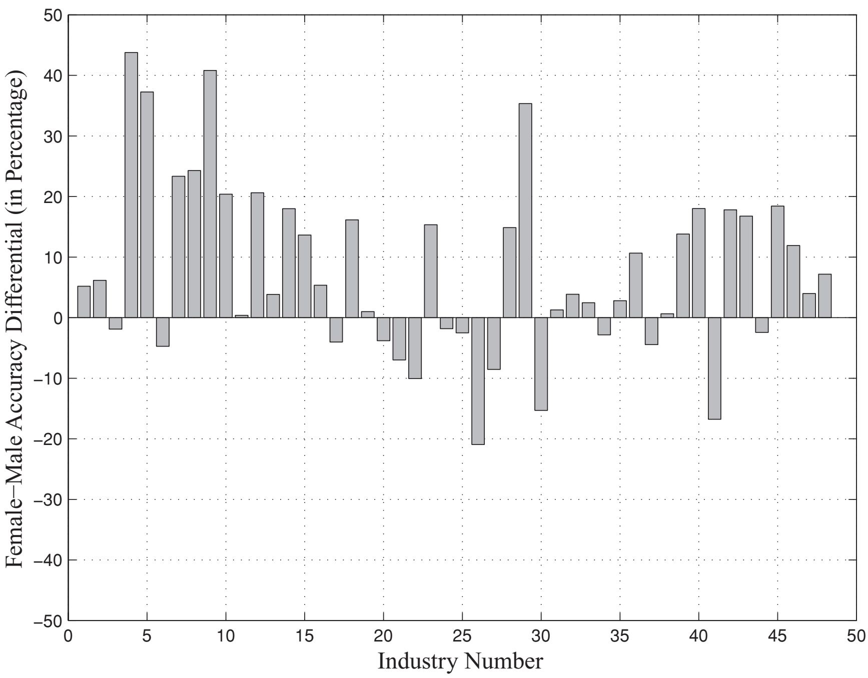

FIG. 2.—Female–male forecast accuracy differential at the industry-level. This figure shows the average forecast accuracy differential for each of the 48 Fama–French industry categories. The female–male forecast accuracy differential for an industry is defined as 100 × (Average female accuracy − Average male accuracy)/(Average male accuracy). The industry average is computed over the entire sample period and over all stocks within the industry.

I estimate several accuracy regressions in which the peer group adjusted measure of forecast accuracy is the dependent variable. The independent variables are the two primary analyst attributes, along with the known determinants of forecast accuracy. Specifically, the set of control variables includes several analyst attributes, brokerage characteristics, and stock characteristics. Although the peer group adjusted forecast error measure controls for firm characteristics and the timing of the forecast, to account for the possibility that some stocks are more difficult to forecast than others, I use several stock characteristics (firm size, book-to-market ratio, past 12-month return, and the level of institutional ownership) as additional control variables.

I estimate the accuracy regressions separately for each forecast type. Both the dependent and independent variables are standardized (mean is set to zero and the standard deviation is one) such that the coefficient estimates can be compared within specifications and across specifications. The accuracy regression estimates are presented in table 5.

The accuracy regression estimates indicate that irrespective of the forecast type, female analysts are more accurate. The accuracy levels are even higher for female analysts who are an all-star analyst. Judging by the magnitude of

TABLE 5

Analyst Characteristics and Forecast Accuracy: Fama–MacBeth Regression Estimates

	Forecast Signal Considered					
Variable	All (1)	Bold (2)	Bold Pos (3)	Bold Neg (4)	Herd Pos (5)	Herd Neg (6)
Intercept	−0.005	−0.008	−0.002	−0.001	−0.013	−0.004
	(−2.64)	(−2.05)	(−0.97)	(−0.41)	(−3.19)	(−0.87)
Female Dummy	0.029	0.031	0.059	0.027	0.022	0.036
	(5.80)	(4.49)	(6.58)	(3.73)	(2.35)	(4.61)
All-Star Dummy	0.033	0.031	0.025	0.041	0.018	0.048
	(5.32)	(4.69)	(2.18)	(4.93)	(1.00)	(3.36)
Female × All-Star	0.004	0.009	0.012	0.006	0.008	0.011
	(2.03)	(2.67)	(2.72)	(2.07)	(2.29)	(3.00)
Control variables						
Affiliated Analyst Dummy	−0.021	−0.022	−0.017	−0.031	−0.018	−0.016
	(−10.89)	(−9.08)	(−6.56)	(−8.81)	(−3.03)	(−2.31)
Lagged Forecast Accuracy	0.132	0.117	0.104	0.246	0.177	0.138
	(15.38)	(13.48)	(12.57)	(5.08)	(10.32)	(10.79)
Brokerage Size	0.011	0.012	0.015	0.013	0.017	0.009
	(7.71)	(6.98)	(5.91)	(5.14)	(4.18)	(1.45)
Firm Experience	−0.041	−0.044	−0.038	−0.027	−0.018	−0.033
	(−11.33)	(−11.58)	(−9.78)	(−7.82)	(−1.08)	(−4.21)
General Experience	0.022	0.023	0.022	0.051	0.008	0.072
	(9.61)	(9.38)	(6.77)	(11.63)	(0.45)	(3.02)
Number of Firms Covered	0.024	0.022	0.021	0.028	0.037	0.035
	(9.04)	(7.54)	(6.43)	(6.33)	(5.34)	(1.54)
Number of Industries	−0.020	−0.019	−0.015	−0.029	−0.039	0.002
Covered	(−8.62)	(−6.99)	(−4.93)	(−7.25)	(−5.52)	(0.36)
Days Since Last Forecast	−0.009	−0.005	−0.016	−0.020	−0.046	−0.032
	(−5.13)	(−2.46)	(−5.71)	(−5.93)	(−5.45)	(−2.89)
Forecast Horizon	−0.098	−0.097	−0.093	−0.108	−0.113	−0.112
	(−15.27)	(−14.17)	(−13.80)	(−13.81)	(−9.95)	(−8.06)
Forecast Frequency	−0.062	−0.064	−0.062	−0.061	−0.055	−0.058
	(−11.39)	(−9.06)	(−11.59)	(−11.93)	(−6.92)	(−7.51)
Firm Size	0.044	0.046	0.050	0.045	0.047	0.037
	(6.48)	(5.65)	(4.85)	(4.74)	(5.92)	(5.26)
Book-To-Market	−0.056	−0.100	−0.110	−0.103	−0.097	−0.120
	(−6.13)	(−5.93)	(−9.16)	(−4.07)	(−8.63)	(−5.10)
12-Month Return	0.073	0.075	0.058	0.075	0.091	0.052
	(8.21)	(6.82)	(4.97)	(4.76)	(5.69)	(3.36)
Institutional Ownership	0.072	0.071	0.077	0.062	0.077	0.065
	(5.21)	(4.32)	(6.68)	(3.06)	(5.98)	(4.92)
Average Number of Obs	4,089	2,663	1,410	1,254	554	778
Average Adjusted R^2	0.155	0.152	0.165	0.178	0.146	0.134

This table reports the estimates from monthly Fama–MacBeth cross-sectional regressions, where the peer group adjusted forecast accuracy measure is the dependent variable. Forecast accuracy is defined as the negative value of price-scaled absolute forecast error ((Earnings Forecast − Actual Earnings)/Price) and the peer group consists of all other analysts who revise the forecast for the same stock in the same month. I estimate the accuracy regressions separately for each of the five forecast types (bold, bold-positive, bold-negative, herding-positive, and herding-negative). Forecasts that are both above (below) the prevailing consensus and above (below) the most recent forecast issued by the analyst are classified as bold-positive (bold-negative) forecasts. Together, they define bold forecasts and other forecasts are classified as herding forecasts. Herding forecasts are classified as herding-positive and herding-negative, depending upon the position of the revised forecast relative to the most recent analyst forecast. All independent variables have been previously defined in table 3. The Pontiff [1996] method is used to correct the Fama–MacBeth standard errors for potential serial correlation. The *t*-statistics for the coefficient estimates are shown in parentheses below the estimates. All variables are winsorized at their 0.5 and 99.5 percentile levels. The dependent and independent variables (except the dummy variables) have been standardized. The sample period spans from 1983 to 2005.

the coefficient estimates, the incremental accuracy level of female analysts is only marginally below the average accuracy of all-star analysts. Comparing accuracy across various forecast types, I find that female analysts are most accurate when they issue bold and positive forecasts (*Female Dummy* estimate = 0.059, t-statistic = 6.58).

The coefficient estimates of the control variables are also consistent with the recent evidence on forecast accuracy. In particular, I find that forecast accuracy is lower for smaller stocks that are relatively more difficult to value. Further, consistent with the evidence in Ljungqvist et al. [2007], forecast accuracy is higher for stocks with higher institutional ownership, and lower when forecasts are issued by affiliated analysts. In unreported analysis, I also find that, consistent with the evidence in Clement and Tse [2005], forecast accuracy is greater for bold forecasts.

3.4 ACCURACY REGRESSION ESTIMATES FOR SUB-SAMPLES

To examine whether the relation between forecast accuracy and analyst characteristics varies with forecast and brokerage characteristics, I estimate the accuracy regressions for several sub-samples. For example, the greater accuracy of female analysts might be concentrated among analysts who work at large brokerages, are more experienced, or revise their forecasts more frequently. I define the sub-samples based on the following variables: firm-specific experience, general experience, number of firms covered, brokerage status defined using brokerage size, forecast horizon, and female analyst concentration (ratio of the number of female analysts to the total number of analysts). The high and low sub-samples refer to high and low quintiles, respectively. The accuracy estimates are summarized in table 6.

The sub-sample results indicate that the full-sample accuracy results are quite robust. The coefficient estimates of female and all-star analyst dummy variables are significantly positive in all sub-samples. Comparing the

TABLE 6

Forecast Accuracy Regressions: Robustness Check Results

	Coefficient Estimate For		
Test	Female Dummy (1)	All-Star Dummy (2)	(Avg.) Adj. R^2 (3)
Sub-samples			
Low Firm Experience	0.031	0.042	
	(6.72)	(9.63)	0.143
High Firm Experience	0.029	0.031	
	(6.55)	(9.70)	0.144
Low General Experience	0.025	0.036	
	(4.07)	(6.82)	0.137
High General Experience	0.027	0.039	
	(3.89)	(8.82)	0.142
Small Number of Firms Covered	0.028	0.046	
	(3.19)	(7.96)	0.135

(*Continued*)

TABLE 6—*Continued*

	Coefficient Estimate For		
Test	Female Dummy (1)	All-Star Dummy (2)	(Avg.) Adj. R^2 (3)
Large Number of Firms Covered	0.033	0.044	
	(2.97)	(8.02)	0.145
Low-Status Brokerage Firms	0.035	0.044	
	(5.65)	(7.72)	0.136
High-Status Brokerage Firms	0.016	0.017	
	(3.03)	(2.82)	0.142
Short Forecast Horizon	0.026	0.036	
	(3.14)	(4.86)	0.131
Long Forecast Horizon	0.033	0.038	
	(4.21)	(5.18)	0.130
Low Female Concentration	0.052	0.045	
	(8.65)	(11.67)	0.129
High Female Concentration	0.024	0.036	
	(3.89)	(8.83)	0.139
Alternative estimation methodology			
Quarterly Forecast Revisions	0.049	0.057	
	(8.29)	(8.46)	0.171
Consider Last Forecast Only	0.037	0.047	
	(5.46)	(6.97)	0.109
Brokerage Fixed Effects	0.040	0.109	
	(4.89)	(5.27)	0.158
Stock, Month, Brokerage Fixed Effects	0.046	0.106	
(No Peer Group Adjustment)	(4.56)	(4.96)	0.175
Keane and Runkle [1998]	0.039	0.052	
GMM Estimation	(4.48)	(8.28)	0.142
Control for Earnings Skewness	0.037	0.057	
	(6.44)	(6.37)	0.156
Basu and Markov [2004]	0.060	0.089	
LAD Estimation	(7.39)	(8.59)	0.106

This table summarizes the estimates from monthly Fama–MacBeth accuracy cross-sectional regressions estimated in table 5 for different sub-samples and different estimation methods. The peer group adjusted forecast accuracy measure is the dependent variable, which is defined as the negative value of price-scaled absolute forecast error ((Earnings Forecast − Actual Earnings)/Price) and the peer group consists of all other analysts who revise the forecast for the same stock in the same month. Analyst attributes, along with other previously defined determinants of forecast accuracy, are the independent variables. For brevity, only the coefficient estimates of the two main variables are reported. Table 5 provides further details about the regression specification. The *t*-statistics for the coefficient estimates are shown in parentheses below the estimates. Sub-samples based on the following previously defined variables (see table 3) are considered: firm-specific experience, general experience, number of firms covered, brokerage status that is defined using brokerage size, forecast horizon, and female analyst concentration (ratio of the number of female analysts and the total number of analysts). The high and low sub-samples refer to high and low quintile, respectively. The last set of tests use different methods. First, I consider the accuracy of quarterly earnings forecasts instead of annual forecasts. Second, I consider only the last analyst forecast for a stock prior to the earnings announcement date. Third, I estimate a panel specification with brokerage fixed effects. Fourth, I use the raw instead of peer group adjusted measures but include stock, month, and brokerage fixed effects in the panel specification. In both fixed effect regressions, the standard errors are clustered by firm. In the fifth test, I use the Keane and Runkle [1998] GMM estimation method to account for cross-sectional dependence. In the next test, I use earnings skewness as an additional control variable. Following Gu and Wu [2003], earnings skewness is the difference between the mean and median realized earnings during the past eight quarters, scaled by the stock price in the previous month. In the last test, I use the Basu and Markov [2004] LAD estimation method.

magnitudes of the coefficient estimates, I find that female and all-star analysts at smaller brokerage firms are more accurate. Interestingly, I also find that female analysts make relatively more accurate forecasts among stocks in which their concentration is lower. The coefficient estimates for the *Female Dummy* in the accuracy regression for the low and the high female concentration sub-samples are 0.052 (t-statistic = 8.65) and 0.024 (t-statistic = 3.89), respectively. This evidence suggests that a non-typical analyst covering a stock is likely due to self-selection and could serve as an indicator of superior ability.

3.5 ADDITIONAL ROBUSTNESS CHECKS FOR ACCURACY ESTIMATES

I conduct several additional tests to further examine the robustness of accuracy regression estimates. First, I re-estimate the accuracy regressions with quarterly earnings forecasts. This analysis is based on 1,561,170 quarterly earnings forecasts issued during the 1983 to 2005 time period, which covers 12,380 CRSP stocks and 13,077 analysts. Second, similar to Clement and Tse [2005], I estimate a regression specification where I only consider the last analyst forecast for a stock within a fiscal year. Third, because female analysts are not distributed randomly across brokerage firms, I estimate a panel regression specification with brokerage fixed effects to ensure that the results do not merely reflect differences in brokerage characteristics.[16]

Next, to ensure that the main results are not influenced by the peer group adjustment method, I use the "raw," unadjusted data and estimate a panel regression specification with stock, month, and brokerage fixed effects. In both fixed effects regression specifications, I use firm-clustered standard errors.

In the fifth test, I use the Keane and Runkle [1998] GMM estimation method to account for cross-sectional dependence in analysts' forecasts. In the sixth test, I use earnings skewness as an additional control variable to investigate whether the male–female accuracy differences documented earlier merely reflect male and female analysts' differential response to skewness in realized earnings. Following Gu and Wu [2003], earnings skewness is the difference between the mean and median realized earnings during the past eight quarters, scaled by the stock price in the previous month. In the last test, I use the Basu and Markov [2004] least absolute deviation (LAD) estimation method to examine whether a linear loss function is able to better capture the forecasting incentives of analysts.

The results from these additional tests are also presented in table 6. In all instances, the results are qualitatively similar to the baseline results obtained using the Fama–MacBeth approach. Further, the results obtained using the fixed effects and LAD methods are somewhat stronger. When I use earnings

[16] The peer group adjustment already accounts for stock and month effects. Thus, the results are very similar when I also introduce stock and month fixed effects in the panel regression specification.

skewness as an additional control variable, consistent with the evidence in Gu and Wu [2003], the earnings skewness variable has a positive coefficient estimate (estimate = 0.142, *t*-statistic = 3.36). Importantly, the coefficient estimate of female and all-star dummy variables become stronger. Taken together, the evidence from these additional tests indicates that the accuracy estimates obtained using the Fama–MacBeth method are robust and are not induced by the specific methodological choice. The results are also unlikely to reflect the potential selection bias induced by the non-random distribution of female analysts across stocks, industries, and brokerage firms.

Overall, the accuracy results indicate that forecasting abilities vary systematically with analyst attributes. All else equal, the all-star analysts are most accurate. Female analysts are less accurate than the all-star analysts but more accurate than male analysts.[17]

3.6 DIRECT TESTS OF THE SELF-SELECTION HYPOTHESIS

In the last set of accuracy tests, I directly examine the self-selection hypothesis. First, I examine whether female analysts exhibit superior forecasting skills at the time of employment and when they are relatively less experienced. Using the same specification as in table 3, panel B, when I examine the correlates of gender for newly employed and relatively less experienced analysts (experience $\leq$ 2 years), I still find that female analysts are more accurate and cover relatively larger stocks and stocks with higher institutional ownership. The untabulated coefficient estimates for *Forecast Accuracy*, *Firm Size*, and *Institutional Ownership* variables are 0.038 (*t*-statistic = 7.37), 0.017 (*t*-statistic = 3.88), and 0.035 (*t*-statistic = 7.54), respectively. The results are similar even when I estimate the accuracy regressions separately for different forecast types and only consider the forecasts of less experienced analysts. I find that female analysts are still more accurate than other analysts.

These estimates of analysts' initial accuracy indicate that female analysts are more skillful and get better job assignments at the time of their initial employment. The superior skill of female analysts at the time of hiring suggests that they are likely to face higher opportunity costs and, consequently, only very qualified female analysts self-select into the profession.

To gather additional support for the self-selection hypothesis, I examine whether female analysts are more accurate among stocks and industries in which their concentration is lower. The analysis is based on the assumption that if a female analyst covers a stock that is typically covered by male analysts (e.g., a mining stock), she must be more skillful than the typical male analyst covering the stock. Figure 3 shows the average female–male forecast

[17] While most of my results are consistent with the evidence in Green, Jegadeesh, and Tang [2009], the accuracy results are opposite. This inconsistency probably arises due to the differences in our methodological choices and the choice of control variables. To allow direct comparisons with the recent evidence on forecast accuracy, I follow the exact methodology in those papers (e.g., Clement and Tse [2005], Ljungqvist et al. [2007]) to measure forecast accuracy and to identify the determinants of accuracy.

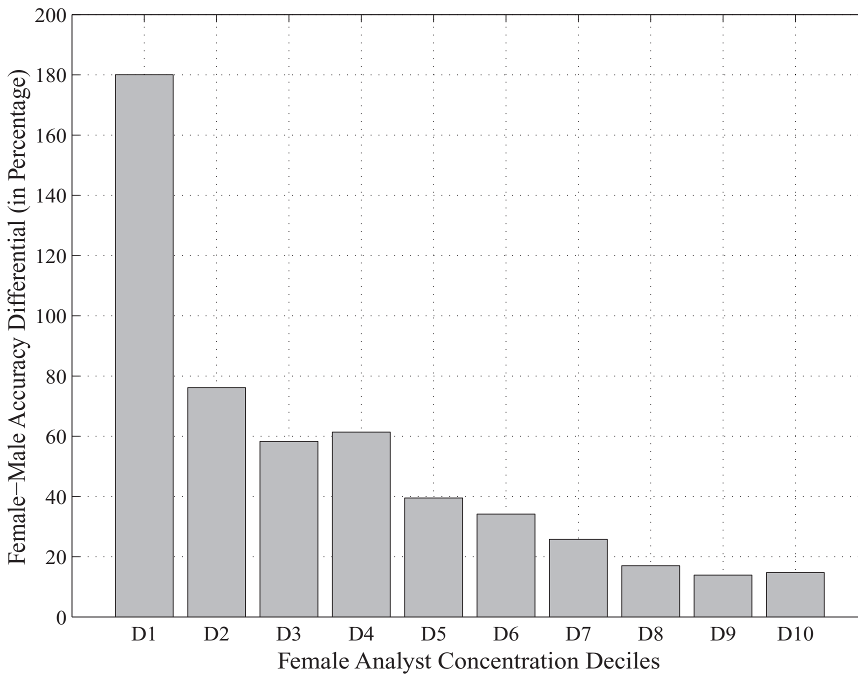

FIG. 3.—Female analyst concentration and the female–male forecast accuracy differential. This figure shows the average forecast accuracy differential for 10 female analyst concentration sorted categories. Female analyst concentration for a stock is the proportion of all analysts covering the stock that are female. The female–male forecast accuracy differential for a stock is defined as 100 × (Average female accuracy − Average male accuracy)/(Average male accuracy). The average accuracy for a stock is computed over the entire sample period and covers all forecasts related to the stock.

accuracy differential for female analyst concentration-sorted categories. The female analyst concentration for a stock is defined as the ratio between the number of female analysts covering the stock and the total number of analysts covering the stock. The graphical evidence indicates that the average female forecast accuracy is greater among stocks in which their concentration is lower. This evidence is consistent with the self-selection hypothesis and indicates that a female analyst covers a stock that is typically covered by male analysts when she has above-average forecasting ability.

4. *Stock Market's Perception of Analysts' Abilities*

The empirical evidence thus far indicates that analysts' forecasting style and abilities vary with their personal attributes. In this section, I investigate whether the stock market's perception of forecasting abilities is influenced by analysts' personal attributes. I use the short-term and long-term market reaction measures to estimate the degree of distortion between the actual and the perceived forecasting abilities.

If the market's perception of forecasting skill is accurate, it would respond strongly to analysts with greater forecast accuracy during the announcement period. The subsequent drift following the forecast revision would be weak or non-existent. Furthermore, after accounting for analysts' skill and accuracy, other personal attributes such as gender would not have any incremental power to explain the return patterns. In contrast, if the market mis-interprets the information contained in analysts' forecast revisions because of social biases such as discrimination and stereotyping, analysts' personal attributes beyond skill would influence the market's short-term and long-term reactions.[18]

4.1 SHORT-TERM MARKET REACTION

To investigate the stock market's perception of analyst abilities, I estimate a series of Fama–MacBeth regressions. The dependent variable in these regressions is the three-day cumulative market-adjusted abnormal stock return, centered on the forecast revision date. The independent variables include female and all-star dummy variables, which have been defined earlier. In addition, this set contains three variables that reflect the main forecast characteristics.

Revision is the price-scaled difference between the analyst's new and the most recent forecast for the stock. It captures the news content of the forecast revision. Forecast boldness is measured by a categorical variable *Bold Signal,* which is set to +1 for bold-positive forecasts, −1 for bold-negative forecasts, and 0 for herding forecasts. *Lagged Forecast Accuracy* is the analyst's peer group adjusted forecast accuracy during the year prior to the forecast. Motivated by the evidence in Gleason and Lee [2003], I also consider two interaction variables (Female × Bold Signal and All-Star × Bold Signal) to examine whether market reaction is stronger when female analysts issue bold forecasts.[19]

Besides these main independent variables, to control for other predictors of forecast accuracy that could influence the market's short-term reaction, the set of independent variables includes the determinants of forecast accuracy defined previously. This set includes several analyst attributes, brokerage characteristics, and stock characteristics. To account for the known influences of stock characteristics on returns, I consider firm size, book-to-market

[18] Of course, these conjectures are based upon the assumption that the market participants are aware of analysts' personal attributes. Given that analysts' names are featured prominently in the news articles and analysts' reports indicate the name of the analyst clearly and frequently along with a photo, this is a reasonable assumption. For an example, see a report from a Morningstar analyst available at http://members.morningstar.com/memberstpages/PM_StockAnalystR.html.

[19] Gleason and Lee [2003] examine whether the market responds to the qualitative features of forecast revisions such as the ranking and the reputation of analysts. They find that analyst ranking variables have the ability to explain returns only when they are interacted with the strength of the revision signal. Thus, their evidence indicates that forecast boldness and analyst characteristics jointly determine the level of the market's reaction.

ratio, past 12-month return, and institutional ownership as additional independent variables. I also include Fama and French [1997] industry dummies to control for industry differences in the market's reaction. Last, to control for the effects of other recent news events, I include the previous one week return and volume turnover as additional control variables.[20]

Table 7 presents the monthly Fama–MacBeth regression estimates, where, as before, the *t*-statistics are based on standard errors that have been corrected for serial correlation. I find that the market responds strongly to the revisions of female analysts. For instance, the results in column (1) indicate that when a female analyst issues a bold positive (negative) forecast, during the three-day event window, the market exhibits a 0.578% higher (lower) reaction, compared to the reaction following a similar forecast issued by a male analyst. The magnitude of market's reaction is somewhat higher (=0.634%) when I account for other known predictors of market reaction in the regression specification (see column (2)). In economic terms, this incremental reaction translates into a $0.634 \times 7 = 4.44\%$ monthly return and is significant.

For robustness, I examine the market's reaction during the week following the revision (days −1 to +5, where day 0 is the revision date). The estimates for the seven-day window (see columns (3) and (4)) are qualitatively similar to the estimates obtained using the three-day event window.[21]

To examine whether there is an asymmetry in the market's reaction to positive and negative revisions, I follow a slightly different method and estimate the short-term reaction regression separately for bold-positive, bold-negative, herding-positive, and herding-negative forecasts. These results are presented in table 7, columns (5)–(8). Consistent with the baseline estimates in column (2), I find that the short-term market reaction is stronger when the forecast is issued by a female or an all-star analyst. For instance, when a female analyst issues a bold-positive forecast, on average, the three-day market reaction is 0.386% higher (see column (5)). And when a female analyst issues a bold-negative forecast, on average, the three-day market reaction is −0.337% lower (see column (6)). The coefficient estimates of the all-star dummy variable are also consistent with the earlier findings.

When I consider herding forecasts, all three dummy variables have insignificant coefficient estimates (see columns (7) and (8)). These estimates indicate that analysts' personal characteristics have an incremental influence on short-term returns only when they issue bold forecasts. The coefficient estimates for control variables are broadly consistent with the previous evidence on announcement period returns. For instance, I find that the market reaction is stronger for smaller firms or when the analyst issuing the forecast is an affiliated analyst.

[20] For brevity, the industry dummy variables and lagged return and turnover estimates are not reported. Most of these variables have insignificant coefficient estimates.

[21] The results are similar if I measure the market reaction after excluding day −1.

TABLE 7

Analyst Characteristics and Short-Term Market Reaction to Forecast Revisions: Fama–MacBeth Regression Estimates

	Forecast Signal Considered							
	All (3 days)		All (7 days)		BoldPos	BoldNeg	HerdPos	HerdNeg
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Intercept	−0.215	−0.229	−0.191	−0.222	0.633	−1.241	0.047	−0.095
	(−5.37)	(−5.53)	(12.47)	(−13.89)	(2.93)	(−3.26)	(1.04)	(−2.16)
Revision	0.148	0.169	0.188	0.190	0.140	0.401	0.069	0.146
	(7.54)	(7.48)	(6.69)	(6.41)	(4.70)	(9.49)	(2.68)	(5.41)
Bold Signal	0.779	0.744	0.896	0.943				
	(15.23)	(15.23)	(11.82)	(13.17)				
Lagged Forecast Accuracy	0.074	0.076	0.051	0.091	0.021	−0.151	0.263	−0.092
	(1.08)	(1.48)	(2.88)	(2.80)	(1.41)	(−5.46)	(2.86)	(−3.56)
Female Dummy	−0.019	−0.078	−0.045	−0.043	0.386	−0.337	−0.061	0.059
	(−0.99)	(−0.40)	(−1.47)	(−1.48)	(2.84)	(−3.76)	(−1.10)	(1.13)
All-Star Dummy	0.022	0.009	−0.107	−0.088	0.512	−0.467	0.105	−0.136
	(0.13)	(0.22)	(−1.71)	(−1.55)	(2.08)	(−3.62)	(0.70)	(−1.63)
Female × Bold Signal	0.578	0.634	0.613	0.713				
	(5.71)	(5.91)	(5.13)	(5.41)				
All-Star × Bold Signal	0.715	0.807	0.912	0.861				
	(5.07)	(4.37)	(4.42)	(3.61)				
Control Variables								
Affiliated Analyst Dummy		0.108		0.242	0.040	−0.116	0.003	−0.046
		(3.33)		(1.96)	(2.48)	(−7.31)	(0.17)	(−2.71)
Brokerage Size		−0.128		−0.130	0.033	−0.079	−0.016	−0.024
		(−3.01)		(−2.10)	(2.81)	(−6.05)	(−0.90)	(−1.71)
Firm Experience		0.120		0.145	−0.027	0.101	−0.035	0.026
		(3.85)		(1.65)	(−2.05)	(6.48)	(−1.80)	(1.66)
General Experience		−0.079		−0.131	0.007	−0.032	0.028	−0.005
		(−1.54)		(−2.65)	(0.45)	(−2.42)	(1.27)	(−0.29)

(*Continued*)

TABLE 7 — *Continued*

	Forecast Signal Considered							
	All (3 days)		All (7 days)		BoldPos	BoldNeg	HerdPos	HerdNeg
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Number of Firms Covered		0.168		0.183	−0.022	0.039	0.008	0.024
		(2.61)		(1.55)	(−1.58)	(2.90)	(0.34)	(1.41)
Number of Industries Covered		−0.016		−0.171	0.055	−0.056	0.007	−0.027
		(−1.45)		(−1.73)	(3.47)	(−3.29)	(0.35)	(−1.48)
Days Since Last Forecast		−0.133		−0.186	−0.108	−0.006	−0.042	−0.105
		(−5.03)		(−4.68)	(−6.86)	(−0.49)	(−1.59)	(−7.78)
Forecast Horizon		−0.116		−0.234	−0.054	0.038	0.012	−0.046
		(−2.11)		(−1.82)	(−2.97)	(1.93)	(0.53)	(−2.32)
Forecast Frequency		−0.141		−0.349	−0.026	−0.047	−0.058	−0.052
		(−3.62)		(−3.47)	(−1.83)	(−3.32)	(−3.28)	(−3.24)
Firm Size		−0.086		−0.140	−0.109	−0.093	−0.022	−0.067
		(−1.77)		(−2.38)	(−4.14)	(−3.49)	(−0.26)	(−2.48)
Book-To-Market		0.105		0.115	−0.018	0.085	0.104	0.112
		(5.22)		(5.16)	(−0.23)	(5.83)	(2.81)	(3.32)
(12-Month Return		−0.029		0.018	0.014	−0.064	−0.024	−0.012
		(−0.21)		(0.70)	(0.98)	(−2.19)	(−1.25)	(−0.68)
Institutional Ownership		−0.119		−0.172	−0.098	0.035	−0.099	−0.095
		(−4.73)		(−5.72)	(−6.40)	(0.27)	(−3.01)	(−3.13)
Average Num of Obs	4,517	4,081	4,517	4,081	1,858	1,646	552	751
Average Adjusted R^2	0.027	0.038	0.026	0.041	0.026	0.030	0.018	0.022

This table reports the estimates from monthly Fama–MacBeth cross-sectional regression estimates, where the dependent variable is either the three-day (columns (1), (2), and (5)–(8)) cumulative market-adjusted abnormal stock return, centered on the forecast revision date, or the seven-day cumulative returns measured over days −1 to +5 (columns (3) and (4)). In columns (5)–(8), I consider sub-samples based on forecast type (bold-positive, bold-negative, herding-positive, or herding-negative), which have been defined in table 4. Most of the independent variables have been previously defined in table 3. The additional independent variables are: *Revision,* which is measured as the price-scaled difference between the analyst's new and most recent forecast; forecast boldness as measured by the categorical variable *Bold Signal,* which is set to +1 for bold-positive forecasts, −1 for bold-negative forecasts, and 0 for herding forecasts; and *Lagged Forecast Accuracy,* which is the analyst's peer group adjusted mean forecast accuracy during the year prior to the forecast. The Pontiff [1996] method is used to correct the Fama–MacBeth standard errors for potential serial correlation. The *t*-statistics for the coefficient estimates are shown in parentheses below the estimates. I winsorize all variables at their 0.5 and 99.5 percentile levels. The independent variables (except the dummy variables) have been standardized. The sample period spans from 1983 to 2005.

To better interpret the magnitude of the market's stronger reaction to the qualitative features of an analyst forecast such as gender, I compare them with more salient features of the forecast such as the analyst's reputation. If investors perceive all-star analysts to be more skillful because their recommendations and forecasts are more accurate (e.g., Stickel [1992], Fang and Yasuda [2008], 2009]), the price reaction following revisions by all-star analysts would be stronger.

I find evidence consistent with this conjecture. A bold positive (negative) forecast associated with an all-star analyst leads to a 0.807% higher (lower) reaction compared to the reaction following a similar forecast issued by a non–all-star analyst (see column (2)). The incremental reaction to bold forecasts by female analysts is not as strong (0.634% vs. 0.807%), but it is economically significant.

4.2 STRENGTH OF MARKET REACTION OVER TIME

For additional robustness, I estimate the short-term return regressions separately for three sub-periods: 1983 to 1990, 1991 to 1997, and 1998 to 2005. The results are presented in figure 4, panel A, where only the coefficient estimates of Female × Bold Signal and All-Star × Bold Signal interactions are shown. The sub-sample results indicate that the coefficient estimates are weak during the 1983–1990 period. The gender interaction is statistically significant, but the magnitude of the estimate is small (=0.221). Over time, the female analyst coefficient estimate exhibits an increasing trend. One interpretation of this evidence is that the influence of female analysts has become stronger over time. While certainly possible, it is also likely that the insignificant coefficient estimates during the 1983 to 1990 period indicate inaccurate forecast revision dates in the I/B/E/S data set (e.g., Clement and Tse [2003]).

4.3 MARKET REACTION ESTIMATES FOR SUB-SAMPLES

To better quantify the stock market's reaction to forecast revisions, I estimate the short-term return regressions separately for three additional subsamples. In the first instance, I examine whether the market responds more strongly to the revisions issued by female analysts when a female analyst covers a stock that is typically covered by male analysts. It is possible that the market is surprised more when a non-typical analyst issues the revision (e.g., a female analyst revises the forecast of a mining stock). Alternatively, the non-typical analyst could be better than the average analyst due to self-selection. In the second test, I entertain the possibility that analysts' personal attributes only play a role when the reputation of the brokerage firm that employs them is less dominant. In other words, this test examines whether the reputation of the brokerage firm or analyst attributes have a greater influence on the market's short-term reaction. In the third test, I examine whether the differential market's response reflects its reaction to other concurrent news events around forecast revisions.

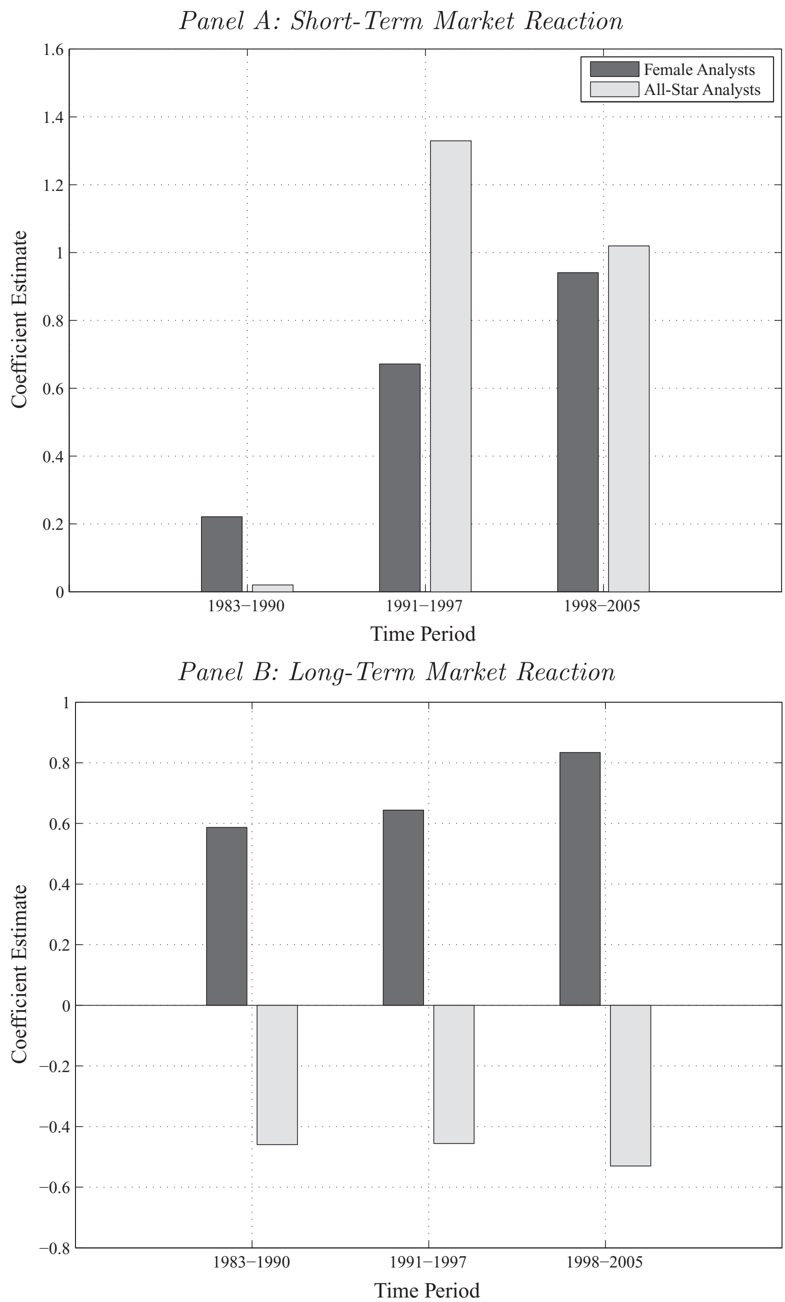

FIG. 4.—Strength of short-term and long-term market reactions over time. The figure shows the Female × Bold Signal and All-Star × Bold Signal interaction estimates from the short-term (see table 7) and the long-term (see table 9) market reaction regressions for three sub-periods. The *Bold Signal* measure takes a value of 1 for bold-positive forecast revisions, a value of -1 for bold-negative revisions, and a value of 0 for herding revisions.

The results from these three robustness tests are summarized in table 8. In the first two columns, I present the estimates for the sub-samples of stocks with female analyst concentration below 15% (the average proportion of female analysts in the sample) and above 15%, respectively.[22] The concentration measure is computed based on the number of male and female analysts who cover the stock in the previous year. I find that the market responds strongly to the revisions issued by female analysts in both sub-samples, and the effect is stronger (0.637% vs. 0.414%) among stocks with lower female concentration. This evidence indicates that the relative proportion of male and female analysts in a stock influences the market's reaction, although the reaction is significant in both instances.

The estimates from the second robustness test are presented in the third and the fourth columns of the table. I estimate the short-term return regression for two sub-samples: (i) small and moderate-sized brokerage firms (deciles 1–9) and (ii) very large brokerage firms (decile 10).[23] The brokerage size is defined using the number of analysts employed by the brokerage firm in the previous year. An additional benefit of the large brokerage firms sub-sample is that the gender of most analysts in this sub-sample is successfully identified. Thus, potential biases induced by missing or inaccurate gender information are likely to be minimal.

The evidence indicates that the analyst attributes are relatively less important when an analyst works at a large brokerage firm. For instance, the coefficient estimates for the *All-Star Dummy* in the short-term return regressions for deciles 1–9 and decile 10 brokerage sub-samples are 1.114 (t-statistic = 3.74) and 0.671 (t-statistic = 2.78), respectively. The pattern is similar, although weaker, for female analysts. These results indicate that the market responds strongly to the opinions of female analysts even when they belong to large brokerage houses. While brokerage reputation influences the market's reaction, analysts' personal attributes, such as gender, have an incremental and economically significant effect on short-term stock market reaction.

The third robustness test is motivated by the evidence in Ivković and Jegadeesh [2004], who find that forecast revisions prior to earnings announcements are more likely to reflect analysts' interpretation of private information, while revisions following the announcements are more likely to reflect analysts' interpretation of public information. One might argue that the market reacts strongly following the revisions by female analysts because they are better able to time their forecasts. That is, female analysts might be more likely to revise their forecasts following earnings announcements, when additional firm-specific announcements are more common, and less likely to revise their forecasts prior to the announcements, when relatively fewer firm-specific news stories are released.

[22] The results are similar when I use other cutoffs (e.g., 10%) to define the two sub-samples.

[23] The results are similar when I define very large brokerage firms as the top 20 firms based on their size.

TABLE 8

Short-Term Market Reaction to Forecast Revisions: Robustness Check Results

	Female Concentration		Brokerage Size		Forecast Horizon	
	Below 15%	Above 15%	Deciles 1–9	Top Decile	<6 mos	≥6 mos
Variable	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Main robustness tests						
Intercept	−0.206	−0.235	−0.200	−0.205	−0.209	−0.350
	(−4.77)	(−5.23)	(−5.24)	(−4.06)	(−4.10)	(−4.37)
Revision	0.109	0.394	0.574	0.809	0.869	0.788
	(7.76	(6.27)	(8.61)	(11.23)	(7.53)	(11.71)
Bold Signal	0.682	0.905	0.762	0.853	0.908	0.796
	(6.37	(5.68)	(6.51)	(5.99)	(5.72)	(4.66)
Lagged Forecast Accuracy	0.081	0.006	0.129	−0.108	0.317	0.143
	(1.17)	(0.59)	(1.73)	(−1.17)	(2.53)	(1.17)
Female Dummy	−0.074	0.046	−0.073	−0.095	−0.104	−0.101
	(−1.20)	(1.06)	(−0.58)	(−1.08)	(−1.15)	(−0.43)
All-Star Dummy	−0.032	0.011	0.083	−0.085	0.204	0.015
	(−0.31)	(0.76)	(0.78)	(−0.44)	(1.34)	(0.08)
Female × Bold Signal	0.637	0.414	0.732	0.594	0.594	0.686
	(5.44)	(3.02)	(4.56)	(3.03)	(3.61)	(3.64)
All-Star × Bold Signal	0.959	−0.096	1.114	0.671	0.904	0.779
	(3.39)	(−1.00)	(3.74)	(2.78)	(4.37)	(3.69)
(Coefficient estimates of control variables are suppressed.)						
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Average Num of Obs	3,134	948	3,168	932	2,055	2,036
Average Adjusted R^2	0.031	0.057	0.040	0.055	0.057	0.051

	Coefficient Estimate For		
	Female × Bold	All-Star × Bold	(Avg.) Adj. R^2
Test	(1)	(2)	(3)
Panel B: Other robustness tests			
Quarterly Forecast Revisions	0.610	0.748	
	(4.05)	(7.67)	0.057
Consider Last Forecast Only	0.711	0.898	
	(6.97)	(6.65)	0.098
Brokerage Fixed Effects	0.701	0.865	
	(4.38)	(5.38)	0.153
Stock, Month, Brokerage Fixed Effects	0.672	0.856	
	(4.95)	(6.10)	0.145
Keane and Runkle [1998]	0.570	0.727	
GMM Estimation	4.87	8.97	0.087

This table reports the short-term market reaction regression estimates for different sub-samples and different estimation methods. In panel A, the regression specification and the estimation method are identical to those in table 6. In panel B, other estimation methods described in table 6 are used. In both fixed effect regressions in panel B, the standard errors are clustered by firm. The dependent variable is the three-day cumulative market-adjusted abnormal stock return, centered on the forecast revision date. In panel A, the first two columns present the estimates for the sub-samples of stocks with the female analyst concentration below 15% (the average proportion of female analysts in the sample) and above 15%, respectively. The female concentration measure for a stock is the proportion of all analysts covering the stock that are female. The third and fourth columns present estimates for two brokerage size based sub-samples: (i) small and moderate sized brokerage firms (deciles 1–9), and (ii) very large brokerage firms (decile 10). The brokerage size is defined using the number of analysts employed by the brokerage firm. The last two columns present the estimates for two forecast horizons: (i) less than six months, (ii) six months or greater. For brevity, in panel A, I suppress the estimates of all control variables and, in panel B, I only present the estimates for the two interaction terms. The t-statistics for the coefficient estimates are shown in parentheses below the estimates.

The previous evidence (see table 3, panel B) indicates that forecast horizon is not significantly correlated with analysts' gender. Thus, it is less likely that female analysts are timing their forecast revisions such that they coincide with the release of other information signals. I also use forecast horizon as a control variable in the short-term return regressions to control for changes in the information environment during the annual earnings cycle. Nevertheless, for robustness, I estimate the return regression for two forecast horizons: (i) less than six months, (ii) six months or greater.

The estimates are presented in the last two columns of table 8. The evidence indicates that, for both short and long forecast horizons, the market responds more strongly to the opinions of female analysts. In unreported results, I find that the evidence is very similar when I consider even shorter forecast horizons. Thus, irrespective of the information environment at the time of forecast revision, the market reacts more strongly to the opinions of female analysts.

4.4 ROBUSTNESS OF MARKET REACTION REGRESSION ESTIMATES

Although female analysts are broadly distributed across firms, industries, and brokerages, the distribution is not random (see section 2.2). For example, larger brokerage firms have a stronger concentration of female analysts. This raises the potential concern that the coefficient estimates in the market reaction regression are biased because the brokerage, stock, or industry characteristics that influence the distribution of analysts could also influence the market's reaction to forecast revisions. In particular, the stronger market reaction following bold forecasts issued by female analysts might not be related to analyst gender but could simply reflect the fact that female analysts cover stocks or work for brokerage firms where bold forecasts are more common.

Some of my empirical tests already account for systematic differences in stock and brokerage characteristics across analyst groups that could influence the market's reaction. For example, the peer group adjustment method accounts for month and stock fixed effects. Further, the evidence from brokerage size–based sub-samples indicates that the results are unlikely to be fully explained by the unobserved characteristics of brokerage firms. Nevertheless, to ensure that the female analyst dummy estimates in market reaction regressions reflect the effect of analyst gender, I estimate panel regression specifications with various fixed effects. In these fixed effects models, the standard errors are clustered by firm. I also use the Keane and Runkle [1998] GMM estimation method to account for cross-sectional dependence in market reaction. For additional robustness, I estimate the market reaction regressions using revisions in quarterly earnings forecasts and a sub-sample of annual forecasts that contains only the last analyst forecast during a fiscal year.

I find that the incremental effect of analyst gender remains similar when I estimate a panel specification with brokerage fixed effects to account for unobserved brokerage characteristics that could influence the market's reaction to forecast revisions. I also estimate a panel specification in which I use the raw rather than the peer group adjusted measures and directly introduce stock, month, and industry fixed effects. Because the peer group adjustment method works quite effectively, these estimates are similar to the baseline regression estimates reported in table 7. The GMM estimates as well as the estimates with quarterly forecast revisions and the sub-sample of "last forecasts before the fiscal year-end" are qualitatively similar to the full-sample results.

4.5 LONG-TERM MARKET REACTION

The evidence from the short-term reaction regressions indicates that the market reacts strongly to the opinions of female analysts. But how complete is that reaction? To further understand the stock market's perceptions of analysts' abilities, I examine the speed with which the market incorporates the information contained in analysts' forecast revisions. If a larger proportion of the total reaction occurs during the announcement period, the return drift following the announcement will be weak. In contrast, if the immediate reaction is incomplete, the post-revision drift will be strong.

I estimate Fama–MacBeth regressions similar to the short-term return regressions. The dependent variable is the k-day ($k = 21, 63, 126, 252$) cumulative market-adjusted abnormal stock return, starting on day +2 following the forecast revision date. All independent variables have been defined previously and are similar to those employed in the short-term market return regressions (see table 7). The results from the long-term market reaction regressions are presented in table 9.

The regression results indicate that the post-revision drift is stronger following the bold forecasts of female analysts. During the six-month period subsequent to the forecast revision drift, the drift is 0.677% higher if a female analyst revises the forecast. In contrast, similar to the evidence in Gleason and Lee [2003], I find that the market impounds the information faster if an all-star analyst revises the earnings forecast. On average, the six-month drift is 0.365% lower following a revision by an all-star analyst. The coefficient estimates are qualitatively similar when I measure drift over 1-, 3-, or 12-month periods.

Given that the average drift during this period is 2.24%, the incremental effects of analyst attributes on post-revision drift are significant. Specifically, in comparison to the mean drift, the average drift associated with the forecasts by female analysts is $100 \times 0.677/2.24 = 30.22\%$ higher. Thus, the difference in the market's response following the revisions of female and all-star analysts is significant, both statistically and economically. Overall, the long-term reaction regression estimates indicate that although the market responds strongly to the revisions of female analysts, the reaction is incomplete. The market does not immediately uncover the information content of analysts' forecast revisions and continues to respond to the news content of the revision for several months.

TABLE 9
Long-Term Market Reaction to Forecast Revisions

	Measurement Period (in Months)			
	One	Three	Six	Twelve
Variable	(1)	(2)	(3)	(4)
Intercept	0.183	0.443	1.291	2.645
	(1.77)	(2.45)	(2.97)	(5.20)
Revision	0.607	0.370	0.739	0.434
	(2.94)	(4.41)	(6.25)	(5.67)
Bold Signal	0.384	0.757	0.811	0.841
	(5.59)	(6.06)	(5.57)	(4.13)
Lagged Forecast Accuracy	0.532	0.576	0.595	0.694
	(4.52)	(5.43)	(7.79)	(8.56)
Female Dummy	−0.001	0.148	0.089	−0.044
	(−0.18)	(1.37)	(0.92)	(−0.15)
All-Star Dummy	0.053	0.089	0.087	0.083
	(0.84)	(1.02)	(1.37)	(0.82)
Female × *Bold Signal*	0.284	0.499	0.677	0.798
	(3.39)	(3.74)	(4.09)	(3.27)
All-Star × *Bold Signal*	−0.189	−0.192	−0.365	−0.515
	(−2.44)	(−2.75)	(−3.51)	(−4.31)
(Coefficient estimates of control variables are suppressed.)				
Control Variables	Yes	Yes	Yes	Yes
Average Num of Obs	4,081	3,948	3,868	3,832
Average Adjusted R^2	0.085	0.112	0.115	0.105

This table reports the estimates from monthly Fama–MacBeth cross-sectional regression estimates, where the dependent variable is the k-day ($k = 21, 63, 126, 252$) cumulative market-adjusted abnormal stock return, starting on day +2 following the forecast revision date. All other details of the long-term market reaction regression model are identical to the short-term market-reaction regression model described in table 7. The t-statistics for the coefficient estimates are shown in parentheses below the estimates.

4.6 STRONGER REACTION DUE TO GREATER MEDIA COVERAGE?

One potential explanation for the strong market reaction to female forecast revisions could be that it reflects greater media coverage to female analysts. Specifically, due to greater media coverage and media-generated attention, the market could treat female analysts as celebrities. In this scenario, even if those analysts do not possess superior forecasting abilities, the market might assign greater value to their opinions and subsequently react strongly to changes in their opinions.

To empirically test the celebrity hypothesis, I follow the Bonner, Hugon, and Walther [2007] method and examine whether there are more news stories about female analysts. For three arbitrarily chosen years (1997, 2000, and 2003) within the sample period, I use the Factiva database to identify the number of news stories that mention the name of the analyst and then obtain the annual media coverage for each analyst.[24] I estimate cross-sectional regressions, where the annual media coverage measure is the dependent

[24] Like Bonner, Hugon, and Walther [2007], I use the "FirstName near3 LastName and BrokerageHouseName" string to conduct the search.

variable. The independent variables in the specification include the three analyst attributes (the female dummy and the all-star dummy) and the following factors that could influence the extent of media coverage: number of analyst forecasts during the year, brokerage size, analyst's experience, number of stocks followed by the analyst, number of industries followed by the analyst, and forecast accuracy.

The media coverage regression estimates are presented in table 10. The evidence indicates that, all else equal, female analysts receive relatively less media coverage. For instance, in 1997, a typical analyst received mentions in about 24 news stories. Being a female analyst reduces that number by 2.542. In contrast, consistent with the evidence in Bonner, Hugon, and Walther [2007], on average, an all-star analyst received mentions in 6.476 more news stories. Consistent with their evidence, I also find that forecast accuracy has an insignificant coefficient estimate in the media coverage regressions. The coefficient estimates for other variables also make intuitive sense. For example, analysts who issue more forecasts and work at larger brokerages

TABLE 10

Analyst Characteristics and Media Coverage: Cross-sectional Regression Estimates

	Year		
	1997	2000	2003
Variable	(1)	(2)	(3)
Intercept	24.208	34.539	41.244
	(9.38)	(9.34)	(14.77)
Female Dummy	−2.542	−1.504	−2.857
	(−4.11)	(−2.70)	(−3.05)
All-Star Dummy	6.476	8.356	7.880
	(8.86)	(8.13)	(7.53)
Female × All-Star	−0.512	−0.880	−0.674
	(−0.32)	(−1.38)	(−0.78)
Forecast Accuracy	0.546	0.550	0.507
	(1.18)	(1.08)	(1.19)
Number of Forecasts	7.066	13.760	15.497
	(8.45)	(12.01)	(12.35)
Brokerage Size	1.062	1.923	2.401
	(1.56)	(2.01)	(2.45)
General Experience	3.559	2.113	6.576
	(5.01)	(2.12)	(6.30)
Number of Firms Covered	1.378	3.758	1.112
	(1.49)	(2.84)	(1.45)
Number of Industries Covered	−1.486	−4.155	0.212
	(−2.89)	(−3.65)	(0.18)
Number of Analysts	2,920	3,363	3,687
Adjusted R^2	0.147	0.137	0.162

This table reports the media regression estimates. The dependent variable is the annual media coverage for an analyst, which is equal to the number of news articles in the Factiva database that mention the name of the analyst. See section 7.1 for additional details. The three analyst attributes and other independent variables have been defined in table 3. The measures reflect the averages for the year. The *t*-statistics for the coefficient estimates are shown in parentheses below the estimates. All variables are winsorized at their 0.5 and 99.5 percentile levels and the independent variables (except the dummy variables) have been standardized.

receive greater media coverage. The results are mostly similar in the 2000 and 2003 regressions.[25]

For robustness, I investigate whether these estimates merely reflect the fact that the names of female analysts are less common, and, therefore, less likely to be mentioned in the media. I re-estimate the media regressions with the unexpected number of news stories for the analyst as the dependent variable. The number of unexpected news stories for an analyst is the residual from a regression model, where the actual number of news stories is the dependent variable, and the expected number of news stories for the analyst is the independent variable. The expected number of news stories is obtained by searching the news articles in Factiva using only the analyst name. In unreported results, I find that the unexpected news stories measure yields results that are very similar to the reported estimates.

Collectively, the media regression estimates indicate that markets' perceptions of superior abilities of female analysts are not induced by the media. On the contrary, the evidence points to the intriguing possibility that the media might be negatively biased in its coverage of female analysts. This finding is consistent with the evidence from political studies, which find that the media provides less coverage to female political candidates (e.g., Kahn [1994]).

5. *Perception of Abilities in the Analyst Labor Market*

5.1 MOTIVATION

The evidence from stock market reaction regressions indicates that stock market participants have more favorable opinions about the forecasting abilities of female analysts. Although I use several variables to measure analysts' realized and predicted forecast accuracy, it is possible that those measures are unable to fully capture their forecast accuracy. The market could respond to those skill differences that cannot be accurately quantified by analysts' forecasting errors and other known predictors of accuracy and ability. Thus, the stronger market reaction to the revisions issued by female analysts might reflect those accuracy predictors that cannot be directly observed.

For instance, female analysts might actually have or be perceived to have better communication skills, higher ethical standards (Dollar, Fisman, and Gatti [2001]), superior ability to forecast longer term earnings projections, superior knowledge about the industry, better client services (Green, Jegadeesh, and Tang [2009]), or better education. The all-star indicator, which reflects analysts' reputation, could capture some of the key qualitative aspects of analysts' forecasts, but the market could value other skill differences that are unobserved.

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[25] Motivated by the evidence in Gadarowski [2004], who finds that media coverage is correlated with firm size, I consider firm size as an additional control variable. I find that firm size has an insignificant coefficient estimate, while other coefficient estimates remain virtually unchanged.

Another potential concern with the market reaction analysis is that many stock market participants may not be aware of analysts' personal attributes such as gender. Thus, it is plausible that the strong market reaction following revisions by female analysts reflects some other unobserved characteristics correlated with gender. To ensure that my results are robust to such concerns, I examine the market's perception of abilities in the analyst labor market. Specifically, I examine whether female analysts face greater frictions in their career paths because participants in the analyst labor market evaluate analysts' abilities based on their gender. Market participants directly observe the personal attributes of analysts in this setting and, therefore, potential concerns that unobserved variables correlated with gender are driving the key results are non-existent.

I estimate promotion and demotion regressions and obtain estimates of career mobility rates of analysts, conditional upon their gender. If the participants in the analyst labor market have more favorable opinions about the abilities of female analysts, these analysts would have a higher probability of moving from low to high status brokerage firms. They are also less likely to be demoted from a high-status to a low-status brokerage firm. In addition, female analysts would have larger brokerage tenure and are less likely to switch jobs frequently.

5.2 MOVE FREQUENCY AND BROKERAGE TENURE ESTIMATES

To set the stage and provide benchmarks for comparison, I examine analysts' "raw" move frequencies. I find that when a male analyst at a low status brokerage firm moves, he moves to a high status brokerage firm in 17.90% of cases. In contrast, female analysts move up in 21.51% of cases, while the all-star analysts have the highest upward mobility estimate. When they move from low status brokerage firms, in 40.07% of cases the move is to a high status brokerage firm. These "raw" career mobility estimates indicate that female analysts have higher upward career mobility rates than male analysts.

To examine whether job stability is influenced by analysts' personal attributes, I obtain estimates for average brokerage tenure. The tenure measure is defined as the average number of years an analyst works at a brokerage firm. I find that the all-star analysts have the most stable jobs. They spend an average of 5.95 years at a brokerage firm. In comparison, the average brokerage tenure of female analysts is 4.81 years, while male analysts have the shortest average brokerage tenure (=3.99 years).[26]

5.3 UPWARD AND DOWNWARD MOBILITY ACROSS BROKERAGES

To quantify the conditional career mobility rates of analysts more accurately, I estimate promotion and demotion probit regressions. I assume that an analyst is promoted when she moves from a low- to a high-status

[26] To obtain accurate tenure estimates, I consider analysts with at least three years of experience. However, the results are not sensitive to this cutoff. I also find that the median estimates are very similar to the mean tenure estimates.

brokerage firm. The demotion events capture the reverse move from a high to a low-status brokerage firm. In certain specifications, lateral moves are included in the set of promotion and demotion events. Following Hong and Kubik [2003], I classify brokerage firms that are identified as the top 10 brokerage firms by the *Institutional Investor* magazine as high-status brokerage firms.[27]

In the promotion regressions, the dependent variable is a promotion dummy that is set to one if an analyst is at a low-status brokerage firm in year t and moves to a high-status brokerage firm in year $t + 1$. The demotion dummy is defined in an analogous manner. I consider both conditional and unconditional events. The unconditional estimates use the subset of all analysts who are present in the sample during years t and $t + 1$. The conditional estimates use the sample of analysts who changed brokers during years t and $t + 1$. The set of independent variables is motivated by the evidence in Hong and Kubik [2003] and includes a control for forecast boldness.

The estimation results are reported in table 11. To begin, in columns (1) and (2), I present the unconditional probit estimates, where, like Hong and Kubik [2003], lateral moves are included in the sample. I find that female analysts are more likely to be promoted and less likely to be demoted. For instance, the evidence in columns (1) and (2) indicates that, all else equal, a female analyst is 1.50% less likely to be demoted and 1.10% more likely to be promoted. Not surprisingly, the all-star analysts have higher promotion and lower demotion probability estimates. They are 3.30% less likely to be demoted and 3.80% more likely to be promoted.

When I condition on the initial brokerage affiliation of the analyst, the probit regression estimates are mostly stronger. For instance, all else equal, female analysts are 1.80% more likely to move to a high-status brokerage firm (see column (4)) and 1.70% less likely to move down to a low-status brokerage firms (see column (6)). And when I consider only conditional events, the results are significantly stronger (see columns (5) and (7)). The female and all-star analysts have a 4.90% and 8.10% higher probability of moving up from a low-status to a high-status brokerage firm, respectively.[28] Similarly, the evidence in column (8) indicates that female and all-star analysts have a 8.10% and 9.10% lower probability of moving down from a high-status to a low-status brokerage firm, respectively.

Using a regression specification similar to the promotion and demotion regressions, I also estimate "firing" regressions. In this regression, the

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[27] The results are similar when I consider the following two alternative definitions of brokerage status. In the first case, the brokerage firm has high status if it is ranked between 1 and 10 using the number of analysts as the ranking criteria. The second status measure uses the Carter-Manaster top 10 rankings obtained from Jay Ritter's Web site (http://bear.cba.ufl.edu/ritter/rank.pdf). The results are also similar when, following Hong and Kubik [2003], I exclude analysts with fewer than three years of experience.

[28] Since I only consider conditional events, the estimates also indicate that female and all-star analysts have a 4.90% and 8.10% lower probability of moving down, respectively.

TABLE 11

Analyst Characteristics and Career Mobility: Probit Regression Estimates

	All Moves		Move From Low-Status Brokers			Move From High-Status Brokers		
Variable	Down (1)	Up (2)	Down (3)	Up (4)	UpCond (5)	Down (6)	Up (7)	UpCond (8)
Panel A: Full sample								
Female Dummy	−0.015	0.011	−0.016	0.018	0.049	−0.017	−0.001	0.081
	(−5.65)	(2.12)	(−3.10)	(3.08)	(3.37)	(−4.08)	(−0.32)	(3.82)
All-Star Dummy	−0.033	0.038	−0.033	0.059	0.081	−0.030	0.021	0.091
	(−12.53	(12.04)	(−5.03)	(8.31)	(8.08)	(−7.94)	(4.59)	(8.42)
Female × All-Star	−0.011	0.009	−0.006	0.027	0.017	−0.001	0.016	0.008
	(−1.05)	(1.93)	(−0.21)	(2.38)	(1.77)	(−0.05)	(1.33)	(0.89)
Forecast Accuracy	−0.003	0.010	−0.026	0.017	0.052	0.002	−0.003	−0.004
	(−0.57)	(2.84)	(−2.55)	(2.53)	(3.14)	(1.02)	(−0.98)	(−1.05)
Firm Experience	0.005	−0.003	−0.005	−0.002	−0.003	−0.003	−0.002	0.001
	(1.34)	(−1.35)	(−1.54)	(−1.22)	(−1.25)	(−1.78)	(−1.14)	(0.46)
General Experience	0.004	−0.002	0.002	−0.001	−0.011	0.014	−0.004	−0.009
	(1.51)	(−1.63)	(1.11)	(−0.51)	(−1.66)	(2.18)	(−0.57)	(−1.50)
Number of Firms Covered	0.002	0.001	−0.003	0.002	0.019	0.001	0.001	0.003
	(1.09)	(0.59)	(−1.14)	(1.22)	(1.96)	(0.37)	(0.32)	(0.12)
Number of Industries Covered	0.005	−0.006	0.012	−0.008	−0.006	0.011	−0.004	−0.012
	(1.33)	(−1.73)	(2.11)	(−1.05)	(−1.66)	(1.65)	(−0.53)	(−1.84)
Forecast Frequency	0.001	0.011	−0.004	0.001	0.010	−0.006	−0.001	0.016
	(0.34)	(2.57)	(−1.64)	(0.57)	(2.56)	(−1.88)	(−0.19)	(2.67)
Forecast Boldness	0.012	0.003	0.071	0.012	0.016	0.029	0.011	−0.016
	(2.64)	(1.01)	(5.19)	(2.14)	(2.85)	(4.53)	(1.00)	(−1.68)
Number of Obs	53,979	53,979	40,431	40,431	3,537	13,548	13,548	2,073
Pseudo R^2	0.018	0.032	0.016	0.038	0.067	0.024	0.057	0.060

(*Continued*)

TABLE 11 — *Continued*

	All Moves		Move From Low-Status Brokers			Move From High-Status Brokers		
Variable	Down (1)	Up (2)	Down (3)	Up (4)	UpCond (5)	Down (6)	Up (7)	UpCond (8)
Panel B: 1983–1993 period								
Female Dummy	−0.014	0.013	−0.017	0.008	0.025	−0.009	0.002	0.035
	(−3.34)	(2.15)	(−2.61)	(1.04)	(2.30)	(−1.18)	(0.24)	(1.44)
All-Star Dummy	−0.032	0.034	−0.026	0.052	0.101	−0.028	0.022	0.127
	(−8.12	(7.86)	(−3.23)	(6.01)	(6.94)	(−4.35)	(3.30)	(4.35)
Female × *All-Star*	−0.001	0.035	0.003	0.025	0.009	0.001	0.009	−0.004
	(−0.77)	(1.77)	(0.72)	(1.71)	(0.82)	(0.47)	(1.17)	(−0.24)
Number of Obs	17,663	17,663	11,121	11,121	1,084	4,327	4,327	832
Pseudo R^2	(0.012)	(0.028)	(0.007)	(0.023)	(0.058)	(0.014)	(0.036)	(0.041)
Panel C: 1994–2005 period								
Female Dummy	−0.017	0.019	−0.022	0.023	0.055	−0.022	−0.003	0.092
	(−6.42)	(2.91)	(−3.89)	(3.78)	(3.82)	(−4.14)	(−0.51)	(4.05)
All-Star Dummy	−0.035	0.042	−0.022	0.078	0.116	−0.032	0.028	0.122
	(−9.27)	(8.65)	(−2.74)	(5.73)	(7.28)	(−5.95)	(4.07)	(7.00)
Female × *All-Star*	−0.027	0.009	−0.036	0.042	0.035	−0.006	0.019	0.011
	(−2.14)	(1.48)	(−1.61)	(1.63)	(1.90)	(−0.38)	(1.23)	(0.90)
Number of Obs	35,691	35,691	18,685	18,685	2,416	7,917	7,917	1,235
Pseudo R^2	0.025	0.042	0.028	0.045	0.071	0.034	0.061	0.096

This table reports the regression estimates for promotion and demotion probit regressions. The marginal effects corresponding to the probit estimates are reported. They reflect the probability of moving to a high- or a low-status brokerage house between years t and $t+1$. Columns (4) and (8) present the estimates from "conditional" models, while other columns present the estimates from "unconditional" models. The "unconditional" estimates use the sample of all analysts who are present in the sample during years t and $t+1$. The "conditional" estimates use the sample of all analysts who changed brokers during years t and $t+1$. High-status brokerage firms are brokers that are identified as one of the top 10 brokerage firms by the *Institutional Investors* magazine. The z-statistics are in parentheses below the marginal effects. In panel A, the sample period spans from 1983 to 2005. Sub-period estimates are presented in panels B and C. All independent variables have been previously defined in table 3.

dependent variable is set to one when an analyst leaves the I/B/E/S sample in year t. The untabulated results indicate that female analysts are more likely to leave the sample. However, without additional information about the background of analysts, it is difficult to interpret this evidence because female analysts are more likely to leave the profession for personal reasons (e.g., to raise children).

5.4 HAS CAREER MOBILITY CHANGED OVER TIME?

For robustness, I estimate the career mobility regressions separately for the 1983–1993 and 1994–2005 sub-periods. This analysis also allows me to investigate whether the probability estimates for upward and downward career moves have changed over time. The sub-period estimates are presented in table 11, panel B.

I find that the marginal promotion probability for female analysts increases from an insignificant estimate of 0.80% for the 1983–1993 period to 2.30% for the 1994–2005 period (see column (4)). Further, conditional upon moving, the marginal promotion probability for female analysts increases from 2.50% to 5.50% (see column (5)). During the second part of the sample, female analysts are also less likely to be demoted. For the 1983–1993 period, the coefficient estimate for the *Female Dummy* is −0.009 (t-statistic = −1.18), while during the 1994–2005 period, the *Female Dummy* estimate is −0.022 (t-statistic = −4.14) (see column (6)). The conditional marginal probability of being demoted shows a similar pattern. The estimates in column (8) indicate that female analysts are 3.50% less likely to be demoted during the 1983–1993 period but during the 1994–2005 period, they are 9.20% less likely to be demoted.

Taken together, the career mobility regression estimates indicate that, conditional on being employed, female analysts face lower frictions in their upward career movements. These frictions have weakened further in more recent years. Female analysts also face lower risks of being demoted. Thus, just like the stock market, the analyst labor market has more favorable opinions about the abilities of female analysts. The participants in the analyst labor market perhaps recognize that the average skill level of female analysts is higher due to the self-selection mechanism. This finding is surprising because the existing evidence from other labor markets indicates that the promotion rates for women are about 2% lower than the promotion rates for men (e.g., Olson and Becker [1983], Blau and DeVaro [2007]).

6. *Summary and Conclusion*

This paper studies the behavior of female equity analysts. Specifically, I investigate whether female analysts have better forecasting abilities than male analysts and whether market participants are able to identify the male–female skill differences. I posit that only female analysts with superior forecasting abilities enter the profession due to a perception of discrimination in the analyst labor market. Consistent with this self-selection hypothesis, I find that female analysts issue bolder and more accurate forecasts, where the accuracy is higher in market segments with lower concentration of female analysts. The female–male accuracy differences are robust and cannot be explained by non-random distribution of female analysts across stocks, industries, or brokerage firms.

Interestingly, stock market participants are at least partially aware of the male–female skill differences. They respond more strongly to the forecast revisions by female analysts even though those analysts get less media coverage. However, the short-term market reaction is incomplete as it is followed by a strong post-revision drift. I also find that the perception of abilities is similar in the analyst labor market where female analysts are more likely to move up to high-status brokerage firms, while their downward career mobility is lower.

Taken together, these results indicate that female analysts have better-than-average skill due to self-selection and market participants are at least partially able to recognize their superior abilities. More broadly, contrary to the evidence from other economic settings, these results indicate that social biases such as gender-based stereotyping, prejudice, or discrimination do not influence markets' perceptions of the forecasting abilities of female equity analysts. Future research could examine whether a similar self-selection mechanism also determines the behavior of other minority groups such as analysts with foreign sounding names.

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