Gender Differences Among Analyst Recommendations[1]

Peter de Goeij[2] Kristien Smedts[3]

First version: February 2007
This version: September 2007

[1]We thank Esther Eiling and Ralph Koijen for helping us collect the data and Thomson Financial for the use of the I/B/E/S recommendation data. We thank Bas Werker, Esther Eiling and Frank de Jong for their comments and suggestions that helped improve the paper.

[2]Tilburg University, Department of Finance and CentER for Economic Research, P.O. Box 90153, 5000LE Tilburg, The Netherlands, email: p.c.degoeij@uvt.nl, phone: (+) 31 (0)13 4662083, fax: (+) 31 (0)13 4662875.

[3]Catholic University of Leuven, AFI, Naamsestraat 69, 3000 Leuven, Belgium. Email: kristien.smedts@econ.kuleuven.be, tel: (+) 32 (0)16 326739, fax: (+) 32 (0)16 326732.

Abstract

We investigate whether individual characteristics, in particular gender, influence the level of recommendations issued by analysts. Additionaly, we study gender specific behavior with respect to public information. Using a large and real-life dataset we show that male analysts have a larger probability to issue strong buy recommendations relative to female analysts when dispersion among analyst recommendations is small. In contrast, female analysts have a larger probability to issue more conservative hold recommendations. Male analysts are thus more likely to deviate positively during the calm periods of agreement. This might indicate their will to stand out of the crowd with more extreme decisions, exactly when noticed most. The relative probability differences can be as large as 7% for the complete sample, but before 2002 these relative probability differences are as large as 15%. This trend break in gender differences is important as female analsyts seem to behave more and more like their male colleagues. Finally we show that gender differences among analyst recommendations vary accross industries.

1 Introduction

A large literature exists examining the determinants of recommendations, with most studies focusing on the relation between recommendations and fundamental valuation models. A general finding is that fundamental valuation models are not very successful in explaining the level and the changes in recommendations (see, among others, Bradshaw (2004), Block (1999) and Cornell (2001)). The reason seems to be that a recommendation is not just a simple valuation decision, but is the result of a complex decision making process and reflects the opinion of the analyst, based upon his perspective and his risk tolerance.

While no clear link exists between traditional valuation models and recommendations, several biases in recommendations have been described. One of the best documented biases is the upward bias in the distribution of recommendations.[1] Driven by career concerns, analysts are clearly reluctant to issue negative reports. Moreover, analysts also have the tendency to herd with the group.[2] These biases suggest that a recommendation is not just the outcome of a rational and objective decision making process, but is also driven by behavioral motives.

In this paper we take such behavioral motives in the recommendation generating process as a starting point. Motivated by compelling evidence that a decision making process is driven by important personal considerations, we focus on individual analyst characteristics. Clearly, one of the most obvious individual characteristics to account for is gender. This is also suggested by the large literature showing that the (financial) decision making process of men and women differs significantly (see Croson and Gneezy (2004)). One of the driving factors seem to be the gender specific risk preferences. It is a common finding that women are more risk-averse decision-makers, take less extreme decisions, play more like another and try to avoid competitive situations. While the evidence in the domains of psychology and sociology is strong and clear, the empirical evidence in the (financial) economics literature is rather mixed and seems to depend on the framing of risks and the type of agents, professionals versus non-professionals. Once professional agents are considered, no real gender differences in risky decision making is observed. However, a recent study by Niessen and Ruenzi (2007) questions this conjecture.

The objective of the paper is, therefore, to examine whether individual characteristics and in particular gender effects can be detected in the level of recommendations issued by analysts. We also study the gender-specific behavior of analysts with respect to available public information as well as individual characteristics. With a large, real-life dataset of risky decisions taken by professional agents, this research will undoubtedly contribute to the current debate on gender differences

[1]For recent evidence on the upward bias in the distribution of recommendations see Barber et al. (2005), Lin et al. (2005) and Chen and Matsumoto (2006).

[2]See, among others, Welch (2000), Hong et al. (2000), Clement and Tse (2005), and most recently Jegadeesh and Kim (2007).

in financial decision making.

Our empirical results can be summarized as follows. First, we observe gender differences in the recommendation issuing process. Controlled for ability, resources and portfolio complexity, female analysts respond differently to public information. When uncertainty among analysts is small, male analysts have a larger probability to issue Strong Buy recommendations relative to female analysts. In contrast, female analysts have a larger probability to issue more conservative Hold recommendations. This indicates that male analysts are more likely to be optimistic and propose affirmative actions. Second, we show that the relative probability differences between male and female analysts are as large as 15% in the first half of the sample and decrease to about 7% after 2002. The few (remaining) female analysts thus resemble more and more the male analysts. Finally we show that gender differences among analyst recommendations are not constant over industries.

The remainder of the paper is organized as follows. Section 2 describes the motivation for this study and gives an overview of the related literature. Section 3 presents the sample selection procedure and provides a descriptive profile of the analyst database. The research methodology is described in Section 4, and empirical results are presented in Section 5. Finally, Section 6 summarizes our findings.

2 Related Literature

Given the well-documented behavioral biases in recommendations, it seems natural to study whether additional behavioral effects, more specifically, gender effects can be detected. This approach is motivated by the extensive literature in psychology, sociology and economics showing that the decision making process of women differs from that of men. In a recent survey, Croson and Gneezy (2004) synthesize studies on preference differences between men and women, focusing on risk taking and reaction to competition. In particular, several studies present evidence supporting the view that women are less risk-prone than men in financial decision making. Jianakoplos and Bernasek (1998) examine household holdings of risky assets to determine whether there are gender differences in financial risk taking. They find that the proportion of wealth held in risky assets is smaller for single women than for single men. In a similar context, Balkin (2000) finds that women follow a less risky investment strategy when saving for their 401(k) investment plans. Finally, Barsky et al. (1997) find that women self-report a lower risk propensity than men.

However, as Croson and Gneezy survey, these findings carry several caveats and exceptions. First, the framing of risks seems to influence the results. For example, in an abstract lottery choice for loss gambles Schubert et al. (1999) find men to be more risk averse than women, while the results for the gain gambles show that women are less risk-prone. In contextual gambles on the other hand, they find no systematic differences in risk attitude between men and women. Second, several studies show that gender-based differences depend on the selection of the agents being studied. Gender differences in risk preferences among professional agents are quite different from those of the general population. Atkinson et al. (2003) show that male and female fixed-income mutual fund managers do not exhibit significant differences in performance, risks taken or other fund characteristics. A similar finding is obtained by Bliss and Potter (2002) for the fund management business. Dwyer et al. (2002) observe that female investors take less risk than male investors. However, once the analysis controls for financial investment knowledge, gender-based risk differences largely disappear. Whether this result is due to adaptive behavior of the professional females or a self-selection mechanism by women is unclear.

A general conclusion from the above empirical evidence is that the observed differences should not be related to gender, but to a different educational background or a different professional environment. In a recent study, however, Niessen and Ruenzi (2007) refute this assertion by re-examining gender effects in the professional setting of mutual fund managers. Interestingly, they find that female fund managers do have a different investment style and follow less risky and less extreme investment strategies.[3] They also find that women follow more time-consistent investment styles. This study is a contribution to this debate, using a large dataset of recommendations of professional stock analysts. If it is true that female stock analysts are more risk averse, less extreme, avoid competition and behave more like another, we can expect them to issue more conservative recommendations. This would translate into female recommendations hiding at the consensus and thus showing more herding behavior. Male analysts, on the other hand, might prefer to stand out of the group and issue more risky and extreme recommendations.

3 Data and Descriptive Statistics

The analyst recommendations used in this study are provided by the Institutional Broker Estimate System (I/B/E/S) database, which is part of Thomson Financial. The recommendations encompass the period 1996 - 2006.[4] Each datarecord includes information about, among other things, the recommendation, the recommendation date, an identifier for the brokerage house issuing the recommendation and for the analyst that gives the recommendation (the surname and first initial). Recommendations are given on a five-point scale. I/B/E/S collects the recommendations from the security analysts and assigns standardized numerical values to

[3]In addition, in the context of corporate decision taking, Cadsby and Maynes (2005) find that women are less extreme decision makers and behave more like another than men.

[4]Our I/B/E/S data has been downloaded in January 2007. A recent paper by Ljungqvist et al. (2007) shows that ex post changes are implemented in the I/B/E/S database. At this point, it is too early to speculate on how the findings of Ljungqvist et al. (2007) would influence the results of the current paper.

them. A rating of 1 reflects a strong buy, 2 reflects a buy, 3 a hold, 4 a sell, and finally a score of 5 corresponds to a strong sell. To allow for a more intuitive interpretation of our results we follow Jegadeesh et al. (2004) and reverse the ordering of the values, so that more favorable recommendations receive a higher score. We trim the I/B/E/S database by deleting incomplete observations. These are observations that lack identification of the analyst, the brokerage house he works for, the company that is being followed and the corresponding industry, the recommendation, or the monthly consensus recommendation. This trimming procedure leaves us with 333,492 recommendations over the sample period of 11 years.

This recommendations' sample is combined with Nelson's Directory of Investment Research (editions 1997 - 2007). Nelson's Directory is a yearly analysts' contact details book and contains an analyst's full name, the brokerage house he is employed for, his specialization, and his contact information. We use this information to manually match the I/B/E/S analyst identification with the full first name and last name of each analyst. Next, based on the first name, we determine the gender of each analyst. We rely on a website that contains a program using Google's database to analyze common patterns involving that first name.[5] It determines from popular usage on the web whether the name is more common for a man or a woman. If we are not sure of the gender of the analyst, we check the name and gender by searching the history of the analyst on the internet. We delete observations when there is ambiguity of the gender. From the 333,492 complete observations in I/B/E/S we are able to match 94% with the corresponding gender of the analyst. Finally, we trim the database by eliminating analysts covering an extreme number of firms (we top off the 99th percentile). Our final sample contains 297,673 datarecords.

Table 1 shows descriptive statistics for the sample of analyst recommendations used in the paper. The total sample consists of recommendations of 7,370 unique analysts from 548 brokerage houses covering 9,295 firms. The annual number of recommendations steadily increases, reaching a peak in 2002. From that point onwards, the number of recommendations decreases rapidly, to reach a level at the end of our sample period comparable to the 1996 level. In addition, for the number of firms covered and the number of analysts employed, we observe a similar trend of an initial increase combined with a later decrease, however less explicit. The number of brokerage houses is larger in the second half of the sample. Finally, female analysts are clearly in the minority as only 17% of all analysts in the complete sample are women. Moreover, there is a clear downward trend in the number of female analysts, falling from 16% of the analyst community until 2001 to only 12% in 2006. Interestingly, this trend break coincides with a turbulent stock market period and a change in the analysts' professional environment. As Conrad et al. (2006) notes the collapse of technology stocks introduced a sometimes contentious debate on the neutrality of analysts with several Wall Street firms, with

[5] See http://www.gpeters.com/names/baby-names.php.

their analysts being sued for giving subjective information to their clients.[6] This introduced increased scrutiny of analysts' practices by the SEC and the states attorneys general. Such reinforcement of the legal and supervisory frame of the profession increases the riskiness of the job, and this could potentially discourage women to stay employed as an analyst. Finally, also note that these results not only point to the low representation of women in the profession, but also show high job turnover rates as the percentage of female analysts employed over the full period of 11 years is larger than the representation of women in any single year. This could point to the high work load, fierce competition and stress that comes with the job. Such a job might be less attractive for women in the long run.[7] These findings are similar to those found by Green et al. (2007), who point to the self-selection mechanism to explain the low representation of women in the analyst profession.

The descriptive statistics of the nature of the recommendations that are issued by the analysts can be found in Table 2. This table reports the yearly average recommendation, its yearly dispersion as measured by the standard deviation of outstanding recommendations and a frequency table of the different recommendation signals split by gender. There are no large differences between the average male and female recommendations, neither between the dispersion of the recommendations. For both gender groups, we observe a rather high mean recommendation. This corresponds to the well-documented upward bias in recommendations, with analysts being reluctant to issue negative reports. Several studies argue that mixed incentives of analysts lie at the basis of the bias. The stock market hype surrounding the end of the second millennium even reinforced this bias, as analysts became more positive over time, with a peak towards the year 2000. With bearish markets starting in 2001, this trend reversed, with a subsequent decrease in analysts' ratings. Barber et al. (2005) and Conrad et al. (2007) note the same dynamics and argue that this trend reversal can be the result of a bad performing stock market and/or an increased regulatory scrutiny of analysts' activities. The optimism in recommendations can also be seen from the frequency distribution in Table 2. Until 2001 both male and female analysts issue few strong sell and sell recommendations: they cover less than 3% of all recommendations. From 2002 onwards the number of negative reports increases up to 10% of all recommendations. This change in behavior can also be seen in the increased dispersion. For the first half of the sample, the standard deviation of the recommendations is rather low at 0.85. In 2002, on the other hand, the standard deviation immediately increases by approximately 15% to almost 1, reflecting the increased dispersion in opinion among analysts. Note that the latter might be caused by the increased diversity in risk of listed companies. However, the increased dispersion is consistent over all

[6] See, for example Teather (2002).

[7] Several authors, such as Gupta et al. (2005) and Niederle and Vesterlund (2006) find that women tend to avoid competitive environments, whereas men actually seek the challenge of competition.

the years in the second half of the sample. Considering the fact that stock markets have been performing very well since 2003, one can therefore argue that their has been structural change in analyst behavior since 2002.

Prior studies have shown that analyst characteristics, other than gender, are important in explaining analyst forecast accuracy (see e.g. Clement (1999)). Such individual analyst characteristics might therefore also impact the recommendations that they issue. A summary of the main individual characteristics of the analysts in our sample is given in Table 3. One of the key determinants appear to be analysts' abilities (see Clement (1999)). In this study, analysts' abilities are proxied by three distinct variables: a star dummy variable, firm specific experience and total experience (both measured in number of years)[8]. The star dummy is based on the yearly prestigious ranking ('the Leaders') published in the October edition of Institutional Investor (see also Hong and Kubic (2003)). Institutional Investor performs a yearly questionnaire among financial analysts to determine the best analysts of the previous year. Such ranking not only accounts for forecast accuracy, but for the broad range of services provided by analysts. Table 3 shows that for the male and female subsamples 3.7% and 3.3% of analysts are ranked as a star, respectively. Even if this suggests that men have a higher probability to be elected as a star analyst, the yearly numbers show that in fact women have a slightly higher change to be ranked a star analyst. This finding is also confirmed by Green et al. (2007). They find that women have a higher probability than men to be rewarded the status of star analyst, even if their earnings forecasts are less accurate. This suggests that women outperform in other services such as client contact. In terms of firm specific experience and total experience, we see that over all years men have a larger firm specific experience than women. On average, men follow a company for 2.10 years, while for women the firm specific experience is a little lower at 2.02 years. The same trend can be observed for total experience. On average, men are employed as an analyst for 4.34 years, while women are only present in the analyst community for 4.16 years. This is not surprising. Above we already pointed to the high job turnover of women in the sector of investment banking.

Recent research has also shown that available resources are important for the analysts's job performance. Therefore we identify the brokerage houses that are considered to be the best each year. Such ranking of the best brokerage houses is also published in the October issue of Institutional Investor. Using this ranking, we identify the top 15 of the investment banks as top brokers. This ranking of top brokers is rather stable over time and covers the large and prestigious brokerage houses. Interestingly, we find that female analysts have a higher probability than men to be employed by a top investment bank. This finding is in line with the evidence presented in Niessen en Ruenzi (2007) for mutual fund managers. They argue that female fund managers are most likely to be employed by large and well-

[8]To obtain variation from the beginning of our sample onwards, we go back to 1993 to compute firm specific and total experience of each analyst.

established companies for reasons of political correctness. Finally, we consider two variables representing task complexity. We take into account the number of firms covered by an analyst in a given year, as well as at the number of industries the analyst covers.[9] The larger the number of firms covered, the more difficult it is to closely follow each company. Moreover, if these companies are from different sectors, the portfolio is even more diverse and difficult to manage. Comparing male and female task complexity, we see that male analysts cover more firms, spread over more sectors than their female colleagues. Over the full sample, men cover 15 different firms over 2.28 sectors, while female analysts only cover 11.69 companies of 1.97 industries. Also note that the number of sectors covered is rather stable over time, while the number of firms covered shows more variation. In the year 2002, the busiest year for the analysts (see Table 1 earlier), we also see that analysts cover more companies than any other year.

Apart from the variation over time, it is also interesting to investigate the cross-sectional dimension of the data by looking at differences in recommendations over different industries. Table 4 shows descriptive statistics split up by industry. In terms of the number of analysts covering a certain sector, there are large differences. This mainly reflects the relative size of each sector in the total economy, with consumer services and technology the largest industries, both covered by over 3,000 analysts. The cross-sectional dimension of the number of analysts employed display gender differences. Some industries are mainly followed by male analysts. The sector of capital goods has only 11% of female analysts. Also the industries technology and energy are dominated by male analysts with a high 88% of male analysts. The sector consumer non-durables, on the other hand, is the most 'female' sector, with 23% of all analysts being female. This percentage is much larger compared to the yearly percentages of women employed in the overall analyst industry. Also health care and consumer services are two of the industries covered by a relatively large percentage of women.

The low or high representation of women in a certain industry might impact the recommendation formation process. The mean recommendation, computed for the gender subsamples can give a first indication of such cross-sectional gender effect. In general, there are no large differences between the mean recommendation issued by the male analysts and the mean recommendation issued by female analysts in a given industry.

4 The Model

Security analysts provide important information to financial markets. They study individual companies and issue stock recommendations. These stock recommendations provide investors with the most direct advice on the appropriateness of their

[9] The sector classification is based on the I/B/E/S SIGC division, and distinguishes 11 distinct sectors (see infra).

investment portfolios. We model the recommendations as follows: 1 = strong sell, 2 = sell, 3 = hold, 4 = buy and finally, 5 = strong buy. The feature of the data suggest the use of an ordered probit analysis, with the recommendation levels as the dependent variable.

With our model we try to explain the probability of the occurrence of each recommendation that is issued by the security analysts by means of individual characteristics, among which gender. The values of the recommendation levels, REC, are limited dependent variables, which implies that the true recommendations levels, REC^* are unobservable. We assume a linear latent relationship:

$$REC^* = X'\beta + \varepsilon, \tag{1}$$

where ε is assumed to be a standardized unit normal distributed error term. We use maximum likelihood to estimate the parameters β, which represent the marginal effects of changes in the independent variables X, on the probabilities $\Pr(REC = k)$ for $k = 1, 2, 3, 4$ and 5. In addition, cutoff points of the different classes are assumed such that:

$$REC = i \text{ if } \gamma_{i-1} < REC^* \leq \gamma_i,$$

$i = 1, ..., 5$, where $\gamma_0 = -\infty$ and $\gamma_5 = \infty$. Note that, except for the endpoints γ_1 and γ_4, the sign of the changes in the probabilities as a function of changes in the regressors is ambiguous (see Long (1997)). In the empirical section below, we therefore focus on relative probability differences evaluated at specific variable levels to provide an interpretation of the estimated parameters.

As independent variables we include the various analyst characteristics we described in the previous section. In addition, we want to capture the behavior of analysts with respect to available public information. Given the existing evidence of gender-specific decision making, we include the consensus recommendation, as well as dispersion of recommendations. First, the consensus recommendation captures the potential herding behavior among analysts. In our analysis we use the mean recommendation that is valid in the month before a particular recommendation is issued by the analyst to proxy for the consensus. We know there is an upward bias in the distribution of recommendations. A negative recommendation is not easily issued and thus a favorable recommendation or a recommendation close to the consensus is a rather safe decision. Therefore, we expect an asymmetry around the consensus with respect to the probability of choosing a certain recommendation level. To model this asymmetry, we include the squared of the consensus level. Overall, we expect a positive effect for herding behavior.[10] The higher the previous consensus, the higher is the probability of issuing a high recommendation. If female analysts are more risk averse decision makers, we expect them to behave more like another and thus to be more susceptible to herding.

[10] While the consensus recommendation in the month before the recommendation is issued does not necessarily capture herding, a significantly positive effect at least indicates that information only slowly disseminates among analysts.

They will, more heavily than their male colleagues, take into account the consensus recommendation.

Second, dispersion around the consensus recommendation reflects the lack of agreement among analysts, and refers to the existing uncertainty on the company's prospects. In our model, such uncertainty is proxied by the standard deviation of the recommendations valid in the month before a particular recommendation is issued by the analyst. We expect a negative effect of uncertainty. The higher (lower) the dispersion of previous recommendations, the more analysts disagree (agree), and thus the higher is the probability of issuing a relatively low (high) recommendation. Moreover, we expect male analysts to be more risk seeking with respect to the market's level of agreement. This would translate into male recommendations that are relatively more optimistic compared to the female recommendations. This way male analysts might try to positively distinguish themselves from the other analysts.[11]

To account for individual analyst characteristics we include the variables proxying for analyst abilities, resources and task complexity as explained in Section 3. To proxy for job experience of the analyst, we use total tenure that the analyst is employed as an analyst, in addition to firm tenure, the period that the analyst has been covering a specific company. We also consider the star rating of Institutional Investor to capture analysts abilities and include this star rating as a dummy variable. As Sorescu and Subrahmanyam (2006) note, this star status is very prestigious as the popular press awaits the recommendations of these well-known and distinguished analysts in great anticipation. These star analysts are likely to be better paid, have more resources and are better informed. We can expect this to translate into superior recommendations. A priory, the sign of the marginal effects of these variables representing analysts' abilities is not clear-cut. Both the theoretical as well as the empirical literature offers opposing views on the relation between experience (and reputation) and the level of recommendations (and herding). If experience and the level of recommendations are negatively related, experienced analyst are more likely to issue lower recommendations (compared to the consensus). The studies of Hong et al. (2000) and Clement and Tse (2005) empirically support this view. If they are positively related, unexperienced analysts have a larger tendency to deviate from the consensus, probably in an attempt to stand out from the crowd and appear talented. This is the hypothesis backed by Zitzewitz (2001). Finally, a recent study of Jegadeesh and Kim (2007) finds no difference in the herding behavior between experienced and unexperienced analysts. Whether the probability to deviate (negatively) from the crowd, and thus the probability to issue extreme recommendations increases or decreases with analysts' capabilities thus remains an open question to which this study contributes.

[11] We believe a Hold recommendation is a less risky decision than a (Strong) Buy recommendation, because a Hold recommendation corresponds in fact to a non-action. This is in line with the interpretation of downside risk.

To proxy for job complexity, we include variables that track the number of firms and the number of industries the analyst has provided recommendations for in the year of the recommendation issue. We also include a combined effect measuring the number of firms covered per industry. Analysts that track companies in different industries have a more difficult task as they can built up less specialized information and knowledge. Therefore they are less likely to deviate (negatively) from the consensus recommendation, as they have less expertise. This explanation is also valid for the number of firms an analyst tracks. The fewer firms one needs to follow as an analyst, the more time can be spent on obtaining the necessary information to make ones report better. We expect the effects of these variables to be positive. Of course, the combined effect of the number of firms and number of industries could also create economies of scale. If a certain analyst follows a number of firms concentrated in a single industry, this might facilitate the gathering and processing of information, e.g. in peer analysis. In our study, we account for this economies of scale effect in job complexity by measuring the number of firms an analyst covers per industry in the same industry as the recommendation that is issued. Combined with the number of industries and number of firms the analyst follows, this variable reflects the dispersion of the analyst's attention.

We also account for the resources available to the analyst. We include a top dummy variable that identifies all analysts employed by the top 15 of the brokerage houses according to the yearly Institutional Investor questionnaire. These brokerage houses have more (financial) resources, often employ the best analysts and are likely to maintain good relations with the companies they cover. Analysts working for top brokers are therefore more likely to be better informed than their colleagues not working for a top brokerage firm. However, the effect of this resource variable on the level of recommendations is unclear and is an empirical question. The same reasoning applies here as the one put forth with the variables capturing analysts' abilities.[12] The sign of the marginal effect is therefore ambiguous.

Finally, as the most important individual analyst characteristic, we allow for gender differences in the model. In particular, we estimate the model separately for male and female analysts. This allows us to identify the gender impact of the different explanatory variables. To assess the gender effects, we test whether individual coefficient estimates between men and women are different. In addition we will provide simultaneous tests of the coefficients.

5 Empirical Results

In this section we describe the results of our empirical analysis. First, we provide full sample results and show that there is a statistical and economical difference

[12] While Jegadeesh and Kim (2007) find no evidence of a link between experience and herding, they do find a positive relation between the size of brokerage house (capturing the most established and prestigious houses and thus largely overlapping with the top brokers) and herding.

between male and female analysts. Second, as mentioned above, we confirm that there is a structural break in the data after 2001 by providing estimates for a split sample before 2002 and after 2001. In the third subsection we show that gender differences among recommendations have steadily decreased over time and seem to increase again in 2006. Next, because the top brokerage firms have been accused and convicted of providing biased recommendations we investigate whether the increased enforcement of the legal and supervisory frame of the analyst profession by the SEC and the federal government has affected analyst behavior. Finally we show that gender differences are not constant over industries.

5.1 Full Sample Results

Table 5 shows the ordered probit results for the entire sample. The first columns present the estimation results of a benchmark model that does not allow for gender differences. The estimated coefficients are all, except for one, significantly different from zero at all conventional significance levels. Moreover, most effects are in line with our expectations.

The results indicate that analysts are susceptible to herding. The dispersion of the previous recommendations issued has a negative effect. In addition, tenure of the analysts has a negative effect, implying that more experienced analysts are more likely to issue lower recommendations. The star status on the other hand, is associated with a higher probability to issue higher recommendations. This could indicate that a star status is mainly achieved by issuing outstanding positive reports. In line with previous studies we are therefore not able to provide an unambiguous explanation of the effect of experience on the level of the recommendations. The estimation results for job complexity indicate that there is no clear evidence how it influences the recommendation issuing process. The positive sign of the number of industries means that analysts are more likely to issue more favorable recommendations the more industries they follow. On the contrary, the negative sign of the number of firms, means that analyst are more likely to issue less favorable recommendations the more firms they follow. Finally, the economies of scale effect when covering multiple firms in a single industry is very small and not significant. Table 3 shows that on average, the number of firms followed by analysts is about three times as large as the average number of industries they follow. Therefore, we conclude that the more complex the job, the more likely it is that the analyst will issue a less favorable recommendation. This effect is however very small and statistically not significant. Finally, analysts working for a top brokerage house have a larger probability to issue lower recommendations in general.

Columns 4-7 of Table 5 show the estimation results for male and female analysts separately. All estimated coefficients, for men and women, have the same sign as the full sample results. Most of the coefficients are significant. More importantly is the question whether there are significant differences between male and female analysts. When considering all estimates simultaneously, Table 6 shows that overall the female analyst estimates are significantly different from the full sample estimates and, more importantly, from the male analyst estimates as well. In addition, Table 5 shows that there are significant individual parameter estimate differences between the male analyst sample and the female analyst sample for half of the (significantly) estimated parameters.

Noticeably, male analysts have a ceteris paribus larger probability to issue lower recommendation levels when dispersion among recommendation is high. Furthermore, female analysts are ceteris paribus more affected by experience as measured by total tenure. The more experienced the female analyst, the more likely she is to issue a lower recommendation level. In addition, female analysts who work for a top brokerage house are more likely to issue less favorable recommendations than male analysts, while the female star analyst is more likely to issue more favorable recommendations than male analysts. Table 3 shows that on average more than 40 percent of the male and female analysts are working for a top broker, while on average only about 2 percent of the analysts in the sample is elected to be a star. This leads us to conclude that the average male analyst working for a top brokerage house is more likely to issue less favorable recommendations.

Ordered probit regression results are notoriously difficult to interpret economically. As the estimation results indicate, dispersion among recommendations is a very important variable in our model for the recommendation forming process. We therefore calculate the probabilities for each recommendation class, for the average analyst, by varying dispersion from its average minus two times its standard deviation to its average plus two times its standard deviation. This enables us to investigate risk aversion differences among gender. Figure 1 shows these probabilities for the average analyst using the estimation results from the male and female sample separately. The figure shows that the dispersion of recommendations has predictive power with respect to the recommendation that will be issued by the analyst. When dispersion in the previous month is high, both male and female analysts are most likely to issue a Hold recommendation (40%), while they have a 30% and 20% probability to issue a Buy and a Strong Buy recommendation, respectively. On the other hand, when dispersion is very low, the probability of Strong Buy, Buy and Hold recommendations all lie around 30% for male and female analysts. Note however that the probability of a Strong Buy recommendation is lower for female analysts. This seems to indicate that female analysts are more conservative and less optimistic in their recommendation behavior than their male colleagues. In line with the descriptive statistics of Section 3, the probability that a Strong Sell and Sell recommendation is issued is below three percent.

From the probabilities for each recommendation class that are shown in Figure 1 it is very difficult to interpret the gender differences in the recommendation classes. On average there do not seem to be large (economic) differences in the probabilities. However, these differences should be interpreted relative to the probability a recommendation class is likely to occur. Therefore we calculate relative probability differences for each recommendation class. The latter are defined as the probability differences between male and female analysts for each recommendation class, *divided by* the probability that the recommendation occurs. The latter is calculated using the full sample estimation results (without gender differences). In this way we provide a good measure of relative importance. The results of this exercise are shown in Figure 2.

This figure provides a graphical interpretation of the economic importance of the differences in the recommendation behavior between male and female analysts. When the relative probability of a recommendation class is larger than zero, male analysts are more likely to choose that recommendation class compared to female analysts. It can be observed that especially when dispersion among the recommendation is low, there are very large differences between male and female analysts. For example, when dispersion is at the lowest point that we consider, the average male analyst has a 7% larger probability to issue a Strong Buy recommendation than the average female analyst. Alternatively, at the same time the average female analyst has a 5% larger probability to issue a Hold recommendation than the average male analyst.[13] This indicates that overall, relative to dispersion, the average male analyst tends to be more optimistic about the company he is evaluating than the average female analyst. We interpret this result as follows. When dispersion among the recommendations is low, male analysts are more likely to positively deviate from the mainstream while female analysts are more risk averse and are more likely to issue more conservative Hold recommendations. When dispersion increases, gender differences decrease. This can likely be explained by the fact that any deviation from the mainstream is less noticed by the market when dispersion is high. Analysts might therefore have most incentives to deviate when the market is more likely to interpret their recommendation as personal skill and not as luck.

For the full sample results we conclude the following. Female analysts behave differently than male analysts. First, they are less likely to positively deviate from the consensus when dispersion among the recommendations is low. Women tend to issue the more conservative Hold recommendations, while male analysts are more optimistic and issue relatively more Strong Buy recommendations. Second, women are more likely to issue lower recommendation levels when more experienced than men. Third, when working for a top brokerage firm, women have a larger probability to issue lower recommendation levels and finally, men have lower probability to issue higher recommendation levels when being a star analyst.

[13]In addition, the average female analyst has a 3% larger probability of issuing a Sell recommendation than the average male analyst and a 10% larger probability to issue a Strong Sell recommendation.

5.2 Split Sample Results

As mentioned in Section 3 above, there appears to be a trend break in the issuing of recommendations after the collapse of technology stocks in 2002. The increased scrutiny of analysts' practices by investors and the SEC, in addition to the threat of litigation has increased the risk of the analyst job. As an immediate result the shares of strong sell and sell recommendations have more than doubled, probably due to the worse performance of the companies immediately after the technology shock. Table 2 however shows that although stock markets have done very well in recent years, the number of least favorable recommendations issued by analysts has not gone down. This indicates that there has been a regime shift in the recommendation generating process. In this section we investigate whether male and female analyst have been affected differently.

The sample statistics as discussed in Section 3 show that less women are working as analyst since 2002. When estimating the recommendation model (1) for the two subsamples 1996 - 2001 and 2002 - 2006 we find interesting results. First, regarding gender differences in recommendation dispersion, we see in Table 7 that the difference between male and female analysts is larger in the first half of the sample than in the second half of the sample (see Table 8). Table 9 shows that when considering all estimates simultaneously, gender differences are present in the first half of the sample as well as in the second half of the sample, although the test statistic is much lower in the latter case. In addition, for both the male and female sample, the estimates for the first half of the sample are significantly different from the second half of the sample, confirming there has been a behavioral change.

The regression results for the two subsamples indicate that although behavioral differences between male and female analysts exist, they have decreased over time.[14] Figure 3 shows that when the dispersion of the recommendations is at the lowest point we consider, the relative probability differences are just over 10% in favor of male analyst for Strong Buy recommendations and up to 15% in favor of female analysts for Hold recommendations. Note also that the differences are over 30% in favor of female analyst in case of Strong Sell Recommendations. In contrast, Figure 4 shows that the relative probability difference for Strong Buy recommendations in favor of male analysts has decreased to 5%, while for Hold recommendations the difference decreased to only 1% in favor of female analysts. Overall we conclude that risk aversion is larger among female analysts as they have a higher probability to issue more conservative recommendations. When dispersion among recommendations increases, gender differences decrease.

These split sample results lead us to conclude that gender differences in analysts recommendations have decreased over time. Female analsyst behave more and more like their male colleagues. Overall we conclude that male analysts are less

[14]This also follows from the individual tests on the coeficient estimates. While in the first subsample, up to 6 parameters are estimated significantly different between the male and female sample, this reduces to only 2 significantly different parameters in the second subsample.

risk averse than female analysts because they have a larger probability of issuing the most favorable recommendations when the market actually agrees most.

5.3 Year Results

To investigate whether the conclusions of the previous subsection are robust over the years, we estimate the model for each year separately. The results can be found in Table 10. With the exception of 1996, we observe that the coefficient for dispersion among recommendations is larger in absolute value for male analysts. The difference between male and female analysts decreases over time however. This is consistent with the split sample estimates above.

To visualize the change in recommendation behavior over the years, we refer to Figure 5. The figure shows the relative probability differences between male and female analysts evaluated at the full sample averages for all independent variables. One can easily see that the gender differences have decreased over time, certainly after 2001. It seems however that in 2006, the final year of our sample, gender differences are increasing again. These results are confirmed by the joint tests shown in Table 11. For the years 1996 - 2000, 2003 and 2006 we find significant gender differences, while for the years 2001, 2002, 2004 and 2005 the differences are not statistically significant.

5.4 Industry Results

To conclude our empirical investigation, we consider gender differences among industries. Table 4 clearly shows that the number of analysts following firms in a particular industry largely varies as well as the percentage of female analysts. First, Table 13 shows the test statistics of the gender difference tests. The tests show that for the industries Health Care, Consumer Durables and Capital Goods, no statistical significant gender differences can be found. In addition, Table 12 shows the ordered probit results for the 11 industries. The results confirm our previous results that gender differences among recommendations exist. However, the size of the differences seem to be unrelated to the percentage female analysts working in each sector.

6 Conclusion

In this paper we studied the impact of individual analyst characteristics, in particular gender, on the recommendation issuing process. Our conclusions are as follows. There are gender differences among analyst recommendations. We show that for the recommendation levels that are issued most, the relative probability differences are as large as 15% in the first half of the sample and decrease to about 7% after 2002. In addition we find that in 2006 the relative probability differences between genders increase again. The results indicate that when dispersion among recommendations is low, male analysts are more willing to be overoptimistic about a stock and are more likely to issue Strong Buy recommendations. Male analysts are therefore less risk-averse and are more willing to make a bold recommendation. Men might propose such affirmative action in an attempt to stand out of the crowd and have their judgement be interpreted as skill (instead of luck). Interestingly, these differences seems to disappear largely after the technology hype in 2001. While a lot of female analysts left the industry at that moment, we find that the few remaining female analysts behave very much like their male colleagues.

The empirical results leave us with interesting questions for future research. First, in research in progress we investigate whether the gender differences in the recommendation issuing behavior can be exploited by the investor by forming a trading strategy. In a second paper, we investigate whether male analysts are more overconfident than female analysts based on the earnings forecasts they issue. If this is indeed the case, a profitalbe trading strategy could be constructed.

References

[1] Atkinson, S.M., S.B. Baird and M.B. Frye, 2003. Do Female Fund Managers Behave Differently? *Journal of Financial Research* 26: 1-18.

[2] Balkin, D., 2000, Gender Effects of Employee Participation and Investment Behavior with 401(k) Retirement Plans. Working Paper.

[3] Barber, B.M., R. Lehavy and B. Trueman, 2005. Comparing the Stock Recommendation Performance of Investment Banks and Independent Research Firms. Forthcoming in *Journal of Finanical Economics.*

[4] Barsky, R.B., F.T. Juster, M.S. Kimball and M.D. Matthew, 1997. Preference Parameters and Behavioral Heterogeneity: An Experimental Approach in the Health and Retirement Study. *Quarterly Journal of Economics* 112: 537-579.

[5] Bliss and Potter, 2002. Mutual Fund Managers: Does Gender Matter? *Journal of Business and Economic Studies* 8: 1-15.

[6] Block, S.B., 1999. A Study of Financial Analysts: Practice and Theory. *Financial Analysts Journal* 55: 86-95.

[7] Bradshaw, M.T., 2004. How Do Analysts use Earnings Forecasts in Generating Stock Recommendations? *The Accounting Review* 79: 25-50.

[8] Cadsby, C.B. and E. Maynes, 2005. Gender, Risk Aversion and the Drawing Power of Equilibrium in an Experimental Corporate Takeover Game. *Journal of Economic Behavior and Organization* 56: 39-59.

[9] Clement, M.B., 1999. Analyst Forecast Accuracy: Do Ability, Resources and Portfolio Complexity Matter? *Journal of Accounting and Economics* 27: 285-303.

[10] Clement, M.B. and S.Y. Tse, 2005. Financial Analyst Characteristics and Herding Behavior in Forecasting. *Journal of Finance* 60: 307-341.

[11] Chen, S. and D.A. Matsumoto, 2006. Favorable versus Unfavorable Recommendations: The Impact on Analyst Access to Management-Provided Information. *Journal of Accounting Research* 44: 657-689.

[12] Conrad, J., B. Cornell, W. Landsman and B. Rountree (2006). How do Analyst Recommendations Respond to Major News? *Journal of Financial and Quantitative Analysis* 41: 25-49.

[13] Cornell, B., 2001. Is the Response of Analysts to Information Consistent with Fundamental Valuation: The Case of Intel. *Financial Management* 30: 113-136.

[14] Croson, R. and U. Gneezy, 2004. Gender Differences in Preferences. Working Paper, Wharton School.

[15] Dwyer, P.D., J.H. Gilkeson and J.A. List, 2002. Gender Differences in Revealed Risk Taking: Evidence from Mutual Fund Managers. *Economics Letters* 76: 151-158.

[16] Green, T.C., N. Jegadeesh and Y. Tang (2007). Gender and Job Performance: Evidence from Wall Street. Working Paper, NBER No. 12897.

[17] Gupta, N.D., A. Poulsen and M.C. Villeval, 2005. Male and Female Competitive Behavior: Experimental Evidence. Working Paper IZA No. 1833.

[18] Hong, H. and J. Kubik, 2003. Analyzing the Analysts: Career Concerns and Biased Earnings Forecasts. *Journal of Finance* 58: 313-351.

[19] Hong, H., J. Kubik and A. Solomon, 2000. Security Analysts' Career Concerns and Herding of Earnings Forecasts. *Rand Journal of Economics* 31: 121–144.

[20] Jegadeesh, N. and J. Kim, 2007. Do Analysts Herd? An Analysis of Analysts' Recommendations and Market Reactions. Working Paper.

[21] Jegadeesh, N., J. Kim, S.D. Krische and C.M.C. Lee, 2004. Analyzing the Analysts: When Do Recommendations Add Value? *Journal of Finance* 59: 1083-1124.

[22] Jianakoplos, N.A. and A. Bernasek, 1998. Are Women More Risk Averse? *Economic Inquiry* 36: 620-630.

[23] Ljungqvist, A., C.J. Malloy and F.C. Marston, 2007. Rewriting History. mimeo. Avilable at SSRN: http://ssrn.com/abstract=889322.

[24] Long, S., 1997. Regression Models for Categorical and Limited Dependent variables. Sage, London.

[25] Lin, H., M. McNichols and P.C. O'Brien (2005). Analyst Impartiality and Investment Banking Relationships. *Journal of Accounting Research* 43: 623-650.

[26] Niederle, M. and L.Vesterlund, 2006. Do Women Shy Away from Competition? Do Men Compete too Much? Forthcoming in *Quarterly Journal of Economics*.

[27] Niessen, A. and S. Ruenzi, 2007. Sex Matters: Gender Differences in a Professional Setting. Working Paper.

[28] Schubert, R., M. Brown, M. Gysler and H.W. Brachinger, 1999. Financial Decision-Making: Are Women Really More Risk-Averse? *American Economic Review* 89: 381-385.

[29] Sorescu, S. and A. Subrahmanyam, 2006. The Cross Section of Analyst Recommendations. *Journal of Financial and Quantitative Analysis* 41: 139- 168.

[30] Teather, D., 2002, Wall Street Faces Prospect of Criminal Charges, The Guardian, April 24.

[31] Thomson Financial, 1997-2007. *Nelson's Directory of Investment Research* 22-32. Nelson, New York, N.Y.

[32] Welch, I., 2000. Herding Among Security Analysts. *Journal of Financial Economics* 58: 369–396.

[33] Zitzewitz, E., 2001. Measuring Herding and Exaggeration by Equity Analysts. Stanford GSB Working Paper No. 1802.

Appendix: Tables

Table 1: **Descriptive Statistics of the Recommendations Sample**

The recommendation data is obtained from I/B/E/S, while gender has been identified using Nelson's Directory of Investment Research.

	No. Rec.	No. Firms Covered	No. Brokers	No. Analysts	% Female
1996	20,514	3,946	178	2,138	16
1997	22,999	4,497	209	2,610	16
1998	28,298	4,921	225	3,149	16
1999	28,719	4,836	227	3,359	16
2000	25,867	4,425	220	3,290	16
2001	26,628	3,940	200	3,221	16
2002	40,419	4,068	208	3,312	15
2003	31,142	3,846	260	3,207	13
2004	27,742	4,023	295	3,191	13
2005	23,520	4,038	288	2,840	13
2006	21,925	4,007	250	2,436	12
all years	297,673	9,295	548	7,370	17

Table 2: **Male versus Female Recommendations**

The frequency distributions of the males and females are computed relative to the male and female analyst subsample, respectively. The recommendation data is obtained from I/B/E/S, while gender has been identified using Nelson's Directory of Investment Research.

	Mean Rec.		Stdev. Rec		Strong sell (%)		Sell (%)		Hold (%)		Buy (%)		Strong buy (%)	
	male	female	male	female	male	female	male	female	male	female	male	female	male	female
1996	3.89	3.87	0.93	0.93	1.86	1.90	2.07	1.48	32.20	34.79	32.96	31.26	30.81	30.57
1997	3.93	3.94	0.89	0.90	1.43	1.58	1.43	1.19	29.91	30.73	36.71	34.28	30.53	32.21
1998	3.90	3.89	0.86	0.86	1.03	1.35	1.38	1.02	31.58	31.79	38.22	38.97	27.79	26.88
1999	3.96	3.95	0.86	0.85	0.92	0.88	1.75	1.34	27.99	29.53	38.74	38.53	30.60	29.72
2000	3.99	3.92	0.83	0.83	0.62	0.78	1.27	0.75	27.53	32.31	39.42	38.34	31.17	27.81
2001	3.84	3.83	0.86	0.85	1.02	0.86	1.71	2.16	34.60	34.70	37.12	37.63	25.55	24.65
2002	3.58	3.57	0.96	0.96	2.01	1.88	7.55	8.31	41.10	40.19	29.36	29.86	19.99	19.76
2003	3.46	3.45	1.00	0.99	3.47	3.28	8.34	8.44	45.75	46.52	24.07	23.04	18.37	18.71
2004	3.52	3.53	1.00	0.99	3.43	3.25	6.75	6.31	44.92	45.49	24.70	24.21	20.21	20.73
2005	3.54	3.47	1.00	1.01	3.22	4.00	6.10	7.23	45.56	45.80	23.67	23.68	21.46	19.29
2006	3.50	3.47	0.97	0.96	3.05	3.17	6.59	6.90	46.95	46.94	24.58	25.90	18.83	17.09
all years	3.72	3.72	0.95	0.94	2.01	1.98	4.34	4.16	37.41	37.68	31.63	31.89	24.61	24.29

Table 3: **Male vs female analyst characteristics**

The percentages of the male and female characteristics are computed relative to the male and female analyst sub-sample, respectively. The Recommendation Data is obtained from I/B/E/S, while gender has been identified using Nelson's Directory of Investment Research.

	Abilities						Resources		Task complexity			
	Star analyst (as %)		Firm tenure (mean)		Total tenure (mean)		Top broker (as %)		No. Firms Covered (mean)		No. Ind. Covered (mean)	
	male	female	male	female	male	female	male	female	male	female	male	female
1996	2.28	2.05	1.73	1.69	2.57	2.51	31.44	38.42	6.95	5.60	1.77	1.59
1997	2.11	1.63	1.79	1.73	2.96	2.82	32.69	39.86	6.63	5.37	1.72	1.53
1998	2.00	2.39	1.81	1.71	3.24	2.98	38.84	49.00	6.48	6.04	1.71	1.59
1999	1.74	2.95	1.91	1.83	3.63	3.33	40.11	51.11	6.33	5.58	1.65	1.50
2000	1.88	2.28	1.97	1.89	4.04	3.72	40.90	50.09	5.86	5.12	1.63	1.43
2001	1.88	2.59	2.03	2.01	4.41	4.03	43.38	54.49	5.96	4.72	1.59	1.38
2002	1.67	2.20	2.19	2.15	4.55	4.13	45.02	56.60	7.60	6.51	1.64	1.48
2003	1.80	1.65	2.33	2.27	4.56	4.21	43.68	51.06	6.59	5.83	1.55	1.45
2004	1.84	2.14	2.34	2.21	4.99	4.59	37.17	45.00	6.35	5.40	1.57	1.42
2005	1.82	1.93	2.47	2.40	5.75	5.46	37.14	43.80	6.06	5.41	1.58	1.43
2006	2.34	1.67	2.59	2.62	6.78	6.46	37.13	44.67	6.45	6.23	1.65	1.48
all years	3.69	3.31	2.10	2.02	4.34	3.93	45.66	52.10	15.05	11.69	2.28	1.97

Table 4: **Industry Differences**

The industries are classified using the I/B/E/S SIGC definitions. The recommendation data is obtained from I/B/E/S, while gender has been identified using Nelson's Directory of Investment Research.

	No. Analysts	% Female	Mean Rec.	
			male	female
Finance	1,664	16	3.64	3.69
Health care	1,436	17	3.79	3.83
Consumer non-durables	1,102	23	3.69	3.71
Consumer services	3,056	17	3.78	3.75
Consumer durables	1,070	14	3.70	3.64
Energy	743	12	3.81	3.71
Transportation	435	13	3.67	3.71
Technology	3,043	12	3.73	3.71
Basic industries	1,222	13	3.59	3.61
Capital goods	1,626	11	3.76	3.74
Public utilities	1,040	16	3.66	3.66

Table 5: **Ordered Probit Results Full Sample**

This table reports estimates of the ordered probit model on the full sample and subsamples for male and female analyst respectively. The recommendation data is obtained from I/B/E/S, while gender has been identified using Nelson's Directory of Investment Research.

	Full Sample		Male Analyst		Female Analyst	
	Estimate	p-value	Estimate	p-value	Estimate	p-value
Consensus(t-1)	1.209	0.000	1.200	0.000	1.284	0.000
Consensus(t-1)^2	−0.097	0.000	−0.096	0.000	−0.104	0.000
St. Dev. of Outstanding Recs(t-1)	−0.225	0.000	−0.232	0.000	−0.174[a]	0.000
Total Tenure	−0.011	0.000	−0.009	0.000	−0.023[a]	0.000
Firm Tenure	−0.016	0.000	−0.017	0.000	−0.010	0.042
Number of Industries	0.012	0.000	0.012	0.000	0.012	0.150
Number of Firms	−0.008	0.000	−0.008	0.000	−0.005	0.047
Same Industry No. Firms	0.001	0.333	0.001	0.298	0.000	0.919
Working for Top Broker	−0.119	0.000	−0.112	0.000	−0.158[a]	0.000
Star Analist	0.058	0.000	0.040	0.000	0.152[a]	0.000
Nobs.	297,673		259,032		38,641	
Pseudo R^2	0.0301		0.031		0.0335	
γ_1	0.680		0.657		0.856	
γ_2	1.237		1.216		1.403	
γ_3	2.695		2.670		2.883	
γ_4	3.575		3.549		3.774	

[a] Female analyst estimate is statistically different from the male analyst individual estimate at the 5% level.

Table 6: **Wald Test Results for Gender Differences**

This table reports the test statistics and the p-values of the Wald tests to check for gender differences. All test statistics are $\chi^2_{10}-$distributed, assuming independence of the samples.

	χ^2_{10}	p-value
Full Sample vs. Male Analyst	4.92	0.896
Full Sample vs Female Analyst	353.46	0.000
Male Analyst vs. Female Analyst	361.18	0.000

Table 7: **Ordered Probit Results Split Sample Before 2002**

This table reports estimates of the ordered probit model on the full sample and subsamples for male and female analyst respectively. The recommendation data is obtained from I/B/E/S, while gender has been identified using Nelson's Directory of Investment Research.

	Full Sample		Male Analyst		Female Analyst	
	Estimate	p-value	Estimate	p-value	Estimate	p-value
Consensus(t-1)	1.138	0.000	1.145	0.000	1.109	0.000
Consensus(t-1)^2	-0.095	0.000	-0.097	0.000	-0.087	0.000
St. Dev. of Outstanding Recs(t-1)	-0.162	0.000	-0.175	0.000	-0.073^a	0.011
Total Tenure	-0.009	0.000	0.012	0.000	-0.014^a	0.001
Firm Tenure	-0.039	0.000	-0.040	0.000	-0.032	0.000
Number of Industries	-0.004	0.257	-0.004	0.345	-0.010	0.407
Number of Firms	-0.008	0.000	-0.009	0.000	0.003^a	0.483
Same Industry No. Firms	0.003	0.018	0.004	0.007	-0.003^b	0.385
Working for Top Broker	0.015	0.015	0.023	0.000	-0.022^a	0.169
Star Analist	0.031	0.065	0.008	0.662	0.153^b	0.000
Nobs.	152,925		131,800		21,125	
Pseudo R^2	0.0166		0.0310		0.0176	
γ_1	0.471		0.466		0.512	
γ_2	0.839		0.843		0.825	
γ_3	2.394		2.388		2.445	
γ_4	3.389		3.385		3.432	

$^{a(b)}$ Female analyst estimate is statistically different from the male analyst individual estimate at the 5% (10%) level.

Table 8: **Ordered Probit Results Split Sample After 2001**

This table reports estimates of the ordered probit model on the full sample and subsamples for male and female analyst respectively. The recommendation data is obtained from I/B/E/S, while gender has been identified using Nelson's Directory of Investment Research.

	Full Sample		Male Analyst		Female Analyst	
	Estimate	p-value	Estimate	p-value	Estimate	p-value
Consensus(t-1)	0.971	0.000	0.958	0.000	1.1085	0.000
Consensus(t-1)^2	-0.077	0.000	-0.075	0.000	-0.088	0.000
St. Dev. of Outstanding Recs(t-1)	-0.182	0.000	-0.184	0.000	-0.176	0.000
Total Tenure	-0.004	0.000	0.005	0.000	-0.004^a	0.238
Firm Tenure	-0.012	0.000	-0.013	0.000	-0.004	0.548
Number of Industries	0.023	0.000	0.023	0.345	0.022	0.077
Number of Firms	-0.007	0.000	-0.007	0.000	-0.007	0.047
Same Industry No. Firms	-0.001	0.462	-0.001	0.371	-0.001	0.703
Working for Top Broker	-0.258	0.000	-0.248	0.000	-0.325^a	0.000
Star Analist	0.002	0.923	-0.010	0.588	0.066	0.156
Nobs.	144,748		127,232		17,516	
Pseudo R^2	0.0257		0.0252		0.0302	
γ_1	0.251		0.228		0.454	
γ_2	0.895		0.868		1.118	
γ_3	2.347		2.322		2.568	
γ_4	3.110		3.082		3.346	

$^{a(b)}$ Female analyst estimate is statistically different from the male analyst individual estimate at the 5% (10%) level.

Table 9: **Wald Test Results for Sample Differences**

This table reports the test statistics and the p-values of the Wald tests to check for differences in the split sample results. All test statistics are $\chi^2_{10}-$distributed, assuming independence of the samples.

	χ^2_{10}	p-value
Male Analyst vs. Female Analyst 1st half of sample	165.30	0.000
Male Analyst vs. Female Analyst 2nd half of sample	35.44	0.000
Male Analysts 1st half vs. 2nd half	312.93	0.000
Female Analysts1st half vs. 2nd half	320.54	0.000

Table 10: **Ordered Probit Results for Seperate Years**

	1996				1997			
	Male Analysts		Female Analysts		Male Analysts		Female Analysts	
	Estimate	p-value	Estimate	p-value	Estimate	p-value	Estimate	p-value
Consensus$(t-1)$	1.131	0.000	1.505	0.000	0.894	0.000	1.431	0.000
Consensus$(t-1)^2$	−0.107	0.000	−0.163	0.000	−0.070	0.003	−0.131	0.005
St. Dev. of Outstanding Recs$(t-1)$	−0.185	0.000	−0.201	0.006	−0.157	0.000	−0.118	0.110
Total Tenure	0.070	0.000	0.006	0.788	0.031	0.000	0.027	0.085
Firm Tenure	−0.074	0.000	−0.086	0.002	−0.083	0.000	−0.097	0.000
Number of Industries	−0.034	0.000	−0.041	0.205	0.001	0.918	−0.047	0.112
Number of Firms	−0.011	0.000	−0.010	0.399	−0.007	0.046	0.013	0.197
Same Industry No. Firms	−0.002	0.539	−0.015	0.197	0.002	0.664	−0.010	0.365
Working for Top Broker	−0.012	0.513	0.020	0.659	0.017	0.341	−0.005	0.910
Star Analist	0.053	0.260	0.085	0.436	−0.040	0.377	−0.017	0.898
Nobs.	20,514		2,633		19,901		3,098	
PseudoR^2	0.018		0.015		0.017		0.027	
γ_1	0.346		0.854		−0.013		0.944	
γ_2	0.688		1.114		0.286		1.207	
γ_3	2.147		2.687		1.790		2.793	
γ_4	3.020		3.511		2.769		3.709	
	1998				1999			
Consensus$(t-1)$	1.424	0.000	1.411	0.000	1.180	0.000	0.643	0.077
Consensus$(t-1)^2$	−0.142	0.000	−0.123	0.000	−0.100	0.000	−0.023	0.623
St. Dev. of Outstanding Recs$(t-1)$	−0.201	0.000	−0.015	0.000	−0.183	0.000	−0.019	0.780
Total Tenure	0.024	0.000	−0.005	0.000	0.010	0.015	−0.024	0.020
Firm Tenure	−0.064	0.000	−0.021	0.000	−0.043	0.000	−0.010	0.571
Number of Industries	0.007	0.448	0.073	0.066	−0.015	0.106	−0.009	0.702
Number of Firms	−0.010	0.001	−0.011	0.000	−0.020	0.482	0.002	0.820
Same Industry No. Firms	−0.003	0.256	0.010	0.614	0.002	0.509	0.003	0.710
Working for Top Broker	0.001	0.933	−0.042	0.638	0.100	0.00	0.015	0.675
Star Analist	0.026	0.522	0.219	0.112	0.096	0.046	0.307	0.000
Nobs.	23,964		4,234		24,533		4,186	
PseudoR^2	0.016		0.018		0.017		0.019	
γ_1	0.746		1.424		0.513		−0.310	
γ_2	1.100		1.657		0.963		0.064	
γ_3	2.710		3.282		2.436		1.649	
γ_4	3.732		4.332		3.471		2.683	

Table 10: **Ordered Probit Results for Seperate Years** *(Continued)*

	2000				2001			
	Male Analysts		Female Analysts		Male Analysts		Female Analysts	
	Estimate	p-value	Estimate	p-value	Estimate	p-value	Estimate	p-value
Consensus	1.792	0.000	2.221	0.000	1.154	0.000	0.032	0.954
Consensus^2	−0.163	0.000	−0.215	0.002	−0.084	0.003	0.051	0.481
St. Dev. of Outstanding Recs	−0.194	0.000	−0.061	0.388	−0.156	0.000	−0.111	0.196
Total Tenure	0.002	0.539	−0.026	0.008	0.018	0.000	0.015	0.096
Firm Tenure	−0.022	0.001	−0.022	0.187	−0.018	0.002	−0.014	0.394
Number of Industries	0.019	0.078	−0.023	0.486	−0.001	0.895	−0.075	0.027
Number of Firms	−0.015	0.000	0.006	0.539	−0.016	0.000	−0.001	0.896
Same Industry No. Firms	0.014	0.000	−0.016	0.151	0.014	0.000	−0.011	0.336
Working for Top Broker	0.009	0.549	−0.103	0.008	−0.010	0.528	−0.052	0.207
Star Analist	−0.039	0.417	0.204	0.042	−0.029	0.524	0.092	0.353
Nobs.	22,268		3,599		23,253		3,375	
PseudoR^2	0.020		0.026		0.019		0.016	
γ_1	1.836		2.606		0.768		−1.744	
γ_2	2.287		2.872		1.179		−1.226	
γ_3	3.886		4.701		2.833		0.377	
γ_4	4.945		5.742		3.837		1.397	
	2002				2003			
Consensus	1.922	0.000	3.134	0.000	1.481	0.000	1.782	0.000
Consensus^2	−0.162	0.000	−0.314	0.000	−0.152	0.000	−0.192	0.000
St. Dev. of Outstanding Recs	−0.213	0.000	−0.354	0.000	−0.200	0.000	−0.141	0.022
Total Tenure	0.006	0.022	−0.002	0.801	0.004	0.114	0.005	0.461
Firm Tenure	0.012	0.005	0.018	0.136	−0.019	0.000	−0.027	0.051
Number of Industries	0.018	0.014	0.024	0.245	0.036	0.000	0.005	0.840
Number of Firms	−0.012	0.000	−0.008	0.198	−0.010	0.000	−0.002	0.825
Same Industry No. Firms	0.002	0.392	0.000	0.950	0.004	0.134	0.003	0.668
Working for Top Broker	−0.233	0.00	−0.237	0.000	−0.215	0.000	−0.364	0.000
Star Analist	−0.036	0.277	0.006	0.925	−0.014	0.744	−0.037	0.771
Nobs.	35,161		5,258		27,423		3,719	
PseudoR^2	0.046		0.052		0.024		0.033	
γ_1	2.438		4.666		1.120		1.617	
γ_2	3.246		5.554		1.777		2.302	
γ_3	4.687		6.961		3.214		3.781	
γ_4	5.562		7.860		3.948		4.493	

Table 10: **Ordered Probit Results for Seperate Years** *(Continued)*

	2004				2005			
	Male Analysts		Female Analysts		Male Analysts		Female Analysts	
	Estimate	p-value	Estimate	p-value	Estimate	p-value	Estimate	p-value
Consensus	0.752	0.000	1.290	0.000	1.176	0.000	0.775	0.018
$Consensus^2$	−0.068	0.000	−0.141	0.001	−0.122	0.000	−0.072	0.188
St. Dev. of Outstanding Recs	−0.181	0.000	−0.170	0.008	−0.174	0.000	−0.108	0.117
Total Tenure	0.012	0.000	0.003	0.732	0.003	0.215	−0.007	0.362
Firm Tenure	−0.035	0.000	−0.023	0.111	−0.015	0.002	−0.010	0.491
Number of Industries	0.036	0.000	0.076	0.027	−0.004	0.701	0.035	0.332
Number of Firms	−0.008	0.022	−0.013	0.143	0.002	0.594	−0.013	0.270
Same Industry No. Firms	−0.004	0.243	0.005	0.578	−0.005	0.175	−0.003	0.768
Working for Top Broker	−0.311	0.000	−0.424	0.000	−0.273	0.000	−0.306	0.000
Star Analist	0.050	0.261	0.057	0.672	0.100	0.057	0.180	0.207
Nobs.	24,636		3,106		20,767		2,753	
$PseudoR^2$	0.020		0.028		0.018		0.018	
γ_1	−0.383		0.551		0.440		−0.293	
γ_2	0.182		1.103		0.986		0.254	
γ_3	1.629		2.607		2.477		1.688	
γ_4	2.356		3.328		3.161		2.398	
	2006							
Consensus	1.224	0.000	1.004	0.005				
$Consensus^2$	−0.128	0.000	−0.088	0.080				
St. Dev. of Outstanding Recs	−0.245	0.000	−0.284	0.000				
Total Tenure	0.003	0.326	−0.013	0.061				
Firm Tenure	−0.021	0.000	0.008	0.523				
Number of Industries	0.032	0.001	−0.049	0.126				
Number of Firms	0.004	0.227	−0.012	0.208				
Same Industry No. Firms	−0.013	0.000	−0.002	0.837				
Working for Top Broker	−0.247	0.000	−0.404	0.000				
Star Analist	−0.080	0.136	0.177	0.250				
Nobs.	19,245		2,680					
$PseudoR^2$	0.022		0.031					
γ_1	0.461		−0.177					
γ_2	1.053		0.422					
γ_3	2.577		1.951					
γ_4	3.317		2.761					

Table 11: **Wald Test Results for Gender Differences per Year**

This table reports the test statistics and the p-value of the Wald test for all gender coefficients to simultaneously equal to zero. For all years the test statistic is $\chi^2_{10}-$distributed

	χ^2_{10}	p-value
1996	19.70	0.032
1997	27.55	0.002
1998	44.52	0.000
1999	25.18	0.005
2000	35.88	0.000
2001	14.70	0.144
2002	15.79	0.106
2003	23.91	0.008
2004	14.56	0.149
2005	12.36	0.262
2006	36.50	0.000

Table 12: **Ordered Probit Results for Industries**

	Finance				Health care			
	Male Analysts		Female Analysts		Male Analysts		Female Analysts	
	Estimate	p-value	Estimate	p-value	Estimate	p-value	Estimate	p-value
Consensus	1.031	0.000	1.224	0.000	1.392	0.000	0.809	0.005
Consensus^2	−0.066	0.000	−0.089	0.008	−0.125	0.000	−0.042	0.265
St. Dev. of Outstanding Recs	−0.179	0.000	−0.076	0.100	−0.267	0.000	−0.144	0.010
Total Tenure	−0.012	0.000	−0.035	0.000	−0.013	0.000	−0.017	0.019
Firm Tenure	−0.017	0.000	−0.004	0.717	−0.027	0.000	−0.033	0.017
Number of Industries	0.039	0.000	0.030	0.389	−0.014	0.205	0.027	0.402
Number of Firms	−0.007	0.024	−0.007	0.504	0.002	0.673	0.007	0.588
Same Industry No. Firms	0.001	0.652	−0.001	0.910	−0.009	0.028	−0.018	0.165
Working for Top Broker	−0.095	0.000	−0.161	0.000	−0.082	0.000	−0.075	0.023
Star Analist	0.102	0.009	0.263	0.004	−0.010	0.838	0.043	0.746
Nobs.	36,852		6,392		28,675		4,913	
PseudoR^2	0.038		0.042		0.030		0.033	
γ_1	0.479		0.721		0.921		−0.048	
γ_2	1.092		1.289		1.436		0.512	
γ_3	2.613		2.923		2.852		1.943	
γ_4	3.492		3.860		3.741		2.857	
	Consumer Non-Durables				Consumer Services			
Consensus	1.102	0.000	1.374	0.000	1.469	0.000	1.789	0.000
Consensus^2	−0.097	0.000	−0.125	0.002	−0.129	0.000	−0.168	0.000
St. Dev. of Outstanding Recs	−0.236	0.000	−0.182	0.003	−0.284	0.000	−0.257	0.000
Total Tenure	−0.003	0.478	−0.026	0.001	−0.011	0.000	−0.024	0.000
Firm Tenure	−0.050	0.000	−0.001	0.958	−0.016	0.000	−0.001	0.879
Number of Industries	0.004	0.740	0.000	0.986	0.013	0.035	−0.008	0.629
Number of Firms	−0.005	0.223	0.003	0.697	−0.018	0.000	−0.001	0.911
Same Industry No. Firms	−0.003	0.482	−0.003	0.700	0.012	0.000	−0.001	0.816
Working for Top Broker	−0.146	0.000	−0.174	0.000	−0.138	0.000	−0.190	0.000
Star Analist	0.236	0.001	0.398	0.000	−0.008	0.801	0.188	0.000
Nobs.	8,753		3,902		44,737		9,224	
Pseudo R^2	0.027		0.030		0.035		0.036	
γ_1	0.231		0.868		1.081		1.818	
γ_2	0.769		1.441		1.636		2.292	
γ_3	2.235		2.929		3.102		3.794	
γ_4	3.083		3.799		3.978		4.669	

Table 12: **Ordered Probit Results for Industries** *(Continued)*

	Consumer Durables				Energy			
	Male Analysts		Female Analysts		Male Analysts		Female Analysts	
	Estimate	p-value	Estimate	p-value	Estimate	p-value	Estimate	p-value
Consensus	1.811	0.000	0.275		0.902	0.000	0.940	0.091
Consensus^2	−0.184	0.000	−0.004		−0.070	0.002	−0.060	0.421
St. Dev. of Outstanding Recs	−0.216	0.000	−0.062		−0.232	0.000	−0.671	0.000
Total Tenure	−0.018	0.000	−0.035		−0.018	0.000	0.003	0.803
Firm Tenure	−0.012	0.193	−0.015		− 0.023	0.000	−0.042	0.109
Number of Industries	0.032	0.010	0.105		0.021	0.111	−0.015	0.814
Number of Firms	−0.003	0.416	−0.010		−0.018	0.000	0.017	0.404
Same Industry No. Firms	0.003	0.526	−0.010		0.015	0.000	−0.029	0.153
Working for Top Broker	−0.173	0.000	−0.176		−0.109	0.000	−0.526	0.000
Star Analist	0.035	0.628	0.125		0.009	0.884	−0.611	0.270
Nobs.	8,160		924		16,837		1,341	
PseudoR^2	0.037		0.024		0.020		0.066	
γ_1	1.752		−1.240		−0.122		−0.866	
γ_2	2.302		−0.728		0.444		0.215	
γ_3	2.790		0.763		1.809		1.568	
γ_4	4.589		1.681		2.660		2.494	
	Transportation				Technology			
Consensus	1.546	0.000	1.427	0.009	1.209	0.000	1.440	0.000
Consensus^2	−0.157	0.000	−0.136	0.007	−0.094	0.000	−0.124	0.001
St. Dev. of Outstanding Recs	−0.214	0.000	−0.057	0.664	−0.279	0.000	−0.189	0.001
Total Tenure	−0.007	0.259	−0.062	0.008	−0.002	0/174	−0.015	0.018
Firm Tenure	−0.002	0.834	−0.026	0.388	−0.008	0.024	−0.013	0.321
Number of Industries	−0.011	0.619	0.048	0.364	0.004	0.468	−0.031	0.180
Number of Firms	−0.005	0.456	0.000	0.990	−0.010	0.000	0.006	0.382
Same Industry No. Firms	−0.002	0.767	0.022	0.235	−0.001	0.603	−0.009	0.181
Working for Top Broker	−0.311	0.000	−0.184	0.031	−0.123	0.000	−0.162	0.000
Star Analist	0.114	0.046	0.490	0.008	0.000	0.990	0.160	0.144
Nobs.	6,256		807		65,385		5,816	
Pseudo R^2	0.026		0.038		0.032		0.031	
γ_1	1.035		1.116		0.674		1.170	
γ_2	1.632		1.835		1.229		1.758	
γ_3	3.039		3.020		2.721		3.204	
γ_4	3.865		3.883		3.640		4.102	

Table 12: **Ordered Probit Results for Industries** *(Continued)*

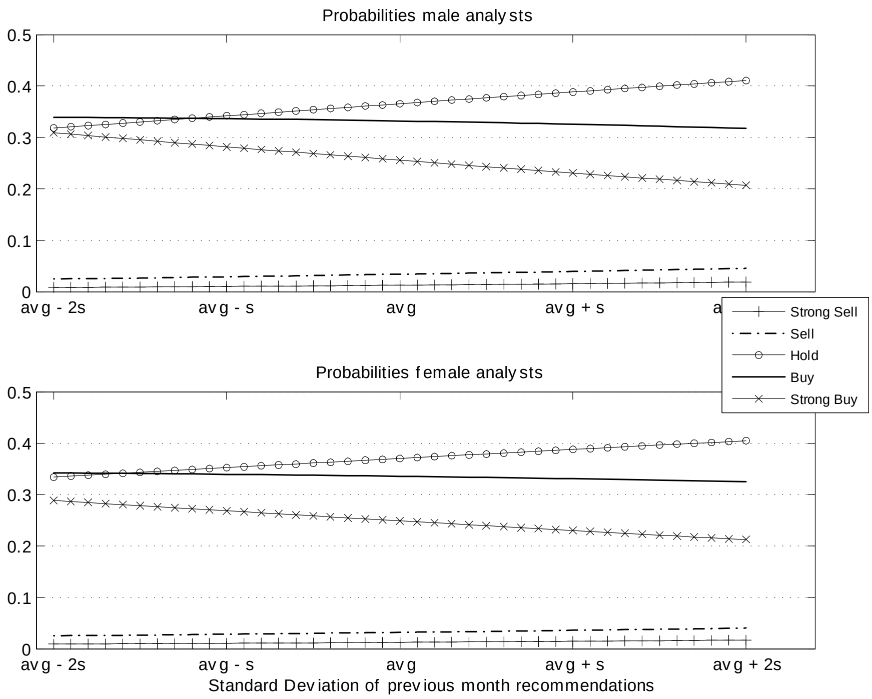
	Basic Industries				Capital Goods			
	Male Analysts		Female Analysts		Male Analysts		Female Analysts	
	Estimate	p-value	Estimate	p-value	Estimate	p-value	Estimate	p-value
Consensus	0.776	0.000	0.965	0.020	1.218	0.000	1.183	0.010
Consensus^2	−0.063	0.001	−0.060	0.287	−0.114	0.000	−0.103	0.091
St. Dev. of Outstanding Recs	−0.175	0.000	−0.193	0.012	−0.236	0.000	−0.250	0.018
Total Tenure	−0.014	0.000	−0.009	0.493	−0.009	0.012	−0.006	0.731
Firm Tenure	−0.018	0.002	−0.022	0.314	−0.028	0.000	−0.063	0.029
Number of Industries	0.027	0.013	0.172	0.000	−0.014	0.084	−0.014	0.674
Number of Firms	0.001	0.786	−0.045	0.000	−0.008	0.001	−0.008	0.364
Same Industry No. Firms	−0.011	0.006	0.038	0.002	−0.003	0.252	0.001	0.961
Working for Top Broker	0.002	0.926	−0.043	0.427	−0.138	0.000	−0.102	0.098
Star Analist	0.148	0.000	0.460	0.001	0.091	0.086	0.234	0.188
Nobs.	15,577		1,791		14,134		1,445	
PseudoR^2	0.017		0.036		0.023		0.026	
γ_1	−0.168		0.677		0.347		0.258	
γ_2	0.378		1.157		0.847		0.801	
γ_3	1.688		2.618		2.343		2.372	
γ_4	2.569		3.529		3.195		3.249	
	Public Utilities							
Consensus	0.891	0.000	1.293	0.001				
Consensus^2	−0.042	0.046	−0.099	0.069				
St. Dev. of Outstanding Recs	−0.248	0.000	0.007	0.938				
Total Tenure	−0.006	0.141	−0.024	0.028				
Firm Tenure	−0.022	0.006	0.022	0.366				
Number of Industries	−0.011	0.386	0.138	0.002				
Number of Firms	−0.002	0.674	−0.063	0.000				
Same Industry No. Firms	−0.005	0.218	0.055	0.001				
Working for Top Broker	−0.077	0.000	−0.181	0.000				
Star Analist	−0.013	0.824	−0.981	0.000				
Nobs.	13,566		2,086					
Pseudo R^2	0.040		0.050					
γ_1	0.204		1.274					
γ_2	0.816		1.728					
γ_3	2.282		3.209					
γ_4	3.259		4.067					

Table 13: **Wald Test Results for Gender Differences per Industry**

This table reports the test statistics and the p-value of the Wald test for all gender coefficients to simultaneously equal to zero. For all industries the test statistic is $\chi^2_{10}-$distributed.

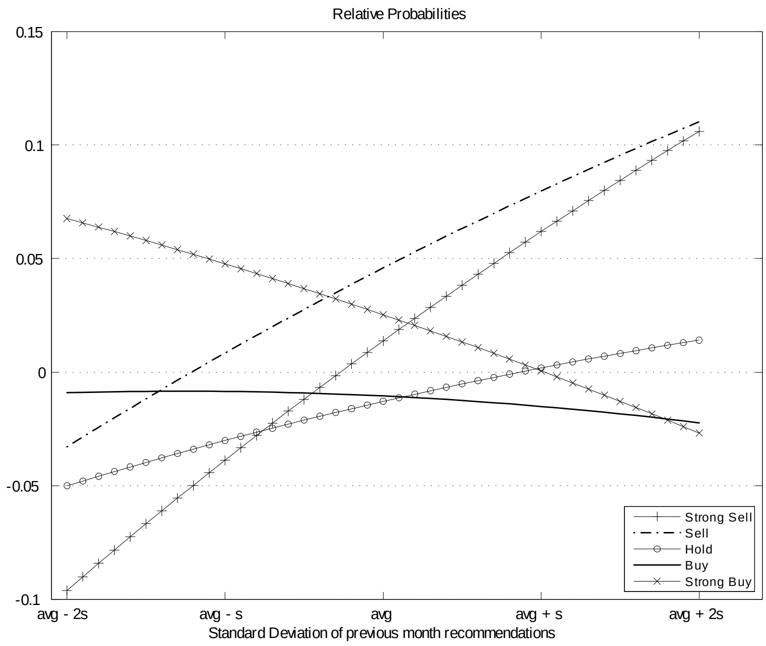
	χ^2_{10}	p-value
Finance	29.07	0.001
Health Care	15.48	0.116
Consumer Non-Durables	21.23	0.020
Consumer Services	35.95	0.000
Consumer Durables	15.17	0.126
Energy	75.62	0.000
Transportation	34.92	0.000
Technology	19.23	0.037
Basic Industries	36.91	0.000
Capital Goods	3.24	0.975
Public Utilities	85.50	0.000

Appendix: Figures



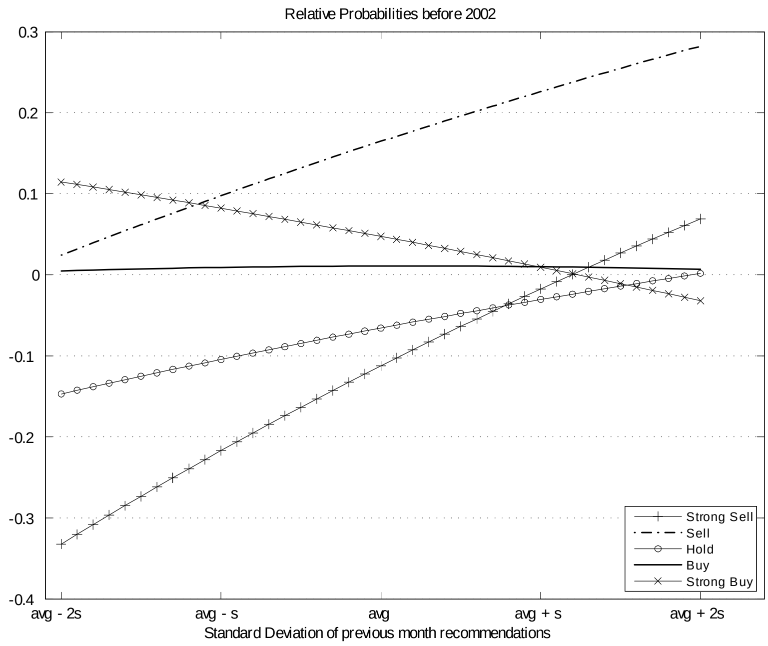
The figure shows the probability that a certain recommendation will be issued by either male (top) or female (bottom) analysts. The probabilities are evaluated using the averages for all parameters, accept for the consensus recommendations proxied by the mean recommendation in the month before the analyst issues a (new) recommendation, which varies from 1 (strong sell) to 5 (strong buy).

Figure 1: **Male and Female Analyst Probabilities for each Recommendation Class Class**



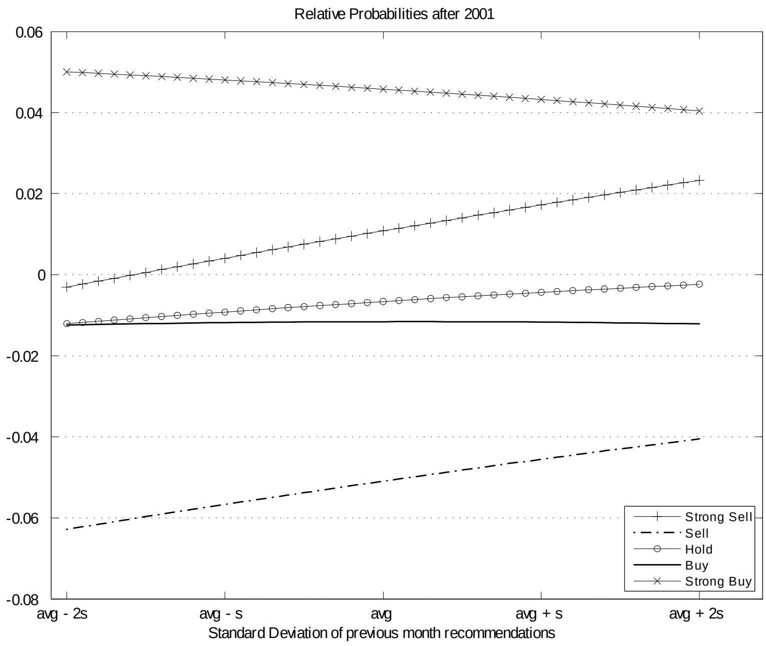
The figure shows the relative probability differences between male and female analyst for each recommendation class. These are calculated by substracting the female analyst probabilities for a recommendation class from the male analyst probabilities. This difference is divided by the probability that the recommendation occurs. The latter is calculated using the full sample estimation results (without gender differences).

Figure 2: **Relative Probability Differences Between Male and Female Analysts**



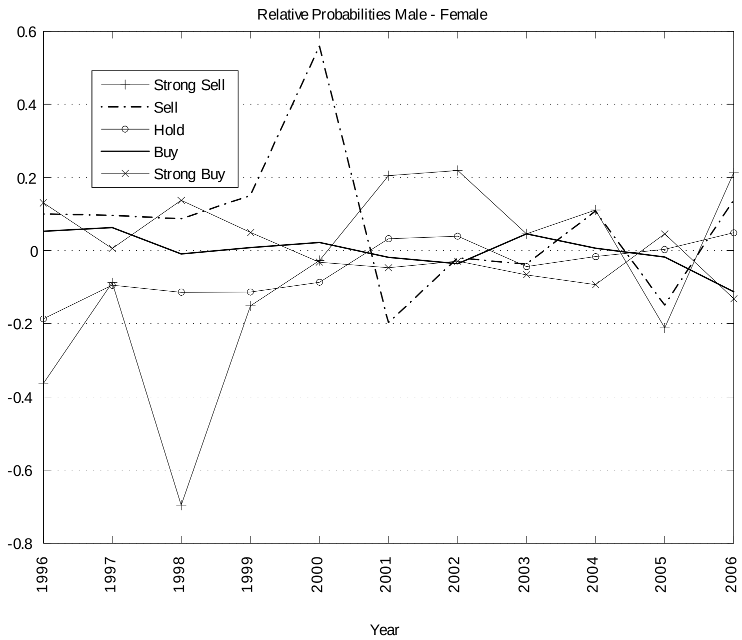
The figure shows the relative probability differences between male and female analyst for each recommendation class. These are calculated by substracting the female analyst probabilities for a recommendation class from the male analyst probabilities. This difference is divided by the probability that the recommendation occurs. The latter is calculated using the full sample estimation results (without gender differences).

Figure 3: **Relative Probability Differences Between Male and Female Analysts 1996 - 2001**



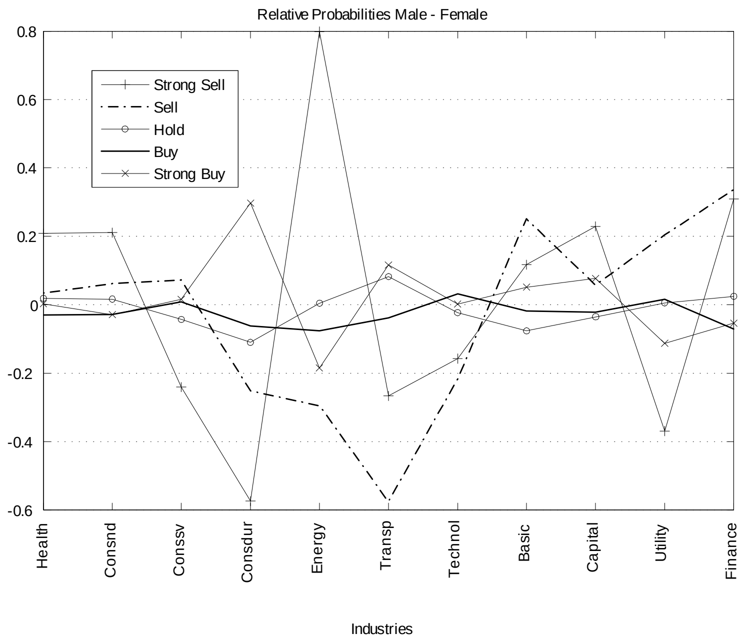
The figure shows the relative probability differences between male and female analyst for each recommendation class. These are calculated by substracting the female analyst probabilities for a recommendation class from the male analyst probabilities. This difference is divided by the probability that the recommendation occurs. The latter is calculated using the full sample estimation results (without gender differences).

Figure 4: **Relative Probability Differences Between Male and Female Analysts 2002 - 2006**



The figure shows the relative probability differences between male and female analyst for each recommendation class evaluated for full-sample averages. These are calculated by substracting the female analyst probabilities for a recommendation class from the male analyst probabilities. This difference is divided by the probability that the recommendation occurs. The latter is calculated using the full sample estimation results (without gender differences).

Figure 5: **Relative Probability Differences Between Male and Female Analysts over the Years**



The figure shows the relative probability differences between male and female analyst for each recommendation class evaluated for full-sample averages. These are calculated by substracting the female analyst probabilities for a recommendation class from the male analyst probabilities. This difference is divided by the probability that the recommendation occurs. The latter is calculated using the full sample estimation results (without gender differences).

Figure 6: **Relative Probability Differences Between Male and Female Analysts for Industries**