Gender Differences Among Analyst Recommendations*

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Abstract

Using a large and unique real-life dataset we study gender differences in the recommendation issuing process of security analysts. We observe gender heterogeneity in the probability to issue a particular type of recommendation. We document that the differences are most pronounced when the dispersion in existing recommendations is low; male analyst have a larger probability to issue extreme positive recommendations and to deviate from the consensus recommendation, exactly at the time the market could interpret this behavior as being skilled. The differences in opinion between Strong Buy recommendations of male analysts and conservative Hold recommendations of female analysts are almost 30% before 2002, while they decrease to 9% after 2001.

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1 Introduction

A large literature in psychology and sociology has shown that there is heterogeneity in the decision making process of men and women. One of the driving factors for this observed heterogeneity seems to be gender specific risk preferences. It is a common finding that women are more risk-averse decision makers (see for example Cohen and Einav (2007)), take less extreme decisions and try to avoid competitive situations (see Niederle and Vesterlund (2007)). Furthermore, women's decisions show much less heterogeneity than male decisions. While the evidence for gender effects in psychology and sociology is strong and clear, the empirical evidence in the (financial) economics literature is rather mixed. The current empirical evidence in financial economics suggests that, once controlling for heterogeneity in professional and competitive environments, gender does not matter the financial decision making process (see for example Croson and Gneezy (2004)). In this study we present empirical evidence that there is gender heterogeneity in a professional working environment.

Several studies present evidence that women are more risk-averse 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 retirement in their 401(k) investment plans. Recently, Cohen and Einav (2007) have shown that women are more risk-averse using a large data set of deductible choices in auto insurance contracts. In the context of corporate decision taking, Cadsby and Maynes (2005) find that women are less extreme decision makers and there is less observed heterogeneity among women's decisions. Finally, Barsky et al. (1997) find that women self-report a lower risk propensity than men. However, Croson and Gneezy (2004) show in their survey that these findings carry important exceptions that are related to the type of economic agents under investigation. Gender heterogeneity in risk preferences of professional agents is very different than from those of the general population. The driving factor of these results seems to be that gender-specific risk attitudes may be confounded with differences in individual opportunity sets, such as knowledge disparities or gender-specific constraints in underlying (financial) choices. 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. Bliss and Potter (2002) document similar findings for the fund management business. In addition, Dwyer et al. (2002) observe that female investors take less risk than male investors. However, when controlling for financial investment knowledge, the gender-based risk differences largely disappear.

The empirical evidence therefore suggests that, once controlling for heterogeneity in financial knowledge and professional environment, gender does not matter for risk preferences. However, Niessen and Ruenzi (2007) study gender differences among mutual fund managers and they find that female fund managers have a different investment style and follow less risky and less extreme investment strategies than their male counterparts. They also find that women follow more time-consistent investment styles.

We investigate whether gender heterogeneity exists in the behavior of sell-side analysts. We argue that analyst recommendations provide us with a great laboratory to explore whether gender differences matter in a professional setting. First, by studying sell-side analysts we can immediately observe the outcome of the decision making process as it is reflected in only five different individual stock recommendation types that are communicated to the public. This is in contrast to studying mutual fund manager behavior for which only the aggregate outcome of their decisions can be observed by checking, in hindsight, how they changed the composition of their portfolios. Second, academics and practitioners are convinced that the recommendation issuing process is not a simple valuation decision, but the result of a complex decision making process that reflects the individual opinion of the analyst based upon his perspective and risk tolerance. Several studies have shown 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)) and several behavioral biases are well documented. If it is true that female stock analysts are more risk averse, less extreme and avoid competition, we expect them to issue more conservative recommendations than men. This implies that female analysts hide behind the consensus and show more herding behavior. Male analysts on the other hand, would prefer to stand out of the group and therefore are more likely to issue more risky and extreme recommendations.

We contribute to the literature in three ways. First, to our knowledge, our study is the first to use such a large real-life dataset to investigate risky financial decisions taken by professionals. It allows us to adequately control for differences in individual opportunity sets (quality of the observations), and not lose in terms of research scale (quantity of observations). Most existing large scale survey studies do not control for knowledge differences or wealth constraints (see for example Sunden and Surette (1998)). On the other hand, studies that do control for such differences are often small-scale analyses and/or experiments (e.g. Atkinson et al. (2003) and Johnson and Powell (1994)).

Second, we observe gender heterogeneity in the recommendation issuing process of professional sell-side analysts. Controlled for experience and available resources we find that both female as well as male analysts have the tendency to herd and to react to disagreement by issuing more conservative recommendations. However, male analysts differ from female analysts in the strength of their signals. Men are always more likely to issue more extreme recommendations (both positive and negative), while female analysts seem to be less risk-prone and are more likely to issue more conservative recommendations. These gender differences are mainly driven by the difference in reaction to the degree of the prevailing differences in opinion. When there is agreement among analysts, male analysts have a larger probability to issue Strong Buy recommendations than 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 extreme affirmative actions. We show that, in the first half of the sample, the relative probability differences between Strong Buy recommendations of men and Hold recommendations of women are on average about 13%. However, when agreement among analyst is large, these differences are almost 30%.

Finally, we observe that gender heterogeneity in the recommendations issuing process has decreased after 2001. Apparently, the remaining female analysts resemble more and more the male analysts. Whether this is adaptive behavior or the result of a self-selection mechanism is still an open question. In the context of security analysts we believe that the latter hypothesis is of particular interest. Niederle and Vesterlund (2007) argue that women and men differ in their selection into a competitive environment. Whereas women tend to avoid competition, men actually seek the challenge of competition. Investment banking has always been a very competitive industry, potentially less appealing to women who tend to shy away from competition. Moreover, the collapse of technology stocks in 2001, subsequent regulation changes by the NASD and increased the scrutiny of analysts' practices by the SEC, potentially discouraged women to become or remain a sell-side analyst.

The remainder of the paper is organized as follows. Section 2 presents the sample selection procedure and provides a descriptive profile of the analyst database. The research methodology is described in Section 3, and empirical results are presented in Section 4. Finally, Section 5 concludes.

2 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.[1] Each data record includes information about, among other things, the recommendation, the recommendation date, an identifier for the brokerage house issuing the recommendation and for the particular 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 and assigns standardized numerical values to 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 the analyst works for, the company that is being followed and the corresponding industry, the recom-

[1] The I/B/E/S data that we use for our analysis below, has been downloaded in February 2007. A recent paper by Ljungqvist et al. (2007) shows that ex post changes are implemented in the I/B/E/S database. In their Appendix A they show that since February 12, 2007 many, but not all of the changes (anonymizations, alterations and deletions) in the recommendations database have been reinstated. We do not have earlier snapshots of the I/B/E/S database available as in Ljungqvist et al. (2007). Therefore it is impossible for us to check whether the changes in the database were random accross gender and subsequently how their findings influence the results of this paper.

mendation, 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 (s)he is employed for, her/his specialization, and 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. 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 first names.[2] It determines from popular usage on the web whether a 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 any 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), and we restrict our sample to companies covered by at least one male and one female analyst simultaneously. Our final sample contains 253,433 observations.

Table 1 shows descriptive statistics for the sample of analyst recommendations used in the paper. The total sample consists of recommendations of 7,091 unique analysts from 537 brokerage houses covering 4,939 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 that slightly above that of 1996. In addition, for the number of firms covered and the number of analysts employed, we observe a similar but weaker trend. 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 16-17% of the analyst community until 2002 to only 13% in 2006. Interestingly, the trend break coincides with a turbulent stock market period and a change in the analysts' professional environment. In this context, Conrad et al. (2006) state that the

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

collapse of technology stocks introduced a sometimes contentious debate on the neutrality of analysts with several Wall Street firms, with their analysts being sued for giving subjective information to their clients.[3] 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 could increase the competition in the industry and this could 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 be indicative for a 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.

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, the yearly dispersion of recommendations 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. On average, male analysts seem to issue slightly higher recommendations, while no gender-trend can be observed in the dispersion of the recommendations issued. 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 this bias.[4] 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. (2007) and Conrad et al. (2007) find the same dynamics and argue that this trend reversal can be the result of a bad performing stock market and/or 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

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

[4] For recent evidence on the upward bias in the distribution of recommendations see Barber et al. (2007), Lin et al. (2005) and Chen and Matsumoto (2006).

Sell and Sell recommendations: combined they cover less than 3% of all recommendations. From 2002 onwards the number of these negative reports increases to more than 10% of all recommendations that are issued. 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 lies around 0.85. From 2002 onwards, this number immediately increases to around 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 the years in the second half of the sample. Considering the fact that stock markets have been performing very well since 2003, we believe that there has been a 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) and Clement and Tse (2005)). Such individual analyst characteristics might therefore also impact the recommendation issuing process. Table 3 summarizes the individual characteristics of the analysts in our sample. We describe analysts' abilities, available resources and task complexity. Analysts' abilities are proxied by a star dummy variable, firm specific experience and total experience (both measured in number of years).[5] 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) and Sorescu and Subrahmanyam (2006)). Institutional Investor performs a yearly questionnaire to determine the best analysts of the previous year. Such ranking not only accounts for accuracy, but for the broad range of services provided by analysts. Table 3 shows that for the male and female subsamples around 2% of analysts is ranked as a star. Moreover, women have a slightly higher probability to be ranked a star analyst. This finding is confirmed by Green et al. (2007) who find that women have a higher probability to be rewarded the status of star analyst. These findings suggest that women outperform men in other services such as client contact and the quality of their written reports. In terms of firm specific experience and total experience, we see that for all years men have more experience than women. This is not surprising given the higher job turnover of women reported above.

[5]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.

Recent research has also shown that available resources are important for the analysts' job performance. Therefore we identify the brokerage houses that are considered to be the best. Similar to the star rating of analysts, a ranking of the best brokerage houses is also published in the October issue of Institutional Investor. We identify the top 15 of the investment banks as top brokers. This ranking is stable over time and covers the large and prestigious brokerage houses. We find that female analysts have a slightly higher probability than men to be employed by a top investment bank. Niessen en Ruenzi (2007) show that this is also the case for mutual fund managers. They argue that female fund managers are most likely to be employed by large and well-established companies for reasons of political correctness. Finally, we consider task complexity by looking at the number of firms covered by an analyst in a given year, as well as at the number of industries the analyst covers.[6] When comparing male and female task complexity, we see that male analysts cover more firms, spread over more sectors than their female colleagues. In 2002, the busiest year for the analysts (see Table 1 earlier), analysts cover more companies than in any other year.

3 Research Methodology

The objective of this study is to analyze gender-specific behavior in the recommendation issuing process. The feature of the recommendation data suggest the use of an ordered probit analysis: we explain the probability of the occurrence of each recommendation that is issued by the security analysts as a function of gender-specific behavior. 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

[6] The industry classification is based on the I/B/E/S SIGC division, and distinguishes 11 industries.

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.

We estimate the above model separately for male and female analysts, to capture gender heterogeneity in the decision making behavior of analysts. Given the existing evidence of behavioral decision making, we include the previous consensus recommendation, as well as the dispersion of previous recommendations as explanatory variables. First, the consensus recommendation captures the potential herding behavior among analysts, a well documented behavioral bias (see, among others, Welch (2000), Hong et al. (2000), Clement and Tse (2005), and most recently Jegadeesh and Kim (2007)). We expect a positive effect for herding behavior.[7] The higher the previous consensus, the higher is the probability of also issuing a high recommendation. Moreover, if female analysts are more conservative decision makers, we expect them to take less extreme decisions. They will, more than their male colleagues, issue moderate recommendations. 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.

Second, dispersion around the consensus recommendation reflects the lack of agreement among analysts. This interpretation of dispersion is also set forth in Diether et al. (2002). They argue that dispersion in earnings forecasts of analysts reflects differences in opinion and they find that a higher level of dispersion corresponds to lower future returns.[8] Theoretically, their results support the price-optimism models as introduced by Miller (1977) suggesting that the larger the disagreement about the stock's value, the higher the current market price relative to the true value of the stock, and thus the lower its future returns. We therefore expect a negative effect of dispersion. The low future returns induces

[7]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.

[8]Dispersion in opinion has also been connected to lower future stock returns by Chen et al. (2001) and Lee and Swaminathan (2000).

analysts to issue rather low recommendations. Again, we expect male analysts to be more risk-seeking and pronounced decision makers. This translates into male recommendations that are relatively more at the extreme positive or negative side of the distribution. In our model, such differences in opinion is proxied by the standard deviation of the recommendations valid in the month before a particular recommendation is issued by the analyst.

Finally, we also include a number of individual analyst characteristics as control variables. Such individual characteristics might also have a gender-specific impact on the level of recommendations issued. The characteristics we control for are the variables proxying for analyst abilities, resources and task complexity as explained in Section 2.[9] 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. 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. Finally, we 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. The expected impact of these controls variables is relatively ambiguous and therefore we do not make any a priori statements of their sign or size.

4 Empirical Results

In this section we present our empirical results. First, we provide full sample results and show that gender differences among financial analyst recommendations are statistically and economically significant. Second, using the observation that there is a structural break in the data after 2001, we provide empirical results for a split sample analysis. We show that gender differences have been larger in the first subsample. To conclude this section we present empirical results for every year individually.

[9]In addition we controlled for many other effects in the individual characteristics by controlling for e.g. non-linearities or cross-over effects. Including these additional variables did not change our findings below.

4.1 Full Sample Results

Equation (1) is estimated separately for male and female analysts. Table 4 shows the full sample estimation results of the ordered probit analysis. Almost all the estimated coefficients are statistically significant at the 5% level for the male and female sample. In addition, the signs of the estimated coefficient are the same, which indicates that men and women behave in similar ways. The analysts' reaction to the consensus recommendation and the dispersion of recommendations is in line with previous findings in the literature (see for example Clement and Tse (2005) and Diether et al. (2002)). Analysts herd and they act more conservatively when disagreement among their peers is large. First, the existing consensus recommendation has a positive impact. The higher the previous consensus recommendation, the higher the probability of issuing a high recommendation. Analysts are therefore more likely to issue a recommendation that is close to the existing consensus recommendation. This implies that analysts are susceptible to herding. Second, dispersion of previously issued recommendations has a negative impact. When there are large differences of opinion among analyst recommendations, analysts are more likely to issue moderate recommendations.

The most important question of the analysis however, is whether there are (significant) differences between male and female analysts' decision behavior. For male analysts, the estimates for both the consensus and the dispersion variable are larger in absolute value. This is in line with our expectations: male analysts react more aggressively to these public signals, resulting in higher probabilities to issue more extreme recommendations than female analysts. For the dispersion variable the gender difference is largest. The behavioral differences between men and women is therefore largely driven by differences in reactions to disagreement. Despite the ambiguous results reported in the prior literature, this paper is therefore the first to show that the gender-related differences carry over to financial decision making among professional agents.

Next, we describe the effects of the control variables. 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 is an indication that a star ranking is achieved when issuing very positive recommendations. The estimation results for job complexity indicate that there is no clear evidence on how it influences the level of recommendations. 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 analysts are more likely to issue less favorable recommendations the more firms they follow. Finally, analysts working for a top brokerage house have a larger probability to issue lower recommendations. When it comes to gender differences in the control variables, female analysts are ceteris paribus more affected by the different control variables, with the exception of the variables Firm Tenure and Number of Industries covered. 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 stars. To conclude, female analysts are more likely to issue higher recommendations the more industries they cover. The differences between the male and female estimations are statistically significant as can be concluded from the Wald test. In addition, Table 4 shows that except for the variables Number of Industries and Number of Firms, all the individual estimates are significantly different between the genders.

Ordered probit regression results are notoriously difficult to interpret economically. In order to obtain economic insight, we therefore calculate relative probability differences between the genders for every recommendation class. These are calculated by dividing the male analyst probabilities for a certain recommendation class by the female analyst probabilities, normalized around zero. When the relative probability is larger than zero, male analysts are more likely to choose that recommendation level than female analysts. We concluded above that dispersion among recommendations is the most important variable in our model. We therefore calculate the relative probabilities by varying the dispersion variable from its average minus two times its standard deviation to its average plus two times its standard deviation, while keeping all the other variables fixed at their sample means. This provides us with a good measure of relative importance and enables us to obtain clear insights into the differences among gender that is driven by the uncertainty among analysts.

When using the estimation results to calculate the probabilities to issue a certain recommendation, they correspond very well to the summary statistics in Table 2. This table also shows that it is not very likely that Strong Sell and Sell recommendations are issued. In our evaluation we therefore limit ourselves to the three recommendation classes that are most likely to occur (with a total probability of at least 90%), which are the Hold, Buy and Strong Buy recommendations.

The results of the calculations are shown in Figure 1. We observe the largest gender differences when dispersion of the recommendations is at its lowest point. In this case the average male analyst has a 10% larger probability to issue an extremely positive Strong Buy recommendation than the average female analyst. At the same time the average female analyst has a 6% larger probability to issue the more conservative Hold recommendation than the average male analyst.[10] When confronted with low dispersion of recommendations, the average male analyst is more likely to be more optimistic about the company he is evaluating than the average female analyst. It appears that male analysts use the opportunity of low dispersion to stand out of the group by being more likely to issue a very optimistic recommendations. This could be an indication that men are more overconfident or that men have a greater desire to please the management of the firms they cover. Finally, when dispersion increases, gender differences decrease. Male analyst are less likely to issue more Strong Buy Recommendations, while female analysts are less likely to more issue Hold Recommendations. We conclude from this that analysts take into account that deviations from the mainstream is noticed less by the market in the case when there is (more) disagreement among analysts. Male analysts seem to have the largest incentives to deviate when the market is most likely to interpret their recommendation as personal skill and ability and not as luck.

4.2 Split Sample Results

As mentioned in Section 2 above, it is clear that there has been a trend break in the issuing of recommendations after 2001. First, the combined probability of issuing Strong Sell and Sell recommendations has increased from 3% before 2002,

[10] Also for the average level of dispersion we see gender differences: male analysts have a 4% higher probability to issue Strong Buy recommendations, while female analysts have a 2% higher probability to issue Hold recommendations.

to around 10% after 2001, for both male and female analysts. One can argue that this change can be accounted for by the very bad performance of companies immediately after the technology shock. However, Table 2 shows that although stock markets have done very well in recent years, the number of least favorable recommendations issued by analysts did not decline. This indicates that a regime shift in the recommendation generating process has taken place. Indeed, Barber et al. (2007b) show that in the wake of numerous high-profile corporate scandals (such as those involving Enron, WorldCom, Adelphia, and Tyco) the National Association of Securities Dealers (NASD) proposed rule 2711, which was approved by the SEC on May 8, 2002. The rule contains a disclosure provision which entails that every brokerage firm is required to disclose in its research reports the distribution of stock ratings across its coverage universe.[11] They show that after the implementation of the rule on September 9, 2002, the recommendation distribution of the ten brokerage firms that were part of the Global Research Analyst Settlement[12], changed significantly.

Second, in Table 1 we can see that the number of female analysts is declining after 2001. Several authors argue that this is most likely the result of occupational self-selection, reflecting a shift in women's career preferences. First, experimental evidence by Niederle and Vesterlund (2007) suggests that men and women have different preferences concerning competition. They conclude that women shy away from competition, while men seem to embrace it. The outflow of female analysts could indicate that women perceive the sector as more competitive than before. Second, the increased scrutiny of analysts' practices by investors and the SEC, in addition to the threat of litigation has without doubt increased the responsibility and, presumably also the risk of the analyst job. Women might find such job occupation too demanding and thus less attractive. The question we try to answer in this section is how this decline of female analysts affects gender differences in the recommendations issuing process.

The estimations of the recommendation model (1) for the two subsamples 1996 - 2001 (Table 5) and 2002 - 2006 (Table 6) yield interesting results, again mainly

[11] A related provision of NASD 2711 is that every brokerage firm must disclose in each of its research reports its definitions for buy, hold, and sell. These definitions were not commonly disclosed prior to the implementation of NASD 2711 (see footnote 7, Barber et al, 2007b).

[12] The Global Research Analyst Settlement was announced to be enforced on April 28, 2003, by the SEC, NASD, NYSE, New York Attorney General Eliot Spitzer, and other regulators.

with respect to the dispersion variable. For the period 1996 - 2001, male analysts are more likely to react more aggressively to analyst (dis-)agreement than their female colleagues. This behavior, however, largely disappears in the period 2002-2006. The difference in the dispersion estimates for the male and female subsamples is much smaller. In addition, the difference is not statistically significant any more. In the recent subsample, women behave much like men in their attitude towards analyst dispersion.[13]

The reduction in gender differences over time is more general as can be concluded from the Wald tests. These tests tell us that although gender differences are significant in both subsamples, it appears that they are less strong in the second subsample. In addition, in the first subsample, five variables, among which the consensus and dispersion variables, are individually statistically significant between the genders. In the second subsample, only the estimates for the variables Total Tenure and Working for a Top Broker are individually significantly different. The gender differences seem to be driven by a different behavior in the two subsamples. For example, note the large increase in importance for the variable Working for Top Broker. Both men and women become much more likely to issue lower recommendations when working for a Top Brokerage firm.

In line with our approach of the previous section, we calculate the relative probability differences for the recommendation classes.[14] The results confirm our conclusions of the previous section and in addition they confirm our interpretation of a structural break in the recommendation issuing process. Figure 2 shows the relative probability differences for the period 1996 - 2001. When dispersion among the recommendations is at its lowest point, the average male analyst has a 15% larger probability to issue an extremely positive Strong Buy recommendation than the average female analyst. At the same time the average female analyst has an almost 14% larger probability to issue the more conservative Hold recommendation than the average male analyst. In total, this constitutes a gender difference of almost 30%. In contrast, Figure 3 shows that the relative probability difference for Strong Buy recommendations in favor of male analysts has decreased to 7%, while for Hold recommendations the difference decreased to only 2% in favor of

[13] A Wald test for significant differences between the subsamples for men and women seperately, confirms that there has been a structural break after 2001 in the data.

[14] We calculate the relative probabilities by using the means for the all the variables, except for the dispersion variable. The means are calculated for each subsample seperately.

female analysts. Finally, note also that gender differences are substantial when looking at the average degree of dispersion: while male analysts have an almost 7% larger probability to issue more Strong Buy recommendations in the period 1996-2001, female analysts have an 8% higher chance to issue more moderate Hold recommendations. For the second period, the average gender differences decrease substantially: male analysts still have a 3% larger probability to issue the most favorable recommendations, while male and female analysts are equally likely to issue Hold recommendations.

While gender differences are present in both subsamples, with a clear preference by male (female) analysts for more extreme (conservative) recommendations, they decrease over time, which causes male and female analysts to be more likely to issue similar recommendations. The reason for this change is an open question. It could be the result of adaptive behavior of the female analysts that remain active in the investment banking business. It could also be the result of occupational self-selection by women, whereby women that have a similar decision behavior than men do not shy away from competition and decide to become or remain a sell-side analyst. The latter could have been caused by the regulation changes that took place during 2002, in the wake of the technology bubble burst.

4.3 Individual Year Results

The estimation results for the individual years are presented in Table 7 and are in line with our findings above. First, for all years individually, we find that analysts, male and female, herd. This can be concluded from the positive effect for the outstanding recommendation. In addition, analysts are more likely to issue lower recommendations when confronted with uncertainty, as implied by the negative effect of dispersion of the recommendations. Second, the gender differences over the years seems to confirm the trend observed in the split sample. For most years, male analysts react more heavily to the consensus recommendations and to prevailing uncertainty. This indicates that male analyst are, for the majority of the years, the more extreme decision makers.

We interpret the estimation results in a similar way as above and calculate the relative probabilities for each recommendations class. In Figure 4 we plot the relative probabilities for the average analyst, in the case that uncertainty among analysts recommendations is at its lowest. We consider this particular case as it has been shown in the previous sections that at this moment, gender heterogeneity is most pronounced. We observe the following. Gender differences are very large in the years 1996 - 2000. During 2001 and 2002, in the wake of the technology bubble burst and during regulatory changes, there is hardly any gender heterogeneity, while for the years 2003 - 2005 gender heterogeneity is clearly present, although smaller than in the first part of the sample. Finally, in 2006 we observe a reversal with respect to our previous findings. In 2006, when dispersion is low, female analysts have a 5% larger probability of issuing Strong Buy Recommendations while men have a 10% larger probability of issuing Hold recommendations. This result is very puzzling as it is contradicts the intuition set forth in this paper.

Our conclusions are as follows. First, the individual year estimations confirm the general trend that gender heterogeneity decreased over time, but it still exists, also in the recent years (see also Table 8 for the Wald tests). Second, the self-selection argument is certainly able to explain a large part of the decrease in gender differences, however some caution should be taken into account. With a female representation that is monotonically decreasing over time, if the self-selection argument holds, we should expect a smooth decline in gender heterogeneity as well. As the latter is clearly not the case, there should be other factors that determine gender heterogeneity in the decision making process of professional economic agents.

5 Conclusion

This paper contributes to the literature that investigates gender heterogeneity in risky decision making. In particular, we focus on the professional and highly competitive investment banking industry and investigate gender heterogeneity in the recommendation issuing process of financial analysts. This provides us with a great laboratory to explore whether gender differences matter in a professional setting as we can immediately observe the outcome of the decision making process, reflected in a limited number of individual stock recommendations.

Our research establishes a link between gender and economic decision making in a professional working environment. We present evidence of gender heterogeneity in the recommendation issuing process of sell-side analysts. We find that male analysts are more extreme and risk-seeking decision makers than female analysts. Female analysts on the other hand, are more likely to issue moderate recommendations. The average male analyst has a larger probability to issue Strong Sell recommendations, while the average female analyst has a larger probability to issue more conservative Hold recommendations. Gender heterogeneity reaches a maximum when dispersion among existing recommendations is at its lowest. Apparently, male analysts use the opportunity of low dispersion among analysts, i.e. that point in time when noticed most, to issue extremely positive recommendations. In addition, in line with existing financial literature we find that when controlling for individual characteristics, both male and female analysts have the tendency to herd. Furthermore, analysts are more likely to issue more conservative recommendations when faced with increased disagreement among their peers.

We observe that in the second half of our sample, gender heterogeneity declines. Over time, male and female analysts seem to behave more and more in a similar way. We believe that this can, for a large part, be attributed to the self-selection mechanism in the choice of job by women. The female analysts behaving similar to male analysts are apparently choosing to stay or be employed in the investment banking business. Nevertheless, in recent years we still observe gender heterogeneity in the recommendation issuing process. It would be very interesting to investigate whether changes in individual characteristics of the (female) analysts can explain to what extent the self section mechanism plays a role in the decrease in gender heterogeneity of the recommendation issuing process of sell-side analysts. This question is left for future research.

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Appendix: Tables

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

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

	No. Rec.	No. Firms Covered	No. Brokers	No. Analysts	% Female
1996	16,816	2,671	176	2,056	16
1997	18,837	3,055	205	2,538	17
1998	23,380	3,362	220	2,996	17
1999	24,227	3,384	222	3,205	17
2000	22,264	3,233	214	3,133	17
2001	23,470	2,972	194	3,074	16
2002	35,977	3,032	203	3,162	16
2003	27,607	2,910	258	3,075	14
2004	23,847	2,932	286	3,061	14
2005	19,510	2,830	279	2,695	13
2006	17,498	2,681	243	2,315	13
all years	253,433	4,939	537	7,091	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 is 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	3.90	3.88	0.93	0.93	1.82	1.82	1.95	1.39	32.25	34.47	32.38	31.42	31.60	30.88
1997	3.95	3.95	0.89	0.90	1.42	1.57	1.27	1.18	29.57	30.38	36.49	34.40	31.26	32.47
1998	3.92	3.89	0.85	0.86	0.91	1.34	1.29	0.88	31.29	31.83	38.34	39.01	28.16	26.94
1999	3.99	3.95	0.85	0.85	0.84	0.90	1.59	1.31	26.98	29.41	39.07	38.51	31.52	29.87
2000	4.00	3.92	0.83	0.83	0.55	0.76	1.19	0.76	27.16	32.27	39.54	38.31	32.05	27.91
2001	3.86	3.83	0.86	0.85	1.03	0.86	1.63	2.11	33.97	34.63	37.46	37.70	25.90	24.70
2002	3.57	3.57	0.95	0.96	2.02	1.87	7.59	8.25	41.23	40.24	29.46	29.91	19.71	19.73
2003	3.45	3.46	1.00	0.99	3.48	3.24	8.54	8.45	45.79	46.56	24.01	23.01	18.19	18.74
2004	3.50	3.53	0.99	0.99	3.48	3.27	6.95	6.28	45.47	45.51	24.62	24.30	19.47	20.63
2005	3.53	3.47	0.99	1.01	3.21	3.95	6.31	7.18	45.93	45.88	23.66	23.80	20.90	19.19
2006	3.47	3.46	0.97	0.96	3.03	3.22	7.04	7.00	47.55	46.82	24.39	26.00	17.99	16.96
all years	3.72	3.73	0.95	0.94	2.00	1.98	4.42	4.13	37.38	37.63	31.61	31.94	24.59	24.33

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 is 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	2.39	2.06	1.75	1.69	2.60	2.51	31.97	38.35	5.75	5.52	1.58	1.58
1997	2.18	1.64	1.83	1.73	2.99	2.82	32.89	39.72	5.41	5.30	1.55	1.52
1998	2.12	2.41	1.88	1.71	3.30	3.00	38.78	48.49	5.47	6.03	1.56	1.59
1999	1.84	2.98	1.96	1.83	3.71	3.34	39.43	50.65	5.46	5.57	1.53	1.50
2000	1.99	2.29	2.01	1.89	4.14	3.73	40.68	50.10	5.19	5.11	1.54	1.43
2001	1.98	2.61	2.07	2.01	4.50	4.03	42.66	54.42	5.41	4.73	1.53	1.38
2002	1.76	2.22	2.23	2.15	4.67	4.14	43.91	56.36	6.97	6.55	1.56	1.48
2003	1.85	1.66	2.38	2.28	4.66	4.22	42.39	50.83	6.02	5.83	1.48	1.44
2004	1.93	2.17	2.44	2.21	5.08	4.60	36.55	44.34	5.62	5.43	1.48	1.41
2005	1.93	1.95	2.63	2.41	5.85	5.48	36.86	43.73	5.20	5.42	1.45	1.42
2006	2.48	1.67	2.80	2.64	6.88	6.44	37.00	44.82	5.27	6.17	1.49	1.47

Table 4: **Ordered Probit Results Full Sample**

This table reports estimates of the ordered probit model on the samples for male and female analyst respectively, for the period 1996-2006. The recommendation data is obtained from I/B/E/S, while gender is identified using Nelson's Directory of Investment Research. In the column labelled 'Ind. Diff.', a * indicates that the individual male and female estimates are significantly different from each other at the 5% significance level.

	Male Analyst		Female Analyst		
	Estimate	p-value	Estimate	p-value	Ind. Diff.
Consensus(t−1)	0.546	0.000	0.519	0.000	*
St. Dev. of Outstanding Recs(t−1)	−0.222	0.000	−0.130	0.000	*
Total Tenure	−0.008	0.000	−0.022	0.000	*
Firm Tenure	−0.011	0.000	−0.009	0.064	
Number of Industries	0.004	0.087	0.009	0.135	
Number of Firms	−0.009	0.000	−0.005	0.000	*
Working for Top Broker	−0.105	0.000	−0.158	0.000	*
Star Analyst	0.040	0.004	0.152	0.000	*
Nobs.	215,123		38,310		
Pseudo R^2	0.035		0.034		
γ_1	−0.431		−0.482		
γ_2	0.140		0.062		
γ_3	1.597		1.542		
γ_4	2.480		2.435		
Wald test Male vs. Female	χ^2_8	94.283	p-value	0.000	

Table 5: **Ordered Probit Results Split Sample Before 2002**

This table reports estimates of the ordered probit model on samples for male and female analyst respectively, for the period 1996-2001. The recommendation data is obtained from I/B/E/S, while gender is identified using Nelson's Directory of Investment Research. In the column labelled 'Ind. Diff.', a * indicates that the individual male and female estimates are significantly different from each other at the 5% significance level.

	Male Analyst		Female Analyst		
	Estimate	p-value	Estimate	p-value	Ind. Diff.
Consensus(t−1)	0.443	0.000	0.436	0.000	
St. Dev. of Outstanding Recs(t−1)	−0.158	0.000	−0.051	0.062	*
Total Tenure	0.014	0.000	−0.014	0.002	*
Firm Tenure	−0.036	0.000	−0.031	0.000	
Number of Industries	−0.016	0.000	−0.005	0.537	
Number of Firms	−0.007	0.000	0.000	0.973	*
Working for Top Broker	0.031	0.000	−0.022	0.168	*
Star Analyst	0.014	0.494	0.150	0.000	*
Nobs.	108,083		20,911		
Pseudo R^2	0.0187		0.0177		
γ_1	−0.800		−0.734		
γ_2	−0.430		−0.430		
γ_3	1.130		1.195		
γ_4	2.132		2.184		
Wald test Male vs. Female	χ^2_8	86.159	p-value	0.000	

Table 6: **Ordered Probit Results Split Sample After 2001**

This table reports estimates of the ordered probit model on samples for male and female analyst respectively, for the period 2002-2006. The recommendation data is obtained from I/B/E/S, while gender is identified using Nelson's Directory of Investment Research. In the column labelled 'Ind. Diff.', a * indicates that the individual male and female estimates are significantly different from each other at the 5% significance level.

	Male Analyst		Female Analyst		
	Estimate	p-value	Estimate	p-value	Ind. Diff.
Consensus(t−1)	0.471	0.000	0.462	0.000	
St. Dev. of Outstanding Recs(t−1)	−0.172	0.000	−0.130	0.000	
Total Tenure	0.006	0.000	−0.003	0.308	*
Firm Tenure	−0.008	0.000	−0.003	0.601	
Number of Industries	0.018	0.000	0.016	0.095	
Number of Firms	−0.008	0.000	−0.005	0.002	
Working for Top Broker	−0.238	0.000	−0.325	0.000	*
Star Analyst	−0.010	0.606	0.064	0.166	
Nobs.	107,040		17,399		
Pseudo R^2	0.0261		0.030		
γ_1	−0.518		−0.584		
γ_2	0.135		0.080		
γ_3	1.590		1.530		
γ_4	2.358		2.311		
Wald test Male vs. Female	χ^2_8	36.255	p-value	0.000	

Table 7: **Ordered Probit Results for Seperate Years**

This table reports estimates of the ordered probit model on the samples for male and female analyst respectively, for the individual years over the period 1996-2006. The recommendation data is obtained from I/B/E/S, while gender is identified using Nelson's Directory of Investment Research. In the columns labelled 'Ind. Diff.', a * indicates that the individual male and female estimates are significantly different from each other at the 5% significance level.

	1996					1997				
	Male Analysts		Female Analysts			Male Analysts		Female Analysts		
	Estimate	p-value	Estimate	p-value	Ind. Diff.	Estimate	p-value	Estimate	p-value	Ind. Diff.
Consensus$(t-1)$	0.339	0.000	0.280	0.000		0.379	0.000	0.421	0.000	
St. Dev. of Outstanding Recs(t−1)	−0.132	0.000	−0.121	0.074		−0.179	0.000	−0.049	0.474	
Total Tenure	0.070	0.000	0.013	0.575	*	0.034	0.000	−0.025	0.116	*
Firm Tenure	−0.063	0.000	−0.088	0.003		−0.076	0.000	−0.101	0.000	
Number of Industries	−0.041	0.000	−0.012	0.595		−0.015	0.064	−0.037	0.089	
Number of Firms	−0.015	0.000	−0.002	0.716	*	−0.008	0.000	0.006	0.218	*
Working for Top Broker	0.006	0.776	0.012	0.800		0.019	0.331	−0.014	0.742	
Star Analyst	0.066	0.200	0.061	0.577		−0.046	0.353	−0.012	0.928	
Nobs.	14,225		2,591			15,779		3,058		
PseudoR^2	0.018		0.013			0.020		0.026		
γ_1	−1.046		−1.264			−0.973		−0.882		
γ_2	−0.714		−1.015			−0.698		−0.624		
γ_3	0.762		0.557			0.821		0.945		
γ_4	1.617		1.384			1.796		1.865		
	1998					1999				
Consensus$(t-1)$	0.368	0.000	0.440	0.000		0.460	0.000	0.484	0.000	
St. Dev. of Outstanding Recs$(t-1)$	−0.162	0.000	0.007	0.916	*	−0.205	0.000	−0.008	0.906	*
Total Tenure	0.028	0.000	−0.004	0.731	*	0.013	0.006	−0.024	0.017	*
Firm Tenure	−0.060	0.000	−0.018	0.342	*	−0.043	0.000	−0.008	0.642	
Number of Industries	0.012	0.131	0.053	0.004	*	−0.013	0.122	−0.018	0.331	
Number of Firms	−0.013	0.000	−0.003	0.414	*	−0.002	0.372	0.005	0.153	
Working for Top Broker	0.015	0.377	−0.032	0.348		0.111	0.000	0.022	0.532	*
Star Analist	0.014	0.755	0.231	0.012	*	0.121	0.021	0.304	0.000	
Nobs.	19,189		4,191			20,093		4,134		
PseudoR^2	0.018		0.018			0.020		0.019		
γ_1	−1.160		−0.469			−0.790		−0.568		
γ_2	−0.796		−0.260			−0.346		−0.202		
γ_3	0.843		1.385			1.140		1.384		
γ_4	1.870		2.437			2.190		2.418		

Table 7: **Ordered Probit Results for Seperate Years** *(Continued)*

This table reports estimates of the ordered probit model on the samples for male and female analyst respectively, for the individual years over the period 1996-2006. The recommendation data is obtained from I/B/E/S, while gender is identified using Nelson's Directory of Investment Research. In the columns labelled 'Ind. Diff.', a * indicates that the individual male and female estimates are significantly different from each other at the 5% significance level.

	2000					2001				
	Male Analysts		Female Analysts			Male Analysts		Female Analysts		
	Estimate	p-value	Estimate	p-value	Ind. Diff.	Estimate	p-value	Estimate	p-value	Ind. Diff.
Consensus$(t-1)$	0.560	0.000	0.534	0.000		0.539	0.000	0.430	0.000	*
St. Dev. of Outstanding Recs$(t-1)$	−0.158	0.000	−0.004	0.946	*	−0.119	0.001	−0.153	0.055	
Total Tenure	0.003	0.522	−0.028	0.004	*	0.021	0.000	0.015	0.094	
Firm Tenure	−0.018	0.011	−0.020	0.249		−0.019	0.002	−0.014	0.411	
Number of Industries	−0.011	0.210	0.005	0.817		−0.032	0.000	−0.055	0.033	
Number of Firms	−0.004	0.060	−0.005	0.330		−0.005	0.011	−0.012	0.019	
Working for Top Broker	0.014	0.405	−0.105	0.007	*	−0.009	0.592	−0.058	0.166	
Star Analyst	−0.030	0.559	0.202	0.044	*	−0.021	0.669	0.093	0.349	
Nobs.	18,688		3,576			20,109		3,361		
Pseudo R^2	0.022		0.025			0.020		0.016		
γ_1	−0.496		−0.577			−0.336		−0.985		
γ_2	−0.040		−0.305			0.060		−0.475		
γ_3	1.575		1.522			1.709		1.133		
γ_4	2.643		2.561			2.724		2.155		
	2002					2003				
Consensus$(t-1)$	0.753	0.000	0.748	0.000		0.461	0.000	0.429	0.000	
St. Dev. of Outstanding Recs$(t-1)$	0.161	0.000	−0.208	0.000		−0.145	0.000	−0.044	0.446	
Total Tenure	0.007	0.011	−0.003	0.650		0.003	0.335	0.007	0.361	
Firm Tenure	0.016	0.001	0.023	0.062		−0.012	0.012	−0.026	0.061	
Number of Industries	0.001	0.832	0.021	0.188		0.025	0.001	−0.009	0.638	
Number of Firms	−0.010	0.000	−0.006	0.051		−0.007	0.000	0.003	0.399	*
Working for Top Broker	−0.223	0.000	−0.235	0.000		−0.199	0.000	−0.356	0.000	*
Star Analist	−0.040	0.242	−0.001	0.990		−0.009	0.840	−0.027	0.829	
Nobs.	30,741		5,236			23,904		37,03		
PseudoR^2	0.046		0.049			0.024		0.031		
γ_1	0.421		0.352			-0.503		-0.620		
γ_2	1.224		1.224			0.164		0.064		
γ_3	2.667		2.624			1.595		1.538		
γ_4	3.551		3.525			2.330		2.247		

Table 7: **Ordered Probit Results for Seperate Years** *(Continued)*

This table reports estimates of the ordered probit model on the samples for male and female analyst respectively, for the individual years over the period 1996-2006. The recommendation data is obtained from I/B/E/S, while gender is identified using Nelson's Directory of Investment Research. In the columns labelled 'Ind. Diff.', a * indicates that the individual male and female estimates are significantly different from each other at the 5% significance level.

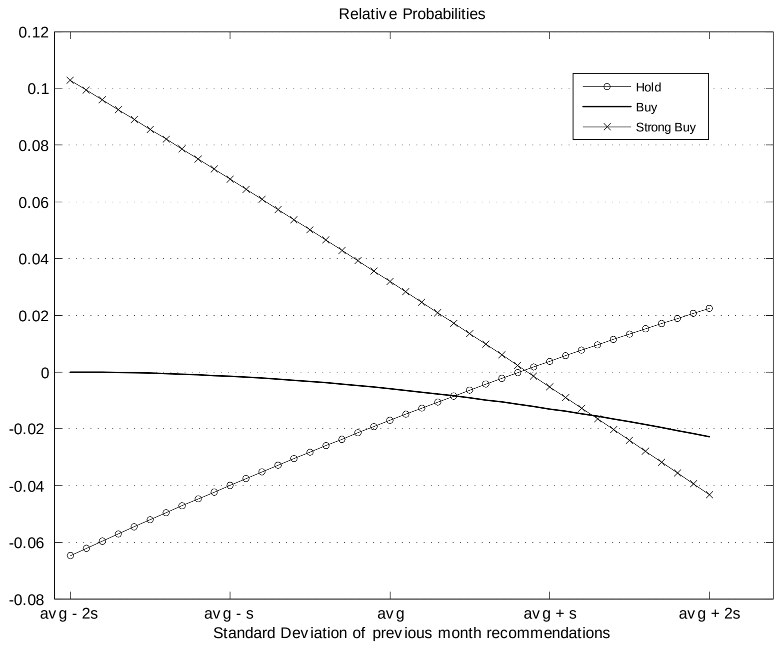
	2004					2005				
	Male Analysts		Female Analysts			Male Analysts		Female Analysts		
	Estimate	p-value	Estimate	p-value	Ind. Diff.	Estimate	p-value	Estimate	p-value	Ind. Diff.
Consensus$(t-1)$	0.321	0.000	0.299	0.000		0.354	0.000	0.289	0.000	
St. Dev. of Outstanding Recs$(t-1)$	−0.160	0.000	−0.068	0.266		−0.152	0.000	−0.078	0.249	
Total Tenure	0.011	0.000	0.003	0.718		0.004	0.145	−0.006	0.438	
Firm Tenure	−0.031	0.000	−0.021	0.153		−0.008	0.116	−0.010	0.466	
Number of Industries	0.036	0.000	0.052	0.041		−0.007	0.489	0.042	0.099	
Number of Firms	−0.012	0.000	−0.007	0.128		−0.001	0.598	−0.015	0.003	*
Working for Top Broker	−0.292	0.000	−0.423	0.000	*	−0.257	0.000	−0.305	0.000	
Star Analyst	0.049	0.283	0.082	0.541		0.075	0.174	0.178	0.209	
Nobs.	20,760		3,087			16,779		2,731		
Pseudo R^2	0.020		0.028			0.017		0.019		
γ_1	−1.010		−1.065			−0.869		−1.063		
γ_2	−0.437		−0.516			−0.311		−0.514		
γ_3	1.015		0.986			1.180		0.928		
γ_4	1.748		1.709			1.869		1.642		
	2006									
Consensus$(t-1)$	0.364	0.000	0.418	0.000						
St. Dev. of Outstanding Recs$(t-1)$	−0.232	0.000	−0.241	0.002						
Total Tenure	0.004	0.230	−0.014	0.053	*					
Firm Tenure	−0.013	0.015	0.010	0.433						
Number of Industries	0.065	0.000	−0.046	0.078	*					
Number of Firms	−0.010	0.000	−0.013	0.005						
Working for Top Broker	−0.256	0.000	−0.398	0.000	*					
Star Analist	−0.063	0.276	0.179	0.245						
Nobs.	14,856		2,642							
PseudoR^2	0.021		0.031							
γ_1	-0.907		-1.073							
γ_2	-0.287		-0.471							
γ_3	1.237		1.051							
γ_4	1.982		1.867							

Table 8: **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 χ^2_8-distributed

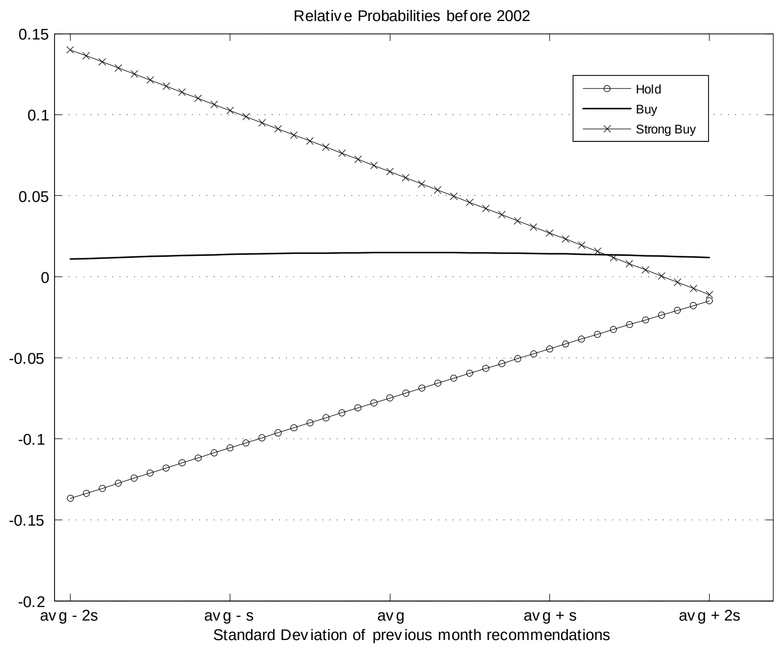
	χ^2_8	p-value
1996	20.482	0.009
1997	27.931	0.001
1998	34.096	0.000
1999	27.063	0.001
2000	28.059	0.001
2001	10.024	0.263
2002	6.104	0.636
2003	28.151	0.000
2004	15.334	0.053
2005	15.284	0.054
2006	30.104	0.000

Appendix: Figures



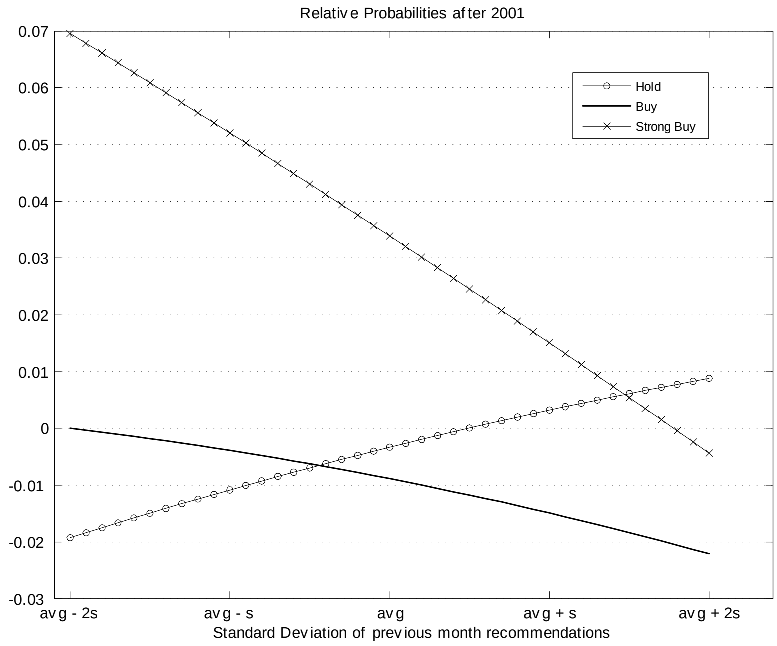
The figure shows the relative probability differences between male and female analyst for the three largest recommendation classes Hold, Buy and Strong Buy. These are calculated by dividing the male analyst probabilities for a recommendation class by the female analyst probabilities, normalized around zero. All variables, accept the dispersion variable, are evaluated at their sample mean.

Figure 1: **Relative Probability Differences Between Male and Female Analysts**



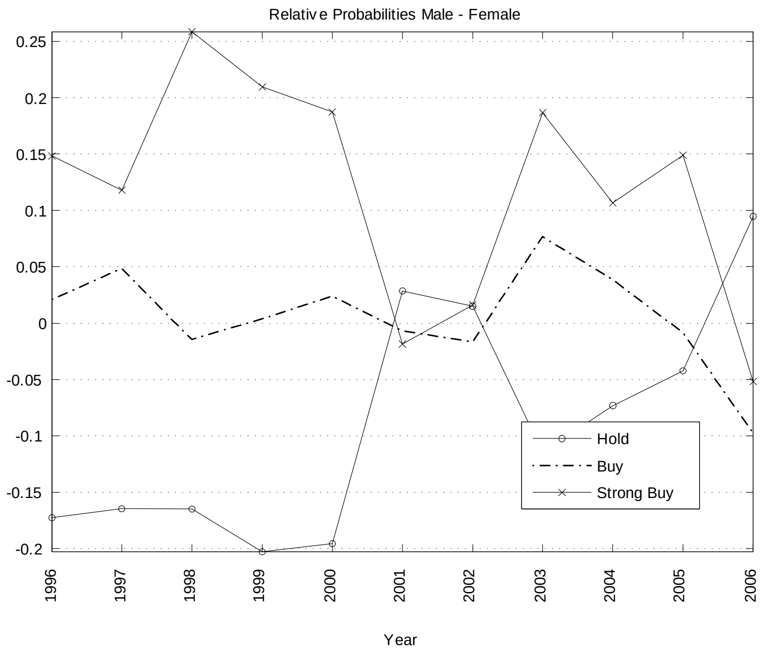
The figure shows the relative probability differences between male and female analysts for the three largest recommendation classes Hold, Buy and Strong Buy. These are calculated by dividing the male analyst probabilities for a recommendation class by the female analyst probabilities, normalized around zero. All variables, accept the dispersion variable, are evaluated at their sample mean.

Figure 2: **Relative Probability Differences Between Male and Female Analysts 1996 - 2001**



The figure shows the relative probability differences between male and female analysts for the three largest recommendation classes Hold, Buy and Strong Buy. These are calculated by dividing the male analyst probabilities for a recommendation class by the female analyst probabilities, normalized around zero. All variables, accept the dispersion variable, are evaluated at their sample mean.

Figure 3: **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 means, and evaluated at the lowest dispersion of recommendations (2 standard deviations below the average). These are calculated by dividing the male analyst probabilities for a recommendation class by the female analyst probabilities, normalized around zero.

Figure 4: **Relative Probability Differences Between Male and Female Analysts over the Years**