Gender Stereotypes in Advisors' Clinical Judgments of Financial Risk Tolerance: Objects in the Mirror Are Closer than They Appear to Be

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Abstract

A sample consisting of 183 financial advisors and 290 advisory clients was used to determine the degree of correspondence between advisors' subjective clinical judgments about their clients' financial risk tolerance and these clients' actual financial risk tolerance. The correlation between advisors' estimates and measured risk tolerance was .41. It was further determined that advisors overestimated the risk tolerance of men and underestimated the tolerance of women. This distortion could not be attributed to income or wealth differences between the males and females.

Key Words: Risk Tolerance, Stereotyping, Subjective Clinical Judgments, Differential Prediction

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In many countries, financial due diligence regulations, as well as ethical guidelines, require that financial advisors “ know their clients” to assure that investment recommendations are “suitable” given the client’s financial and personal circumstances. Either implicitly (e.g., U.S., Canada) or explicitly (e.g., Australia, Ireland) risk tolerance is generally considered to be one of the personal circumstances that the advisor needs to learn about the client. However, the methods for how this information is to be acquired are not spelled out explicitly. By choice or circumstances, financial advisors sometimes make inferences about their clients’ risk tolerance under conditions of limited time and knowledge. Without an objective measure of financial risk tolerance, they render this judgment on the basis of their experience with a particular client, knowledge about other clients that have similar demographic characteristics (see Grable & Lytton, 1998; 1999), and intuition. These types of decisions are known as subjective clinical judgments (Garb, 1989).

While individuals in a variety of professions and walks of life are usually confident of their decisions based on clinical judgments (Dawes, Faust, & Meehl, 1993; Griffin, Dunning, & Ross, 1990; Tyszka & Zielonka, 2002), because they believe that these opinions reflect their unique training and experience, the actual accuracy of professionals’ clinical judgments has been questioned (Faust, 1986; Grove & Meehl, 1996; Grove, Zald, Lebow, Snitz, & Nelson, 2000; Peterson & Pitz, 1986; Zielonka, 2002; Zielonka, 2004). For example, Snelbecker, Roszkowski, and Cutler (1990) studied financial advisor’s interpretations of client statements conveying varying degrees of risk tolerance, and found that while the advisors showed some consistency in their judgments, substantial differences were evident in individual advisors' interpretations of the same exact statements.

A major problem with clinical judgments is that they are subject to a variety of cognitive biases (Garb, 1996; Gilovich, Griffin, & Kahneman, 2000; Wedell, Parducci, & Lane, 1990), including gender stereotyping (Rubinstein, 2001; Zeldow, 1976). Although a variety of definitions have been proposed, the essential nature of stereotypes is that they are generalized beliefs about a demographic or social group. Macrae, Milne, and Bodenhausen (1994) demonstrated that stereotypes serve as “energy-saving devices” which allow one “… to free up limited cognitive resources for the execution of other necessary or desirable activities” (p.45). In a sense, stereotyping is thus a heuristic, which can lead to erroneous conclusions in certain cases.

Gender is a characteristic often used in forming a judgment about a client’s risk tolerance (Grable & Lytton, 1998; 1999), and although the literature comparing the genders on risk tolerance shows compellingly that men are actually more risk tolerant in a variety of contexts (Byrnes, Miller, & Schafer, 1999), including financial risk tolerance (Olsen & Cox, 2001; Roszkowski, Delaney, & Cordell, 2004), this does not mean that gender stereotypes are not operating when subjective judgments are made about a given person. According to Martin (1987), many gender stereotypes are inaccurate not because they are totally false, but rather because people exaggerate the proportion of men and women with a given characteristic, even if there is an actual confirmed gender difference on that characteristic. Brigham (1971) defines stereotyping as over-generalization, with the person believing that “‘almost all’ (say 95%) of the members of Group X possess Attribute Y, while in reality only ‘most’ (say 65%) of Group X possess Attribute Y” (p.17). In other words, the relevant issue is not if the two genders differ on risk tolerance, since it is known that they do, but rather, whether the actual differences are as large as people believe them to be.

The purpose of this research is to (1) determine advisors’ ability to predict the financial risk tolerance of their clients, and (2) assess whether financial advisors tend to stereotype the risk tolerance of male and female clients. Findings from this study should help researchers and practitioners better understand the attitudinal biases, if any, that may operate when advisors assess a client’s risk tolerance and ultimately make investment recommendations.

Review of Literature

Gender-Stereotyping of Risk Tolerance

Several studies have been conducted regarding people’s perceptions of the degree of risk tolerance of men and women relative to the true incidence. The challenge has been to determine what is the actual incidence of a given characteristic compared to what people believe it to be (McCauley & Stitt, 1978). Martin (1987) studied the accuracy of gender stereotypes for a variety of attributes, including willingness to take risks. To determine the base rates (actual incidence) of these characteristics among males and females, she asked 150 visitors (94 women, 56 men) at a university open house to provide self-ratings on these characteristics. She then had a sample of 103 undergraduates (77 females and 36 males) estimate the percentage of people with that characteristic in the general population. The undergraduate's estimates were compared to the percentage of the visitors' self reports by computing a male to female ratio in the actual incidence and a male to female ratio in the estimated incidence. According to Martin: "If sex stereotypes about a particular characteristic are relatively accurate, the diagnostic (estimate) ratio should not differ in magnitude from the criterion (actual) ratio. If sex stereotypes are exaggerations of sex differences, the estimate ratio should be more extreme (in the stereotypic direction) than the actual ratio" (p. 491). On "willingness to take risk," the actual (criterion) ratio was 1.33, whereas on the estimate (diagnostic) ratio, the value was reported to be 1.64, a statistically significant difference. In other words, males were viewed as more risk tolerant than they really were and females were seen as more risk averse than was the case.

In Martin's (1987) study, no comparisons between male and female judges were reported. However, there is some research (e.g., Judd, Ryan, & Park, 1991) suggesting that stereotyping about one's own group (in-group) may differ from stereotyping about a group to which one does not belong (out-group). Siegrist, Cvetkovitch, and Gutscher (2002) compared male and female judges on their stereotyping of the in-group and the out-group by having 91 undergraduates (61 females and 30 males) make a choice on seven loss and seven gain scenarios where the options differed in risk and then asking the subjects to indicate which option they thought most other female students and most other male students in the U.S. would have chosen. The authors concluded that both males and females overestimated male's risk seeking, but that the women's overestimates were greater than the men's. Both genders were accurate in their prediction of women's lower risk preferences. In other words, women tended to stereotype men, but not vice versa. These results are not entirely consistent with those reported in two studies conducted by Eckel and Grossman (2002; 2003).

In the one study by Eckel and Grossman (2003), 256 college students (136 male and 120 female) were paid for completing a sensation-seeking survey. They then had to wager that money on one of five gambles. The gambles, which differed in degree of risk, were coded 0 through 4, to reflect the linear increase in the risk of the gambles. Each participant in the study also had to predict which gamble every other person taking part in the study would chose to play (3,642 predictions). For every correct prediction, the subject was promised $1.00. The only information that each player had about the other players was visual cues available through observation of the other person. The mean actual gamble choice, based on the five-point scoring system, was 3.79 for males and 3.08 for females. (The mean difference does not seem that dramatic, but 33 percent of the men and only 13 percent of the women picked the riskiest gamble.). The men predicted an average of 3.35 for other males and 2.56 for the females. The women's predicted gambles averaged 3.29 for the males and 2.62 for the other females. The correlation between actual and predicted choices was low for both the male and female judges (.17 for males, .15 for females, and .16 when aggregated across gender). The authors concluded that (a) there was a significant gender difference in actual risk tolerance favoring males; (b) both genders under-predicted the actual risk tolerance of the other players, be they male or female; (c) each was a more accurate judge of the risk tolerance of its own gender than of the opposite gender; and (d) both genders correctly predicted that males would be more risk taking than the females, but there was some evidence of stereotyping in the data since the actual mean gamble was most discrepant from the predicted mean gamble in case of males judging females (0.52 difference) and lowest in the case of males judging other males (0.44 difference).

Eckel and Grossman's earlier study (2002) was similar in design to the one described above. The participants were also undergraduates (104 males and 96 females) who were compensated for completing the same sensation-seeking questionnaire and were then asked to risk this money by playing one of five gambles and to estimate the decisions made by the other participants in the experiment (being paid for each correct guess). The first gamble was a sure bet, involving no risk. The remaining four gambles increased systematically in expected value (payoff), but the standard deviation of the payoff (i.e., risk) went up accordingly. As in their other study, the gambles were coded 0 through 4, with zero reflecting the sure choice bet. Males made riskier bets, with over one-third selecting the riskiest gamble and less than 2 % selecting the least risky bet. Among women, the respective choices were 13 % for the most risky bet and over 8 % for the least risky bet. For males, the mean actual choice was 3.72 (on the four-point scale), whereas for females the actual average bet was 3.10. Men correctly predicted that the other males would choose a riskier bet than the females (mean predicted male bet of 3.33 versus female bet of 2.48). Likewise, women were accurate in predicting that men would pick the riskier bets (with a mean predicted bet of 3.26 for the men and 2.61 for the other females). As in their other study, both genders underestimated the level of risk tolerance of the other players. In contrast to their other study, however, members of neither gender were better in forecasting their own gender's performance relative to the prediction for the opposite gender. Both males and females were closer to predicting the actual betting behavior of men than of women, but males under-predicted the risk tolerance of females to a greater extent than did the other females. The correlations between actual and predicted choices were markedly higher in this study compared to the other one. Depending on who was judging whom, the correlations were in a narrow range of between .35 (males judging females) and .43 (females judging female). Eckel and Grossman noted that "Within sex pairings, both sexes were better at predicting women's than men's choices, but not significantly so" (p.290). Overall, aggregating across gender of judges and those judged, the correlation between actual and forecast level of risk in the bet was .42.

Stereotyping Assessed by Differential Prediction and Standard Scores

Although none of the previous studies on the gender stereotyping of risk tolerance had used differential prediction to detect stereotyping, it is possible to do so by means of this methodology. That is, to study whether there is gender-stereotyping of risk tolerance on the part of financial advisors, one needs to assess whether differential prediction exists when an objective measure of risk tolerance is used to predict the financial advisor's subjective clinical judgment regarding a client's degree of risk tolerance. Differential prediction refers to a situation in which a regression-based prediction equation developed on the entire group does not predict equally well for all relevant subgroups, such as males versus females. In other words, differential prediction exists when there is a significant difference in the regression equations for males and females due to differences in the slopes, intercepts, or both (Bartlett, Bobko, Mosier, & Hannan, 1978). Differences in slopes indicate that a predictor (i.e., risk tolerance test) predicts the criterion (i.e., advisors subjective clinical judgment) better for one group than for another. Differences in intercepts indicate that the members of one group tend to obtain lower predicted criterion scores than the members of another group who have equal predictor scores (i.e., risk tolerance test scores) (Sackett & Wilk, 1994). Some authors term differences in slope as differential validity (Linn, 1978) because the different slopes mean that there are differences in the magnitude of the correlation between predictor and criterion across subgroups.

Stereotyping can be diagnosed in several related ways, as described below. The first three approaches are variants of differential prediction methodology.

Hierarchical Multiple Regression. Probably the most straightforward approach is a hierarchical regression where the dependent variable (advisor's judgment) is regressed on the independent variable (risk tolerance test score) and a variable indicating group membership (client's gender). If gender explains variance in the clinical judgment that is not accounted for by the risk tolerance test, then this constitutes evidence of differential prediction and therefore stereotyping.

Analysis of Covariance. A second method is to conduct an analysis of covariance using the clinical judgment as the dependent variable, client's gender as the independent variable, and the risk tolerance test score as the covariate. If after partialing out the risk tolerance test score, there remain differences on the subjective clinical judgment ratings for the two genders, then it can be taken as proof of stereotyping.

Residuals from a Simple Regression. The third approach involves the examination of residuals. This method consists of three steps: (1) developing a common (pooled) regression equation without regard to the clients' gender, using the subjective clinical judgment rating as the criterion and the risk tolerance test score as the predictor, (2) computing a difference between the actual subjective clinical judgment and the predicted clinical judgment (called a residual), and (3) comparing the residuals between male and female clients. A residual is the variance not explained by the predictor. This difference between the actual clinical judgment and the predicted clinical judgment rating expresses the degree of mis-prediction, which can take the form of either over-prediction or under-prediction. If the residuals between the two genders differ, it means that the equation is not working equally well for the two. A negative residual means that the predicted subjective judgment rating of the client's risk tolerance is higher than the actual subjective judgment score assigned by the advisor, whereas a positive residual indicates that predicted subjective judgment score is lower than the actual subjective judgment score given to the client by the advisor. If gender stereotyping by advisors exists, then one would expect to see negative residuals for female clients, and positive or zero residuals for male clients. In other words there would be evidence of stereotyping if for men, the clinical judgment scores predicted by the risk tolerance test are higher or equal to the ones that they actually received from their advisors, whereas for women, the risk tolerance test predicted higher clinical judgment ratings than were actually assigned to them by the advisors.

Standard Scores. A fourth technique to testing for gender stereotyping on the part of financial advisors consists of converting the advisors' ratings of the clients and the clients' risk tolerance test scores into a common metric (a standardized score), computing a difference between the ratings and the test scores, and comparing the difference scores by gender. Under stereotyping, the male clients would have a either a positive or near zero difference (rating minus test score), whereas the females would have a negative difference score between the advisor's rating and the risk tolerance test score.

Method

Participants

The sample consisted of 183 financial advisors and 290 of their clients. The advisors, who worked primarily in the insurance industry and were all graduates of a master's in financial services degree program, subjectively rated their clients on level of financial risk tolerance, with 76 advisors rating only one client each and 107 advisors rating two clients each. There were few female clients and even fewer female advisors. The gender distribution of the advisors was 176 males, 6 females, and 1 unknown. The clients' gender distribution was 243 males, 39 females, and 8 unknown. The demographic summary of the advisors and clients is presented in Tables 1 and 2, respectively.

Procedure

To determine the client's actual risk tolerance, a standardized test of risk tolerance was administered and compared to the financial advisors' subjective clinical judgment about that person's risk tolerance. The independent variable or predictor was the client's score on the standardized test of financial risk tolerance and the dependent variable was the financial advisor's subjective clinical judgment about the client's level of risk tolerance (without knowing the test score). If no gender stereotyping is occurring, then the advisors should be equally accurate in their subjective clinical judgments about the financial risk tolerance of males and females, relative to what the test indicates. If, on the other hand, stereotyping is occurring, then compared to the test, either or both of the following conditions would occur: (a) males are judged to be more risk-taking than the test shows and (b) females are judged to be more risk averse than the test shows. In order to obtain a comprehensive understanding, the four approaches to assessing stereotyping described previously were used in the analysis of the data.

Measures

Each advisor was asked to select two of his or her clients and provide a rating of these clients' level of risk tolerance for financial risks using a scale of 1 to 10, with 1 representing extreme risk aversion and 10 indicating extreme risk-taking. (Only the endpoints were described.) In addition, the advisor was asked to administer a test of risk tolerance developed by The American College to these same clients. (Not all clients complied with the request, hence the reason for why some advisors had only one client participate.) The test, called *the Survey of Financial Risk Tolerance* (SOFRT), consists of 40 questions (57 scored items) using a comprehensive approach to tolerance assessment (e.g., probability and payoff preferences, emotional reactions, portfolio preferences, etc). The raw score on the SOFRT can range from 0 (extreme risk aversion) to 100 (extreme risk seeking). The reliability is .91 as assessed by internal consistency (Roszkowski, 1992) and .81-.83 test-retest (Roszkowski, Delaney, & Cordell, 2004). Evidence of the SOFRT's criterion-related validity can be found in expected correlations with ownership of conservative and aggressive investments evidence and relationship with demographic variables related to risk tolerance. The advisors did not see the client's SOFRT scores when making their subjective clinical judgment rating. The data were collected to investigate the validity of the SOFRT.

Insert Tables 1 and 2 about Here

Results

The summary statistics on the variables of interest are reported in Table 3 by gender of client as well as advisor. Because the gender of the advisor may be relevant, the ratings assigned by female advisors and male advisors are disaggregated. However, in view of the small number of female advisors in the sample ($n = 6$), there was little power to pick up statistically significant differences. This study reports the data by gender of advisor primarily to determine if there are any interesting patterns to guide future research.

Insert Tables 3 about Here

Differential Validity

Based on responses from 290 clients, the Pearson correlation between advisor's subjective clinical judgment and actual risk tolerance was .41 ($p < .001$). For the 282 clients with gender information, the correlation was .40 ($p < .001$) overall, .34 ($p < .001$) for male clients and .54 ($p < .001$) for the female clients. The male and female correlations were not statistically different using a two-tailed test ($z = 1.40$, $p = .162$). As such, it is not possible to establish statistically the existence of differential validity by gender of the client, although descriptively one exists in the sample.

Multiple Regression Approach

A hierarchical multiple regression was run using the advisors' subjective clinical judgments as the criterion. The advisors' subjective clinical judgments of clients were regressed on the clients' tested risk tolerance (SOFRT scores), the clients' gender, the advisors' gender, and the interaction of the clients' and advisors' gender (the variables being entered in the respective order specified). Table 4 shows that only the SOFRT score and client's gender were significant predictors. Gender-stereotyping of client risk tolerance by advisors is indicated by the significance of client gender in explaining the advisor's rating beyond what gender has in common with actual risk tolerance as measured by the SOFRT (R increased from .40 to .47 after client gender was added). Advisor gender was not significant nor was the interaction of advisor gender and client gender. However, the interaction term's probability level is relatively low (p = .207) and suggestive, given the small number of females in the sample (see Aguinis, 1995; Aguinis, Pierce, & Stone-Romero, 1994; Aguinis & Stone-Romero, 1997).

Insert Tables 4 about Here

An assumption underlying multiple regression is that the observations are independent. Given that 108 financial advisors rated two clients, their observations were not independent. However, several tests indicate that this was not a problem. The Durbin-Watson statistic equaled 1.79, which indicates that no serial autocorrelation exists (values of 1.5 to 2.5 are considered normal). As a further test, the ratings given by the 108 advisors to their two clients were correlated, resulting in a Pearson coefficient of only .14 (p = .163), which again points to independence between the two clients from the same advisor. As a final test, one of the two clients was dropped randomly, and the regression analysis was repeated on the smaller sample (n =179), again using the advisor's rating as the criterion and the SOFRT and client gender as the predictors. With only the SOFRT in the equation *R* equaled .41. After entering gender, the *R* increased to .45. The change in *R* was statistically significant (*F*-to-enter (1,176) = 6.32, *p* = .013). In other words, the same pattern was evident with just one client per advisor as with the full sample. Consequently, in the remaining analyses, the full sample was utilized.

Analysis of Covariance Approach

The dependent variable was the advisors' subjective ratings of client risk tolerance on the 10-point scale. The SOFRT score served as the covariate and client's gender and advisors' gender as the two independent variables. The effect of the covariate was statistically significant (*F* (1,276) = 39.24, *p* = .000, partial eta ^{2} = .124, and observed power = 1.00). The client's gender was also significant (*F (*1,276) = 11.68, *p* = .001, partial eta ^{2} = .041). The effect of advisor gender was not significant (*F* (1,276) = 0.17, *p* = .687, partial eta ^{2} = .001), but the power was low (.07). The client gender by advisor gender interaction also failed to reach statistical significance (*F (*1,276) = 1.60, *p* = .207, partial eta ^{2} = .006), but power was only .242.

In view of their clients' actual risk tolerance (SOFRT scores), the mean advisor rating should have been 5.60 for females and 4.22 for females (a difference of 1.28 points) instead of the actual ratings of 5.65 (males) and 3.87 (females), which constitutes a 1.78-point difference between the genders. As can be observed, the bigger difference between adjusted and actual ratings occurred for females. On average, advisors overestimated males by only 0.05 points, whereas they underestimated females by 0.35 points.

Although the differences between male and female advisors were not statistically significant, it is worth noting that on the adjusted advisor ratings, the female advisors tended to gender stereotype to a greater extent than their male counterparts. After adjusting for actual risk tolerance, the female advisors had a mean difference of 2.74 points (in favor of the males) between the ratings of male and female clients (6.08 minus 3.34). Among male advisors, the average difference in the adjusted ratings for their male and female clients was 1.28 points favoring the males (5.59 minus 4.31).

Residuals Approach

A regression was run using just one variable, the SOFRT scores, to predict advisors' ratings of their clients. For the sample as a whole, the difference between actual and predicted advisor rating on the 10-point scale was zero (as it should be based on the mathematics of regression). However, there were statistically significant differences in the residuals of male and female clients (F (1,277) = 10.65, p = .001, partial eta ^{2} = .037). Males had an average residual (see Table 3) of +0.18 points whereas females had an average residual of -.13. (This difference in residuals was also significant when tested with the Mann-Whitney U test: U= 2630.00, Z=-4.46, p = .000). In other words, in the common equation developed without regard to gender, the objective measure (i.e, SOFRT) under-predicted advisors' subjective ratings of male clients and over-predicted their subjective ratings of female clients. This pattern suggests that gender stereotyping of risk tolerance occurred. The advisor's gender did not produce statistically significant differences in residuals (F (1,277) = 0.21, p = .649, partial ^{2} = .001) but again power to do so was low (.074). The gender of the client by gender of the advisor interaction was also not significant (F (1,277) = 1.32, p = .252, partial eta^2 = .005, power = .208), but inspection of the descriptive data from Table 3 suggests that there may be an interaction which could not picked up due to low power. Descriptively, female advisors seem to stereotype more.

Standardized (T-Score) Approach

The ratings provided by the advisors were on a 1 to 10 scale whereas the SOFRT scores were on a scale of 0 to 100. In order to compare these "oranges and apples," both scores were converted to T-scores with a mean of 50 and a standard deviation of 10 (see Table 3). For each client, the T-score on his or her SOFRT was subtracted from his/her T-score on the advisor's rating. The mean difference was + 0.48 for male clients and –2.81 for female clients. In other words, the subjective rating was higher than the objective measure for males and vice-versa for females. This difference was submitted to both a t-test and a Mann-Whitney U test. A t-test may be biased when sample sizes are not equal and if variances are heterogeneous. The Levene test for homogeneity of variances did not reach statistical significance (F = 1.66, p = .198), but following Zimmerman's (2004) recommendation, a separate-variances t- test was nonetheless used instead of the pooled variance t-test because the male and female sample sizes were dramatically unequal. The difference in T-scores between males and females was significant on the basis of both the t-test (t (60.29) = 1.76, p =.039) and the Mann-Whitney U test (U=3820.00, Z = -1.943, p =.05), indicating that advisors tend to perceive male clients' risk tolerance level to be greater than it actually is, and perceive female clients' risk tolerance to be lower than it actually is, with the degree of error being greater for women clients relative to men clients.

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Is the Gender Stereotyping Due to Spurious Relationships?

A correlation between two variables does not imply that one is the cause of the other. Two variables may be closely correlated but neither one is the cause of the other because both are caused by a third, unexamined variable. To determine whether educational and economic factors could account for the apparent Gender-stereotyping, additional regression analyses were conducted. In these regressions, age, education, personal income, and wealth (in addition to the SOFRT score and Gender) were used to predict advisor ratings. Net wealth and personal income were correlated (r =.61), so in a stepwise multiple regression, only one of the two enters the prediction equation. Both income and wealth were found to explain additional variance in the advisor's risk tolerance ratings beyond what the SOFRT and client Gender explain, *but client Gender remained a significant predictor even when the other variables were entered into the mix.*

Next, an ANOVA was conducted in which the dependent variable was the residual (from the common regression predicting advisor rating from just the test score). The independent variables were client Gender and client income. Both Gender (F (1,249) = 9.59, p =.002, eta^2 =.04) and income (F (6,249) = 2.16, p = .047, eta^2 = .05) were significant, but the interaction was not (F (4,249) = .0.67, p = 616). The test for linearity was significant for all subjects combined (F (1,254) = 11.62, p = .001) and for males (F (1,217) = 6.51, p = .011). It appears that in addition to Gender, advisors stereotype by income/wealth. That is, they underestimate the risk tolerance of low-income clients and overestimate the risk tolerance of high-income clients. For example, the men in the lowest of the seven income categories were underestimated on average by 0.25 points on the 10-point rating scale, whereas the men in the highest income level were overestimated by 1.81 points. Most (86%) of the women clients were in the two lowest income brackets, so the only meaningful comparison is between these two brackets. The women in the lowest income bracket were underestimated by 1.22 points whereas their counterparts in the next bracket were underestimated by 0.74 points (but this was not a statistically significant difference).

Women scored significantly lower than men on the SOFFRT risk tolerance test, so another possibility is that irrespective of the client's Gender, advisors overestimate high risk tolerance and underestimate low risk tolerance. Consequently, the sample was divided into a high risk-tolerance subgroup and a low risk-tolerance subgroup on the basis of a median split (median = 43). For the purposes of this analysis, if the SOFRT score was 43 and below, it was considered low risk tolerance. Conversely, if the score was 44 and above, it was considered high. The residuals (from the simple common regression equation) were then compared for males and females in the high and low risk tolerance cohorts (see Table 5).

Insert Tables 5 about Here

Results showed that it is not the risk tolerance score but the Gender that matters. The ANOVA indicated that Gender was a significant factor (F (1,278) = 11.33, p = .001), but that low versus high-risk tolerance was not (F (1,278) =1.99, p =.160). The interaction term, while not significant, was borderline (F (1,278) = 3.10, p =.079). Inspection of Table 5 suggests that if an interaction does exist in the population, it is an ordinal interaction. In both the high and low risk tolerance groups, the women clients had negative residuals (they were under-predicted) while males had positive residuals (they were over-predicted).

Discussion

How accurate are advisors in gauging a client's risk tolerance through subjective clinical judgments? Overall, the correlation was .41. This moderate correlation between subjective clinical judgment and test score indicates that there is some degree of accuracy in the subjective clinical judgments made by advisors. The correlation of .41 between predicted and actual risk tolerance derived in this study is remarkably close to the correlation of .42 that Eckel and Grossman (2002) reported between the riskiness of actual and predicted bets made by their undergraduate subjects, but it is markedly superior to the .16 correlation that Eckel and Grossman observed in their unpublished study. (In the unpublished manuscript, Eckel and Grossman did not discuss the reasons for the difference between their two studies.) It is rather disappointing that the accuracy of professional advisors, who had some experience with their clients, was not any higher than that of undergraduates who only had visual clues (and perhaps some casual knowledge) of their targets as the basis for their estimates.

When the correlation between subjectively estimated and actual risk tolerance was examined separately within each gender, it was .34 for males and .54 for females. Thus, descriptively, there was more proportionality between the ratings and test scores for females relative to males, but the differences between the correlations failed to reach statistical significance and so they can't be generalized to the population. Had the difference been significant, it would have meant that the slope of the line predicting subjective clinical judgment from risk tolerance test score is steeper for females than for females. This in turn would indicate that for female clients, there is less randomness in the relationship between advisor's clinical judgment and their actual risk tolerance. However it must be remembered that a higher correlation does not preclude the existence of a systematic error in the clinical judgments due to differences in the Y intercept. Despite their greater predictability, women could still be systematically underestimated on risk tolerance.

Indeed, in the current study evidence was derived through several statistical techniques to show that systematic errors do occur when advisors judge the risk tolerance of their clients. It appears that financial advisors have a somewhat distorted sense of the risk tolerance of males and the risk aversion of females, with the latter being the greater error. The phrase in the title of this article – "Objects in the Mirror Are Closer than They Appear to Be" – refers to this cognitive bias exhibited by the financial advisors in this study. While there are actual differences in risk tolerance favoring men, as demonstrated here and in numerous other studies, the discrepancy between the genders is not as extreme as the financial advisors seem to implicitly believe (as reflected in their subjective clinical judgments). In reality the risk tolerances of women and men are closer than advisors believe when relying on mirrors (i.e., perception) of the world. In other words, advisors do tend to exaggerate the differences, which means that they are stereotyping. The good news is that the degree of their distortion is relatively minor.

Financial advisors need to take some concrete steps to avoid stereotyping. What can be done to prevent or alleviate this tendency to stereotype? Using a risk tolerance test is perhaps the best solution. Admittedly, given the real differences in risk tolerance between men and women, the gender of the client does carry some diagnostic value, especially if no other information about the person is available. However, any reasonable person has to admit that a risk tolerance test score is clearly more informative in establishing a given client's actual degree of risk tolerance than is the client's gender (see Grable & Lytton, 1998; Grable & Lytton, 1999). Thus, the results of this study point to the need for advisors to assess their clients' risk tolerance directly through reliable and valid means rather than by subjective clinical judgment, which is prone to gender stereotyping. The virtue of standardized testing of risk tolerance is that tests are not open to ambiguity and interpretation to the same extent as clinical judgments. Given the research by Locksley, Borgida, Brekke, and Hepburn (1980) that expectations based on stereotype do not influence judgments about a member of a stereotyped group once evidence of the individual's behavior is available, it is less likely that advisors will stereotype their recommendations once they have the more objective test data. So, with risk tolerance test scores to guide them, advisors should be less likely to err.

If for some reason, an advisor chooses not to use a valid test , at the very least he or she should be aware of the natural proclivity to exaggerate gender differences, especially since this bias may occur automatically and subconsciously (for a discussion of the automaticity issue see Dasgupta & Asgari, 2004; Devine, 1989; Devine, 2001). Besides the use of a risk tolerance test, there may be other techniques that may minimize or prevent stereotyping from creeping into the judgmental process. For example, a reduction in stereotyping may occur if one conjures a mental image that is a counter-stereotype (rather than a stereotype) when dealing with a member of a stereotyped group (Blair & Banaji, 1996; Blair, Ma, & Lenton, 2001), but the validity of this technique is open to question (Bargh, 1999), and such procedures are certainly more burdensome to deploy than a test.

The findings presented here are noteworthy in light of evolving regulatory investment industry guidelines. Advisors are obligated to “know their clients.” Clearly, more than subjective clinical judgments are called for by such requirements. Factors such as a client’s time horizon, investment preferences, expectations, and risk attitudes need to be properly assessed and documented. Results from this research suggest that commonly used judgments of risk tolerance based on a planner’s experience and intuition tend to be inadequate both in terms of their level of actual precision as well as because of their likelihood to be biased by stereotyping. Not only do the test results and subjective impressions not correlate strongly, but the heuristic that states that men are more risk tolerant than women seems to be over applied by advisors as they subjectively assess client’s attitudes. Nor is stereotyping limited to gender, given the finding that income and wealth also result in stereotypes of risk tolerance.

These observations have significant implications for investors and policy makers. Assuming that it is true that risk and return are positively related, in the aggregate, investors who take less risk are likely to accumulate fewer assets than others. In view of the actual lower risk tolerance of women, many authors have commented about the danger of recommending investments that will result in low rates of return. The operation of stereotyping in advisors judgments exacerbates this possibility. As Eckel and Grossman (2002) noted, the danger is that, “Using visual characteristics such as gender as a signal, an advisor might alter the range of options offered to a client to reflect the advisor’s perception of the client’s risk preferences” (p. 291). The findings reported here may help explain why women accumulate less wealth than men over time. It is probably mainly due to women’s lower risk tolerance, but perhaps advisors underestimate women’s true level of risk tolerance and invest in less risk securities than warranted.

Although there are dire consequences of under-estimating women’s risk tolerance, systematic stereotyping can result in unsuitable investments for both men and women. It may be one of the determinants of stock market bubbles. If advisors systematically overestimate the risk tolerance of men, who are the major investors, the types of investments chosen will likely be more risky than is appropriate. At some point the imbalance between risk tolerance and portfolio risk will snap, resulting in the liquidation of portfolios.

Limitations and Recommendations

This research with financial professionals supports findings presented by others, based on laypersons, that there is gender-stereotyping on risk tolerance (Eckel & Grossman, 2002; Eckel & Grossman, 2003; Martin, 1987; Siegrist, Cvetkovich, & Gutscher, 2002). As observed by Martin (1987), the results reported here indicate that males tend to be viewed as more risk tolerant than they actually are, while women are apt to be seen as more risk averse than is the case. In the literature, the evidence is mixed on whether each gender is a better judge of the risk tolerance of its own gender than of the opposite gender, and which of the two genders tends to stereotype more. Unfortunately, the current analysis could not answer that question definitively because there were relatively few female clients and an even smaller number of female advisors in the sample to permit for a powerful analysis of these interactions. (The low number of women advisors reflects an industry trend where less than 20% of all advisors are women [Tucker, 2002].) Given the small number of female financial advisors in the sample, no statistically significant differences in stereotyping by gender of advisor were anticipated unless the magnitude of the effect was very large (see Aguinis, 1995;Aguinis, Pierce, & Stone-Romero, 1994; Aguinis & Stone-Romero, 1997). Descriptively, the data do suggest that women advisors may be more prone stereotype than male advisors, which is consistent with research conducted by Holm (2004) and Siegrist et al., (2002) using students as subjects, but contrary to the findings reported by Eckel and Grossman (2002), who found males to stereotype to a greater extent. A worthy area of further exploration with a larger sample of female advisors and female clients is whether female advisors are indeed more likely to stereotype, as reported by some previous studies and hinted by the descriptive data reported in the present study.

Further research is also warranted on the possibility that an advisor’s perception of a client’s level of risk tolerance involves an interaction between client gender and client level of risk tolerance. Descriptively, data collected in this study suggest that advisors see greater risk tolerance differences between males and females at the low end of the risk tolerance continuum than at the high end and that they may be more accurate in pegging the risk tolerance of the clients at the high end of the risk tolerance continuum.

Two additional limitations inherent in this study should be accounted for in future research. First, it is not known what was the degree and quality of contact between advisor and client. Nor is there any information on the type of materials, statements, or heuristic tools used by advisors to formulate their judgments. In other words, it is unknown how advisors arrived at their impressions of client risk tolerance, other than to say that it was subjective and made quickly. There is a rich literature on what's been termed the "paramorphic representation of clinical judgment" whereby an attempt is made to represent the decision in terms of external variables, typically through the use of multiple regression (Dawes, 1971; Doherty & Brehmer, 1997; Hoffman, 1960; Nunes, 1999; Roszkowski, Spreat, & Isett, 1983) . This may be a fruitful avenue for further research for understanding financial advisors' judgments about clients' risk tolerance. Second, the results from this study were based on advisors working primarily in the insurance industry. It is possible that results could vary if other types of advisors were investigated.

In summary, this research confirmed a number of findings presented in earlier studies with different types of subjects and different methods for establishing the operation of gender stereotypes. Even accounting for the inherent limitations of the sample, the results reported here carry both theoretical and practical implications and establish the need for continued research on stereotyping in the financial services industry. The major implication is that the best way to curtail suitability problems is to require financial advisors to use reliable and valid measures of risk tolerance. Relying on subjective clinical judgments and heuristics, as data from this study suggest, can lead to erroneous conclusions.

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Table 1
Demographic Description of Advisors

	Male (*n* =176)	Female (*n* = 6)	All (*n* =183)
Age			
M	51.89	48.17	51.77
SD	8.89	6.85	8.84
Marital Status (%)			
Single	1.1%	16.7%	1.6%
Married	91.0%	50.0%	89.6%
Divorced	6.2%	33.3%	7.1%
Widowed	1.7%	0.0%	1.6%
Primary Practice			
Financial Planning	19.3%	33.3%	19.8%
Law	1.2%	66.7%	1.1%
Life/Health Insurance	67.8%	0.0%	67.8%
Securities	4.1%	0.0%	4.0%
Other	7.6%	0.0%	7.3%
Position			
Exclusive Multiline Agent	2.7%	0.0%	2.6%
Full-time Career Agent	37.8%	0.0%	36.8%
General Agent or Manager	7.4%	0.0%	7.2%
Personal-Producing Agent	15.5%	25.0%	15.8%
Supervisor or Assistant Manager	4.1%	0.0%	3.9%
Broker	12.2%	0.0%	11.8%
Brokerage Manager	5.4%	0.0%	5.3%
Home Office Employee	8.8%	0.0%	8.6%
Other	6.1%	75.0%	7.9%
Median Personal Income (in 2003 $)	$153,151	$113,041	$151,376
Median Family Income (in 2003 $)	$181,248	$130,406	$180,210
Median Wealth (in 2003 $)	$930,910	$654,653	$926,228

Table 2
Demographic Description of Clients

	Male (n =243)	Female (n =39)
Age		
M	49.66	49.38
SD	10.67	12.63
Marital Status		
Single	5.4%	10.5%
Married	90.5%	57.9%
Divorced	2.5%	7.9%
Widowed	1.7%	23.7%
Education		
Less than high school	1.2%	5.4%
High School	7.4%	16.2%
Some College	17.7%	24.3%
Bachelor's Degree	39.9%	32.4%
Master's Degree	16.5%	13.5%
Law Degree	4.5%	5.4%
Doctorate	12.8%	2.7%
Employment Status		
Private Sector	40.7%	37.8%
Government	3.7%	10.8%
Self-employed	44.8%	43.2%
Retired	10.8%	8.1%
Years with Same Employer		
M	15.22	14.54
SD	12.63	12.96
Median Personal Income	$99,500	$53,563
Median Family Income	$119,009	$79,083
Median Wealth	$305,080	$210,000
Median Personal Income (in 2003 $)	$130,406	$70,201
Median Family Income (in 2003 $)	$155,975	$103,647
Median Wealth (in 2003 $))	$399,843	$275,229

Table 3
Descriptive Statistics on Independent and Dependent Variables by Advisor and Client Gender

Client	Advisor	*n*	Subjective Rating		SOFRT Test		Rating in T-Score		Test in T-Score		Common Regression Residual	
			M	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*
Male	Male	236	5.63	1.84	43.93	11.03	51.11	9.58	50.55	9.89	+0.17	1.75
	Female	6	6.67	1.51	53.17	7.19	56.51	7.82	58.83	6.45	+0.55	1.44
	Total	242	5.65	1.84	44.16	11.04	51.24	9.57	50.76	9.89	+0.18	1.74
Female	Male	35	4.00	1.80	38.00	10.37	42.65	9.35	45.24	9.30	-1.04	1.52
	Female	4	2.75	0.96	33.25	5.38	36.16	4.98	40.98	4.82	-1.95	1.22
	Total	39	3.87	1.76	37.51	10.03	41.99	9.17	44.80	8.99	-1.13	1.50
Total	Male	271	5.42	1.91	43.17	11.11	50.02	9.95	49.87	9.96	+0.01	1.77
	Female	10	5.10	2.38	45.20	12.01	48.37	12.36	51.69	10.76	-0.45	1.82
	Total	281	5.41	1.93	43.24	11.13	49.96	10.02	49.93	9.97	0.00	1.77

Table 4
Hierarchical Multiple Regression Model Summary Predicting Advisor's Rating of Client's Risk Tolerance from SOFRT Test Scores, Client Gender, Advisor Gender, and Client Gender-Advisor Gender Interaction

Predictor Added	*R*	R^2	Adjusted R^2	SE of Estimate	Change Statistics			
					R^2 Change	*F* Change	*df*	*p* Change
SOFRT	.401	.161	.158	1.77	.161	53.51	1/279	.000
Client Gender	.469	.220	.214	1.71	.059	20.87	1/278	.000
Advisor Gender	.469	.220	.211	1.71	.000	0.02	1/277	.902
Client –Advisor Gender Interaction	.473	.224	.213	1.71	.004	1.60	1/276	.207

Table 5
Residuals as a Function of Level of Risk Tolerance and Gender

SOFRT	Gender	*n*	*M*	*SD*
Low Risk Tolerance	Male	119	+0.24	1.77
	Female	28	-1.42	1.25
	Total	147	-0.08	1.80
High Risk Tolerance	Male	124	+0.12	1.71
	Female	11	-.0.40	1.88
	Total	135	+0.08	1.73
Total	Male	243	+0.18	1.74
	Female	39	-1.13	1.50
	Total	282	0.00	1.76