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INVESTOR COMPETENCE, TRADING FREQUENCY, AND HOME BIAS

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ABSTRACT

People are more willing to bet on their own judgments when they feel skillful or knowledgeable (Heath and Tversky (1991)). We investigate whether this "competence effect" influences trading frequency and home bias. We find that investors who feel competent trade more often and have a more internationally diversified portfolio. We also find that male investors, and investors with higher income or more education, are more likely to perceive themselves as competent investors than are female investors, and investors with lower income or less education. Our results are unlikely to be explained by other hypotheses, such as overconfidence or information advantage. Finally, we separately establish a link between optimism towards the home market and international portfolio diversification.

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I. INTRODUCTION

Investor competence is a common thread that ties together two important puzzles in international and financial economics – the home bias problem (too little is invested outside of the home market) and the trading frequency problem (investors trade far too often). In a world where investors' subjective probability distributions are ambiguous, psychological factors such as perceived competence can play an important role in explaining investor behavior. Using survey data, we measure perceived competence and show that it is an economically important variable that helps explain these important puzzles.

A large literature in psychology has studied behavior when the probability distribution of the outcome of a lottery is ambiguous (Camerer and Weber (1992)). Ellsberg (1961) identifies the concept of ambiguity aversion, which occurs when people prefer to bet on lotteries with known probabilities of winning, rather than lotteries with ambiguous outcome distributions. Heath and Tversky (1991) identify a related concept, the competence effect, which posits that ambiguity aversion is affected by the subjective competence level of participants. When people feel skillful or knowledgeable in an area, they would rather bet on their own judgment (even though it is ambiguous) than on an equiprobable chance event (e.g., drawing balls from an urn with known contents), even though the outcome of the chance event has an unambiguous probability distribution. However, when participants do not feel competent, they prefer to bet on the unambiguous chance event. Therefore, the effects of ambiguity aversion are conditional on the subjective competence level of participants.

The competence effect is best illustrated using an example (from Heath and Tversky (1991)). In their experiment, a participant answers a set of knowledge questions concerning history, geography, or sports. For each question, the participant is asked to report his or her confidence in the answer, i.e., the subjective probability that his or her given answer is correct.

Finally the participant is presented with two choices, either to bet on his or her own answer, or to bet on a lottery in which the probability of winning is the same as the stated confidence. Heath and Tversky find that when people feel very knowledgeable about the subject matter (i.e., they feel 'competent'), they are more likely to bet on their own judgments rather than the matched-chance lottery. When people feel less knowledgeable, however, they tend to choose the matched-chance lottery.

The competence effect is particularly relevant to investor behavior. In financial markets, investors are constantly required to make decisions based on ambiguous, subjective probabilities. It is likely that their educational background and other demographic characteristics make some investors feel more competent than others in understanding the array of financial information and opportunities available to them. In the first part of this paper, we explore the relation between investor characteristics and self-rated competence. In most behavioral economics research, the underlying psychological bias is not observed directly, and therefore, these studies have to proxy for the bias. A well-known example is found in Barber and Odean (2001), where gender is used as a proxy for degree of overconfidence. Ours is among the few behavioral finance papers that directly measure the underlying psychological bias. Using data from several UBS/Gallup Investor Surveys, we measure investor competence through survey responses. This allows us to empirically model competence as determined by a set of investor characteristics, e.g., gender, education, and income. We find that male investors, and investors with higher income and more education, are more likely to believe they are competent than are female investors, and those with less income and education.

We also study the link between competence and investor behavior. Most empirical behavioral economics research studies one psychological bias to explain one type of investor behavior. While these studies provide important insights, they do not directly compare which biases are relatively more important in affecting investor behavior. Furthermore, if a psychological bias is deeply ingrained, it should affect multiple aspects of investor decision-making. Our paper takes a first step towards addressing these issues. We study two types of investor behavior, namely trading frequency and home bias. Although there exist extensive literatures on both trading frequency and home bias, these two phenomena have always been treated separately. In this paper, we argue that these two aspects of behavior are driven (at least in part) by the same underlying psychological bias, namely, the competence effect.[1]

With regard to trading frequency, we hypothesize that investors who feel more competent tend to trade more frequently than investors who feel less competent. This occurs because investors who feel more knowledgeable in making financial decisions should be more willing to act on their judgments (Heath and Tversky (1991)). Our empirical results are consistent with this hypothesis.

We argue that the competence effect also contributes to home bias. Home bias refers to the tendency to overweight domestic equities and underweight international equities in investment portfolios (see, e.g., French and Poterba (1991)). When an investor feels competent about understanding the benefits and risks involved in investing in foreign assets, he is more willing to invest in foreign securities. In contrast, when an investor feels less competent, he is more likely to avoid foreign assets. Consistent with these predictions, our results suggest that investors with more competence are more likely to invest in international assets.

We are careful to investigate alternative behavioral mechanisms that could account for similar effects. Our results suggest that overconfidence, while correlated with competence, does not subsume the competence effect. We also investigate a measure of optimism in the context of the home bias problem. We provide what we believe is the first evidence of a direct link between

[1]Kumar and Lim (2004) argue that one psychological bias, narrow framing, is responsible for two biases, namely the disposition effect and underdiversified portfolios.

optimism towards the domestic market and home bias. While the optimism factor is important, the evidence on the importance of competence is robust to including optimism in the model.

The rest of the paper is organized as follows. Section II reviews related literature and develops our hypotheses in more detail. Section III discusses the data. Section IV presents the empirical analysis. Some concluding remarks are offered in the final section.

II. Theory and Hypotheses

II.A. Ambiguity Aversion and the Competence Effect

The classic example of ambiguity aversion is found in Ellsberg (1961). Consider two urns, one containing 50 red balls and 50 black balls, and the other containing 100 balls in unknown combination of red and black. A participant can choose to draw one ball from either urn, and guess its color. The participant receives a positive payoff if and only if he guesses correctly. Ellsberg finds that people would rather bet on the first urn (the known probability event) than on the second urn (the ambiguous event).

In the Ellsberg setting, participants are asked to choose between two chance events, with no subjectivity involved. In financial markets, however, investors make decisions based on subjective probabilities. For example, an investor might need to determine the probability of IBM's stock price decreasing by at least $1 if the Fed raises short-term interest rates by 25 basis points. Does ambiguity aversion hold under subjective probabilities? According to Heath and Tversky (1991), the answer to this question depends on the investor's subjective competence level. When people feel skillful or knowledgeable, they prefer to bet on their own judgment (an ambiguous event) versus betting on an equiprobable chance event (a known probability event). In contrast, when they do not feel skillful or knowledgeable, they prefer the chance event.[2]

The competence effect can be illustrated with an experiment. Participants first report their subjective knowledge level about the game of football. Next, they are asked to predict the winner of a football game and also report their subjective probabilities of the predictions being correct. Then they are asked to choose between two bets, either to bet on their own judgment, or a lottery that provides an equal chance of winning. In this example, subjective competence is captured in two dimensions: the self-rated knowledge level, and the subjective probability of the football prediction being correct. The results of this experiment are shown in Figure I (adapted from Heath and Tversky (1991)). The percentage of participants choosing to bet on their own judgments increases with both measures of subjective competence. When subjects feel that they are highly competent in predicting the results of football games, they prefer to bet on their own judgment. In fact, even when presented with a lottery with a greater chance of winning, they would still prefer to bet on their football predictions. In other words, they are willing to pay a premium to bet on their own judgments. When people do not feel competent, however, they prefer the matched chance lotteries.

In the long-established economic tradition of expected utility theory, only the probability distribution of the payoff matters; the confidence that the agent has over the distribution is irrelevant. In other words, preferences and probability distributions are assumed to be independent of each other. The psychology literature cited above offers evidence to the contrary. People are more willing to act on their judgments when they feel more competent in the area. In other words, beliefs and preferences are not independent, they are entangled.[3]

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[2]Fox and Tversky (1995) and Fox and Weber (2002) provide further evidence that subjective feeling of competence plays a role in the willingness to act on one's own judgment.
[3]See review papers by see Shoemaker (1982), Camerer (1995), and Starmer (2000) for summaries of other challenges to expected utility theory and new types of preferences that have been

In financial markets, not all investors feel equally competent in making investment decisions. In general, an investor with a high school education and annual income of less than $25,000 may feel less competent as an investor relative to a highly-educated investor with a much higher income. It is worthwhile emphasizing that competence is a self-perceived skill or knowledge, not necessarily the investor's true level of skill or information. For example, an advanced degree in any subject might make a person feel smart and insightful, and such a person might therefore feel competent towards many things in general, including making financial decisions.

There is an avenue for overconfidence to affect investment decisions within the framework of competence theory (in addition to overconfidence potentially having an independent effect). Within the context of the football betting example mentioned above, consider a bettor whose empirical success in picking winners is 70 percent. If the bettor is not overconfident, he would correctly perceive himself to be accurate 70 percent of the time. The competence effect states that the bettor would prefer to bet on his football picks versus being rewarded for selecting a red ball from an urn with 70 red balls out of a total of 100 balls. Overconfidence can distort an investor's subjective probabilities, which accentuates the competence effect. For example, overconfidence might inflate the investor's subjective probability that he will pick a winner from 70 percent to 80 percent.[4] In this case, the overconfident bettor would prefer to a greater degree to bet on his football picks versus picking from an urn with 70 red balls. In fact, the bettor would prefer his picks relative to being rewarded for selecting a red ball from an urn with 80 red balls.

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proposed in light of these challenges. In a recent paper, Polkovnichenko (2005) uses new preferences to explain household portfolio allocations.

[4]In the psychology literature, overconfidence can mean either believing that the distribution of your knowledge is tighter than it actually is or, believing that your mean skill is higher than it actually is. In the text, we use the term overconfidence in a general sense, though the meaning should be clear by the context of the surrounding text. As explained in the next footnote, when we explicitly refer to distributions that are too tight, we use the term miscalibration.

In the empirical analysis that follows, we test for the effects of overconfidence that flow through the competence channel, and also test for a separate overconfidence effect.

As described next, we argue that the level of competence an investor feels in making financial decisions changes his willingness to act on his judgments, and therefore is an important determinant of investor choices. We focus on two well-documented investment anomalies: too frequent trading and home bias.

II.B. Competence and Trading Frequency

Odean (1999) and Barber and Odean (2000, 2002) argue that investors tend to trade too often. In addition, the evidence suggests that single, young, male investors trade the most frequently (Barber and Odean (2001)). This high trading activity is usually attributed to the psychological bias of investor overconfidence. In the finance literature, overconfidence is usually defined as overestimating the precision of information about the value of a financial security (Odean (1998), Gervais and Odean (2001)). This 'miscalibration' leads to intensified differences of opinion among investors, which in turn causes trading (Varian (1989), Harris and Raviv (1993)).[5]

The empirical link between overconfidence and trading frequency has been studied extensively in recent research. Existing studies disagree on how overconfidence is defined and measured. Deaves, Luedes and Luo (2004) perform an asset market experiment, and find that overconfidence, measured as miscalibation, leads to higher trading frequency. However, in their experiment, these authors do not find a correlation between gender and degree of miscalibration. Combining survey responses and trading records of German retail brokerage investors, Dorn and

[5]In the psychology literature, miscalibration can mean either 'expected probability not equal to realized relative frequency' or 'believing that the precision of probability distribution is tighter than it really is.' In our paper, miscalibration refers to the distribution for subjective probabilities being tighter than the true probability distribution.

Huberman (2003) show that there is no relation between trading frequency and their measure of overconfidence, i.e., an investor's 'illusion of knowledge,' measured as the discrepancy between the investor's self-assessed knowledge and his or her true knowledge about investments. Glaser and Weber (2005) argue that there are three aspects of overconfidence, namely miscalibration, the 'better-than-average' effect (i.e., people tend to think that they have higher than average skills), and illusion-of-control (i.e., the tendency to believe that one's personal probability of success is higher than an objective probability would warrant). Using data from 215 online investors, they find that, contrary to the predictions of Odean (1998) and Gervais and Odean (2001), miscalibation does not lead to high trading frequency. However, the better-than-average effect is associated with more frequent trading. Glaser and Weber conjecture that an investor who believes himself to be better than average is more likely to invest according to his opinion about the future performance of a stock, even though he knows that other market participants disagree with him. This contributes to differences of opinion about a stock, which leads to trading.

The competence effect is distinct from overconfidence. In the overconfidence framework, the traditional paradigm of maximizing expected utility still holds. Overconfidence increases trading frequency by increasing the heterogeneity of investor beliefs. We argue that high competence leads to high trading frequency, through a different mechanism. Investors are more willing to bet on their judgments when they feel more skillful or knowledgeable. In other words, they are more likely to act on their beliefs, and trade securities, when they feel more competent, and vice versa. Therefore, we hypothesize that when investors feel more competent, they tend to trade more frequently. This 'willingness to act' aspect is absent in the overconfidence framework.

II.C. Competence and Home Bias

We now turn to the link between competence and an investor's portfolio allocation to foreign assets. The home bias literature shows that investors tend to allocate too much of their overall portfolio to domestic equities and too little to international equities (French and Poterba (1991), Lewis (1999)). Others have documented 'home bias at home.' Coval and Moskowitz (1999) find that U.S. fund managers exhibit a strong preference for firms with local headquarters. Huberman (2001) reports the geographical bias of regional Bell shareholders, i.e., a larger proportion of the shareholders of a regional Bell operating company tend to live in its service area than would be expected. Benartzi (2001) and Huberman and Sengmuller (2004) document that employees tend to invest a large proportion of the assets of their retirement plans in their own company's stock. Home bias at home has also been reported among Finnish (Grinblatt and Keloharju (2001)), Swedish (Massa and Simonov (2005)), and Chinese (Feng and Seasholes (2004)) investors.

What causes home bias? One explanation is information costs.[6] Investing in foreign equity markets may require understanding foreign accounting standards and legal environments. Coval and Moskowitz (2001) find that fund managers earn an extra 2.7 percent per year from their local investments compared to non-local investments. Therefore, they argue that a regional information advantage leads to 'home bias at home.' Vissing-Jørgensen (2004) finds that high wealth households are more likely to invest in foreign assets than are low wealth households. She argues that this is consistent with high wealth households paying the information cost associated with investing in foreign assets. However, several studies present evidence that cannot be

[6]Other potential explanations for home bias include a) domestic equities provide better hedges for domestic risks; b) high cost of investing in foreign equities, e.g., international taxes, government capital restrictions, etc.; and c) prevalence of closely held firms in most countries causing the world float portfolio to be significantly different from world market portfolio. Further, Demarzo et. al. (2004) argue that frictions in goods markets cause investors in a local community to hold similar, under-diversified portfolios. Most empirical studies suggest that these effects are either too small to account for the degree of home bias observed in the data, or actually increase the degree of the bias (Cooper and Kaplanis (1994), Baxter and Jermann (1997), Tesar and Werner (1995), and Dahlquist et al. (2003)). See Lewis (1999) for a review.

explained by the information cost argument.[7] Benartzi (2001) and Huberman (2001) find that investors who demonstrate local bias do not experience superior returns, nor do they tend to trade more frequently. These results are not easily explained by an information advantage story. The behavioral finance literature offers an alternative explanation, namely, people tend to be more optimistic towards home markets than towards international markets (Kilka and Weber (2000), Strong and Xu (2003)).

In this paper, we argue that investor competence plays a role in explaining home bias. When an investor feels that he fully understands the benefits and risks involved in investing in foreign assets, he is more willing to take action to invest in foreign assets. On the other hand, when an investor feels incompetent, he is likely to refrain from taking action, thus leading to underinvestment in foreign assets. The same argument could be extended to home bias at home.

Heath and Tversky's analysis has often been used as evidence of a familiarity effect (Huberman (2001)). Investors who are primarily familiar with their home country (versus being familiar with foreign countries) will have a tendency to invest primarily in home country stocks. But familiarity is not the whole story. Heath and Tversky (1991) emphasize that competence is more than familiarity. The competence effect also evokes the feeling that an individual is good at investing in general, and in foreign stocks in particular. A U.S. investor can be unfamiliar with foreign languages and cultures but if he feels competent in his investing skills, he might be willing to allocate part of his portfolio to foreign markets.

One might be concerned that an investor's self-rated competence is correlated with the level of information that the investor has. Thus, even if we do find foreign allocation to be increasing in investor competence, this could indicate an information advantage. To address this concern, in section IV.B, we show that investor competence is not positively associated with an

[7]Using ownership data of individual Swedish firms, Dahlquist and Robertsson (2001) argue that foreign investors' apparent preference for stocks with less information asymmetry is actually due to these investors being mainly institutional investors, not due to information costs.

investor's past returns. Therefore, in our sample, it is does not appear that investor competence is positively associated with the investor's level of information.

III. DATA SOURCES AND MEASURING COMPETENCE

We use data from the UBS/Gallup Investor Survey. Each month, UBS/Gallup conducts telephone interviews with approximately 1,000 randomly selected investors. The only criterion for an investor to be included in the survey is that household total investment be more than $10,000. The UBS data represent a general investor pool, and this is important because a particular class of investors might exhibit certain characteristics that distinguish them from the general population. For example, Odean (1999) and Barber and Odean's (2000, 2001, 2002) evidence of excessive trading is obtained from one particular subset of investors – investors who hold accounts with one discount brokerage firm. Using data from a single 401(k) plan, Agnew et al. (2003) find that the average number of transactions per year is 0.26, less than one fifth of that reported in Odean (1999); and the annual asset turnover is 16 percent, less than one fourth of the turnover reported in Barber and Odean (2000). The large discrepancies between these findings likely emanate from differences in behavior among different classes of investors. It is also possible that one investor may have multiple investment accounts, and manage these accounts differently due to institutional reasons, which might not be detected when studying one type of account. Using the UBS/Gallup data, we avoid this issue by studying decisions pertaining to an investor's aggregate investment portfolio.

While the UBS data have the advantage of covering a wide range of investor classes and account types, there are disadvantages to using survey data. One can not be sure that respondents understand all the questions, nor that they answer truthfully. There can also be issues related to non-response bias (i.e., whether the respondent's answers are representative of the views of the general population). Also, the UBS data do not have detailed portfolio breakdowns at the individual stock level, and for the most part we do not know respondents' actual investment performance. As reported below, when there is overlap, we are able to replicate the existing results in the literature. This gives us confidence that data deficiencies do not skew our results.

The survey questions that are of particular interest to us are listed in Table I. In the June 1999 and April 2000 surveys, respondents are asked to report their trading frequencies. The responses are coded in six categories, ranging from 'at least once a day' to 'less than once a year.' In the March 2002, June 2002 and September 2002 surveys, participants are asked to report the percentages of their portfolios currently invested in assets of foreign countries or foreign currencies.

Table II reports the characteristics of the investors surveyed by UBS/Gallup. The investors are on average 49 years old, with median annual income of $67,500. These numbers are comparable to that of Barber and Odean (2001), whose sample of investors are on average 50 years old, with median annual income of $75,000. The investors in our sample are well educated: 60 percent have finished college, and 26 percent have post-graduate education.

To measure investor competence, we use data from the November 1996 survey. In this survey, investors are asked the following question: 'How comfortable do you feel about your ability to understand investment products, alternatives and opportunities?' The responses range from 1 (very uncomfortable) to 5 (very comfortable). For the November 1996 survey, the average self-rated competence is 3.7.

To perform our empirical analysis, we need simultaneous measures of investor competence and either trading frequency or the degree of home bias. The survey question related to competence only appears in November 1996, which does not coincide with the appearance of either the trading frequency or the home bias questions. Therefore, we construct an empirical model for investor competence. In our analysis below, we use the estimated coefficients from this model to construct predicted competence for each investor on any given survey, including those surveys that contain the trading frequency and home bias questions.

We start by investigating the determinants of investor competence using the November 1996 data. We model competence as a function of investor characteristics such as gender, education, age and income. Using an ordered logit regression, our proposed model includes three of these characteristics: gender, education, and income. Age is dropped from the specification because it does not load significantly. As specification tests, we perform the Pearson and deviance goodness-of-fit tests. The Pearson goodness-of-fit test yields p-value of 0.29, while the deviance goodness-of-fit test has p-value of 0.18. Both of these tests fail to provide evidence against the specification.

Recall that competence is defined as the subjective skill or knowledge level in a certain area (Heath and Tversky (1991)). In our setting, investor competence is an investor's perceived financial skill or knowledge. We posited in section II.A that higher education and income make a person feel competent, which might lead to higher perceived competence in all domains, including financial decisions. As shown in Table III, the estimated coefficients indicate that investor competence increases in education. For example, consider an average investor in our sample, a male investor with annual income of $72,640. If his education level were to increase from college to post-graduate, the predicted competence for this investor would increase from 4.00 to 4.11. Also consistent with our previous conjecture, investor competence increases with income. For the typical male, college-educated investor in our sample, if his income were to increase by one standard deviation from $72,640 to $97,835, the expected investor's competence would increase from 4.00 to 4.07.

Table III also shows that male investors are more likely to feel competent than female investors. Comparing a college educated female investor, with annual income of $72,640, to a male investor with the same demographics, the gender differential accounts for an increase of

0.39 in predicted investor competence, from 3.61 to 4.00. Notice that in previous studies, gender has been used as a proxy for overconfidence (Barber and Odean (2001)). These authors argue that male investors are more overconfident than are female investors. If being male indeed proxies for overconfidence, at least part of the increase in competence from 3.61 to 4.00 reflects the effect of overconfidence on competence that we described at the end of Section II.A. As described below, we also include gender as a stand-alone variable in some of the analysis that follows, to separately identify any effect of overconfidence that occurs outside of the competence channel. Finally, to investigate whether our competence variable is in fact distinct from overconfidence, we examine the correlation between competence and gender, which is a dummy variable, set to 1 if the investor is male, and 0 otherwise. The correlation between competence and gender is only 0.21 in the November 1996 data, indicating that our competence measure has unique variation, distinct from overconfidence (as proxied by male gender). We examine overconfidence more below.

IV. Empirical Analysis of the Effects of Competence on Investor Behavior

IV.A. Investor Competence and Trading Frequency

Using our model of competence, we now investigate the relation between competence and trading frequency. Barber and Odean (2001) find that young, male investors tend to trade more frequently than older, female investors. Using Survey of Consumer Finance data, Vissing-Jørgensen (2004) finds that wealthier households tend to trade more frequently. Therefore, we control for gender, age, and income when studying trading frequency. We use income to proxy for wealth because our data do not have a direct measure of wealth.

Table IV reports univariate relations between trading frequency, investor competence, and other characteristics. Recall that in Section II.B, we hypothesized that higher perceived competence increases an investor's propensity to act on his beliefs, and therefore competence should be positively associated with trading frequency. The results in Table IV are consistent with this hypothesis. We observe a significant shift in the distribution of trading frequency as investor competence changes. When competence is less than or equal to 4.0, 27.5 percent of investors trade at least once a month. When competence is greater than 4.0, 44.8 percent of investors trade at least once a month. Overall, the average number of days between trading for all investors is 93.7 days. For those investors with competence less than or equal to 4.0, the average number of days between trading is 109.3 days. In contrast, for those investors with competence greater than 4.0, the average number of days between trading is only 67.9 days. This large difference in days between trading is both economically and statistically significant and is consistent with more competent investors trading more frequently.

Given that we use survey data while many existing studies use actual trading data, it is important to determine whether our sample produces results similar to those in the extant literature. The results in Table IV indicate that young, male investors and investors with higher income tend to trade more frequently than older, female investors and investors with lower income. (These findings are confirmed in a multivariate setting in column 2 of Table V.) These results are consistent with the findings of Barber and Odean (2001) and Vissing-Jørgensen (2004). Therefore, we find no evidence that the source of our data (i.e., a survey) is distorting our results.

So far, we have presented univariate analysis. In Table V, we perform ordered logit regressions to explore the relative importance of each variable in explaining trading frequency. We code the six categories of trading frequency as follows: category = 1 if trading frequency is 'less than once a year'; 2 if 'at least once a year, but not more than once a quarter'; 3 if 'at least once a quarter, but not more than once a month'; 4 if 'at least once a month, but not more than once a week'; 5 if 'at least once a week, but not more than once a day'; 6 if 'at least once a day.'

The regression results in the first column of Table V suggest that the effect of competence on trading frequency is positive and highly significant.

The positive coefficient estimate indicates that trading frequency increases with investor competence. The effect of competence is very large in magnitude. When investor competence increases by one standard deviation, from its mean level of 3.75 to 4.07,[8] the probability of an investor trading more than once per week increases from 9.6 percent to 15.5 percent. While this increase in trading frequency is large, it is consistent with the magnitude of other implications from the data. Recall that holding income and education constant at the population averages, male investor competence minus female investor competence equals 0.39. From Table IV, we know that this 0.39 increase in competence leads to an increase in the proportion of investors who trade at least once per week from 8.5 percent (for female investors) to 13.4 percent (for male investors). Thus, the gender effect is on par with the one standard deviation competence effect described above.

Next we introduce investor demographics as control variables: gender, education, age and income. Recall that investor competence is estimated using gender, education, and income; therefore, competence is highly correlated with these characteristics. To address the issue of multicollinearity, we orthogonalize the characteristic variables as follows. First, we estimate a logit regression using Male as the response variable, and investor competence as the explanatory variable. A new variable, MaleX, is computed as the residual of this regression. MaleX represents the variation in Male that is not captured by investor competence. The same procedure is repeated several times to produce orthogonalized versions of the College, Post-Graduate, and Income variables.

[8] Mean competence is 3.68 in November 1996 survey, in which competence is measured by investors' actual responses to a survey question. For the two subsets of sample with sufficient demographic information to perform the regressions in Table V and Table VIII, investor competence is calculated using the model presented in Table III. For these two sub-samples, mean competence is 3.75, and standard deviation is 0.32.

In column 3 of Table V, we regress trading frequency on competence and the orthogonalized demographic variables. In this specification, the competence variable captures the effects of gender, education, and income on trading frequency that occur *via the competence channel*. The orthogonalized 'X' variables capture the effects of gender, education, and income that are independent of the competence channel.

In column 3, the coefficient for investor competence is positive and highly significant. The estimated coefficient is 1.525, which is very similar to 1.697, the coefficient estimate in column 1, where investor competence is the only explanatory variable.[9] Interestingly, the coefficient for MaleX is not significant. In other words, investor competence captures most of the variation in Male that is associated with trading frequency. Barber and Odean (2001) argue that male investors tend to trade more frequently than female investors because male investors are more overconfident. Our results offer an alternative perspective: more frequent trading by male investors could be driven by investor competence. Neither of the coefficients for CollegeX or Post-GraduateX is statistically significant, which suggests that investor competence also captures the effect of education on trading frequency. In other words, it is possible that education leads to feelings of competence, which in turn lead to an increase in trading frequency – but we find no evidence of an independent education effect. The coefficient estimate for IncomeX is 0.013 and is statistically significant. This implies that only part of the effect of income on trading frequency is due to its effect on investor competence.

There exists a large and influential literature in financial economics that studies the effect of overconfidence on trading frequency. For example, as discussed above, Barber and Odean (2001) argue that male investors tend to be more overconfident than female investors, leading male investors to trade more frequently than female investors. More recently, Glaser and Weber

[9] Notice that the "X" variables are residuals from logit regressions. They are not linear functions of Competence. Therefore, as is evident in Table V, column 3, adding the "X" variables as explanatory variables can change the estimated Competence coefficient.

(2005) report that the 'better-than-average' aspect of overconfidence is associated with higher trading frequency. In Table V, we show that more frequent trading by male investors could be driven by investor competence, rather than an independent overconfidence effect. Gender, however, does not perfectly proxy for overconfidence, so our efforts thus far may not have completely disentangled the two effects. In the analysis below, we further investigate how our results hold up when we control for other measures of overconfidence.

In the first three columns of Table VI, we attempt to control for the 'better-than-average' aspect of overconfidence in the multivariate analysis. Here the 'better-than-average' effect, called 'Overconfidence' in the regressions, is measured by an investor's forecast of his own portfolio return over the next twelve months minus his forecast of the stock market return over the next twelve months. As shown in Table II, on average, an investor forecasts his own portfolio return to be 3.2 percent higher than the market return over the next twelve months. For the June 1999 and April 2000 surveys, the correlation between this measure of overconfidence and investor gender (equal to 1 if the investor is male, 0 if female) is 0.08, which is statistically significant at 0.05 level. The correlation between constructed competence and overconfidence for the June 1999 and April 2000 surveys is only 0.04, which is not statistically significant. Therefore, this measure of overconfidence is consistent with other finance research that documents a male overconfidence effect, while at the same time it is statistically distinct from the competence effect that we focus on in this paper. As shown in Table VI, column 1, after controlling for 'better than average' overconfidence, the effect of competence remains highly statistically significant. The magnitude of the coefficient decreases only slightly, relative to the univariate regression coefficient reported in Table V, column 1. Better than average overconfidence is positively and significantly related to trading frequency in column 1.

So far, we have considered two proxies for overconfidence and have shown that investor competence is a significant determinant of trading frequency, controlling for these proxies of overconfidence. Besides using direct proxies for overconfidence, we now consider an indirect approach, which deals with another aspect of overconfidence. Recall that we define investor competence as the self-perceived ability to understand investment opportunities. One could think of overconfidence as the difference between self-perceived investment ability and an investor's true ability: Overconfidence = Competence – True Ability. Therefore, if competence drives trading frequency, we have the ordered logit regression model:

$$\log\left(\frac{\Pr(\text{TradingFrequency}_i \leq j)}{\Pr(\text{TradingFrequency}_i \rangle j)}\right) = \alpha_j + \beta * \text{Competence}_i + \varepsilon_i$$

In the UBS surveys, investors are asked to forecast the stock market return over the next twelve months. We use these forecasts as a measure of "true ability". Define ForecastError as the absolute value of the forecasted minus the realized return over the next twelve months. If overconfidence drives trading frequency, and assuming an investor's true ability is measured as (δ_0 + δ_1*ForecastError), i.e., the smaller the forecast error, the higher the true ability, then the regression model should be:

$$\log\left(\frac{\Pr(\text{TradingFrequency}_i \leq j)}{\Pr(\text{TradingFrequency}_i \rangle j)}\right) = \alpha_j + \gamma * \text{Overconfidence}_i + \varepsilon_i$$

$$= \alpha_j + \gamma * (\text{Competence}_i - (\delta_0 + \delta_1 * \text{ForecastError}_i)) + \varepsilon_i$$

$$= \alpha_j - \gamma * \delta_0 + \gamma * \text{Competence}_i - \gamma * \delta_1 * \text{ForecastError}_i + \varepsilon_i$$

Therefore, if competence and forecast error are both included as explanatory variables for trading frequency, the competence story would predict that only the coefficient estimate for investor competence is statistically significant, while the coefficient estimate for forecast error should be statistically indistinguishable from zero. In contrast, the overconfidence story would predict the coefficient estimate for forecast error to be different from zero. These predictions are tested in columns 4 and 5 of Table VI. Since we use data from two surveys conducted at different times, i.e., June 1999 and April 2000, forecast errors are de-meaned by survey to avoid the influence of general market conditions at the time of the survey. In both columns, the coefficient estimate for forecast error is small in magnitude and statistically insignificant, while the coefficient estimate for investor competence remains positive and highly statistically significant. These results are consistent with the prediction of the competence story and inconsistent with the prediction of the overconfidence explanation.

The results in Tables IV, V, and VI are consistent with our first hypothesis: trading frequency increases with investor competence. Now we turn to our second hypothesis: higher investor competence leads to less home bias.

IV.B. Investor Competence and Home Bias

In the March 2002, June 2002, and September 2002 surveys, investors report their foreign asset holdings (see Table I). We use these data to investigate the relation between investor competence and home bias.

Vissing-Jørgensen (2004) reports that wealthier households tend to hold more foreign assets. Therefore, we control for income (our closest proxy to wealth) when we model home bias. Kilka and Weber (2000) find that people are more optimistic towards their home markets than they are about international markets. Strong and Xu (2003) simultaneously survey fund managers around the world and find a strong tendency for managers to be more optimistic about their home country market than about the rest of the world. The authors of both of these papers suggest that home bias is driven by this optimism. Therefore, when studying the relation between investor competence and home bias, we attempt to control for investor optimism towards the U.S. market.

In February 2002, May 2002, August 2002 and November 2002, investors respond to the following question: ‘Focus on the financial markets in four areas of the world and rank order them by how optimistic you feel about them. The financial markets are: in the United States, in Europe, in Japan, in countries often referred to as the emerging markets.' We define a dummy variable, OptimismUS, equal to 1 if an investor is the most optimistic towards the U.S. markets, and zero otherwise. Overall, 72 percent of investors are more optimistic towards the U.S. market than towards financial markets in other regions of the world.

Since the optimism question is not asked in March 2002, June 2002, or September 2002 (the surveys that address foreign investing/home bias), we do not have a direct measure for OptimismUS for these surveys. Therefore, we construct an empirical model of optimism towards the U.S. market in the same manner as we did for investor competence. We start by investigating the determinants of investor optimism towards the U.S. market using data from the February 2002, May 2002, August 2002 and November 2002 surveys. We regress OptimismUS on investor characteristics, like gender, education, age and income. Then for all other surveys, we construct predicted optimism towards the U.S. market for each investor, using his individual characteristics and the coefficients obtained from the regression above. The mean fitted OptimismUS is 0.72. The correlation between fitted OptimsmUS and fitted investor competence is 0.27.

One might think that an investor's optimism towards the U.S. market is affected by current performance of the U.S. market, as well as investor demographics. To address this possibility, we repeat the analysis allowing OptimismUS to be a function of both investor characteristics and performance of the U.S. market, e.g., the concurrent return of S&P500 index, or University of Michigan's consumer sentiment index. The results are very similar to those reported below.

Table VII reports univariate relations between home bias and investor competence, optimism towards the U.S. market, gender, education, age, and income. There is significant home bias in our sample. Overall, 36.3 percent of all investors hold foreign assets. The remaining 63.7 percent of investors do not own any foreign assets. For those investors with competence less than or equal to 4.0, only 31.9 percent hold foreign assets. In comparison, when investor competence is greater than 4.0, 47.0 percent invest in foreign assets. This increase is highly significant, both economically and statistically. This evidence is consistent with our hypothesis that investor competence mitigates home bias.

The results in the table also permit the analysis of optimism towards the U.S. market. If home bias is caused by optimism towards the home market, then higher OptimismUS should be associated with less foreign holdings. Indeed, when fitted OptimismUS is less than its average value of 0.72, 38.4 percent of investors choose to hold foreign assets. However, when OptimismUS is greater than 0.72, only 34.5 percent of investors choose to invest in international markets. The difference is statistically significant at the 0.05 level. Although not a main focus of our study, this observed relation between home bias and OptimismUS is important. Existing papers like Kilka and Weber (2000) and Strong and Xu (2003) focus on optimism only; they do not study portfolio allocation. Therefore, these papers do not establish a direct link between optimism towards the home market and actual portfolio allocation. Our study links home market optimism with foreign asset holdings.

Multivariate logit regression results are reported in Table VIII. The response variable is a dummy variable, set to 1 if an investor holds foreign assets. The first column of Table VIII shows that investors with higher competence are more likely to hold foreign assets, and investors with higher optimism towards the U.S. market are less likely to hold foreign assets. The coefficients for both investor competence and OptimismUS have the predicted signs and are significant at the 0.01 level. Importantly, the magnitude and significance of the competence variable is robust to the inclusion of the optimism variable.

As discussed in Lewis (1999), most of the existing rational models fail to generate effects large enough to account for the magnitude of home bias observed in the data. Therefore, it is important to analyze the economic significance of investor competence. It turns out that the effect of competence is economically very large. Holding OptimismUS constant at its mean of 0.72, when investor competence increases by one standard deviation from 3.75 to 4.07, the likelihood of an investor holding foreign assets increases from 36.6 percent to 47.1 percent. Holding OptimismUS at its mean of 0.72, if investor competence increases to its maximum of 5, the probability that an investor holds foreign assets increases to 75.9 percent. Therefore, our estimated effects of investor competence on home bias are economically large.

We next investigate whether the positive association between fitted investor competence and foreign asset holdings is due to the positive association between competence and education. It is possible that investors with better education are more likely to learn the benefits of international diversification, and therefore are more likely to hold foreign assets. To address this concern, we study whether the effects of investor competence and OptimismUS remain when we control for other investor characteristics, like gender, education, age and income.

Similar to the trading frequency analysis, because fitted competence and fitted OptimismUS are estimated using investor's gender, education, age, and income information, these variables are correlated with each other. We repeat the orthogonalization process described in Section IV.A. For example, we regress Male on Competence and OptimismUS. The residuals of this regression, called MaleX, represent the variation in Male that is not captured by Competence and OptimismUS.

The fourth column of Table VIII reports the effect of Competence on home bias, with OptimismUS and the orthogonalized investor characteristics as control variables. The estimated coefficient of the Competence variable is highly significant and has the predicted sign. These results are consistent with our hypothesis that investors who feel more competent are more likely to participate in foreign markets. Interestingly, in Column 4, after the orthogonalization, none of the investor characteristic variables are statistically significant. This result suggests that these investor characteristics affect home bias via the competence and/or optimism channels. In particular, both CollegeX and PostGraduateX have statistically insignificant coefficients, so the only effect of education on home bias that we detect is through the competence and/or optimism channel.

As we discussed in Section II.C, an information story might explain home bias. For example, if the competence variable captures an investor's information advantage, instead of perceived knowledge/skills, our results might indicate that an information advantage increases an investor's likelihood of holding foreign assets. To distinguish between competence and information, one needs to distinguish between perceived knowledge/skills and actual information. We do this by considering the relation between information and returns. Investors who are better informed should earn higher returns than those less informed. However, investors who perceive themselves to be better informed may not earn higher returns. Therefore, if our measure of investor competence captures subjectively perceived knowledge instead of true information, then there is no reason for it to be positively associated with realized abnormal returns.

In Table IX, we study the relation between investor competence and realized portfolio returns over the twelve months prior to the survey.[10] To control for market conditions, we add fixed effects for each survey. We find no evidence that investor competence is associated with higher returns. In fact, the data indicate the contrary: a one-unit increase in investor competence is associated with decrease in annual returns by more than 7 percent. The evidence in Table IX suggests that it is unlikely that our investor competence variable is simply capturing an information effect.

[10]In Table IX, White (1980) heteroskedasticity adjusted standard errors for coefficient estimates are reported. One might be concerned that investors with similar degree of competence may hold similar portfolios, which can result in clustered errors in the regressions in Table IX. To deal with this concern, we repeat the regressions allowing for the model errors to be clustered based on levels of competence. The resulting standard errors for coefficient estimates are similar to those reported in Table IX.

We do not have investors' actual portfolio holding data; therefore, we do not control for individual investors' risk exposure in the regressions in Table IX. Is it possible that investors with lower competence tend to take on more risk, and therefore earn higher returns on average? To address this possibility, for each survey, we calculate the mean self-reported portfolio returns for high and low competence investors. According to the CAPM, if low competence investors tend to take on more risk than high competence investors, then the mean returns for low competence investors should be more sensitive to market returns than those of high competence investors. As we show in Figure II, this is not the case. The mean returns for both low and high competence investors are equally sensitive to market returns (i.e., the slopes on the lines are indistinguishable). There is no evidence that low competence investors take on more risk than high competence investors. Therefore, it does not appear to be the case that risk exposures drive the results in Table IX.

V. Summary and Conclusions

The competence effect predicts that the likelihood that a person will invest according to her own judgment increases with her perceived knowledge about investing. Unlike many empirical studies of behavioral finance, which rely on proxies for underlying psychological biases, we directly measure investor competence through survey evidence. We first build an empirical model to understand the factors that affect investor competence. We find that male investors, and investors with higher income or more education, are more likely to perceive themselves as competent investors than are female investors, and investors with lower income or less education.

We study the effect of competence on investor behavior. The majority of existing empirical studies in behavioral finance use one psychological bias to explain one type of investor behavior. However, if a psychological bias is deeply ingrained, it should affect multiple aspects of investor behavior. In this paper, we study the effect of investor competence on two types of investor behavior: trading frequency and home bias. Trading frequency and home bias have long been treated separately in the literature. However, we show in this paper that both of these behaviors can be linked to investor competence.

We argue that investors who believe that they are more skillful or knowledgeable in making financial decisions should be more willing to act on their judgments. Indeed, our results indicate that investors who feel more competent tend to trade more frequently than investors who feel less competent. The competence effect also contributes to home bias. When an investor feels more competent about investing in foreign assets, he is more willing to shift a portion of his assets overseas. In contrast, when an investor feel less competent, he is more likely to avoid investing in foreign assets. Consistent with this argument, we find that investors with higher competence are less likely to exhibit home bias.

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Table I
Survey Questions, from UBS/Gallup Investor Survey

	Survey Questions	Data Availability
Trading Frequency	In general, how often do you trade in the financial markets?	June 1999 April 2000
Home Bias	What percent of your portfolio is currently in assets of foreign countries or foreign currencies?	March 2002 June 2002 September 2002
Investor competence	How comfortable do you feel about your ability to understand investment products, alternatives and opportunities? The responses range from 1 (very uncomfortable) to 5 (very comfortable).	November 1996
Overconfidence	What overall rate of return do you expect to get on your portfolio in the next twelve months?	June 1999 April 2000 February 2002 March 2002
	What overall rate of return do you think the stock market will provide investors during the coming twelve months?	May 2002 June 2002 August 2002 September 2002 November 2002
Optimism toward U.S. market	Focus on the financial markets in four areas of the world and rank order them by how optimistic you feel about them. The financial markets are: in the United States, in Europe, in Japan, in countries often referred to as the emerging markets.	February 2002 May 2002 August 2002 November 2002

Table II
Investor Characteristics

Optimism towards the U.S. market is defined as follows. An investor rank orders financial markets from four areas of the world by how optimistic he feels about them. The financial markets are: the United States, Europe, Japan, and emerging markets. Optimism towards the U.S. market is set to 1 if an investor is the most optimistic towards the U.S. market, set to 0 otherwise. Overconfidence is defined as the margin by which an investor thinks that his own portfolio return could beat the market return over the next twelve months. Overconfidence is calculated as follows: (forecast of own portfolio return over the next twelve months) minus (forecast of stock market return over the next twelve months). Data are from the following surveys: November 1996, June 1999, April 2000, February 2002, March 2002, May 2002, June 2002, August 2002, September 2002 and November 2002. The total number of observations is 7,452.

	Percent	Mean (Median)	Std Dev
Competence (1=low, 5=high)		3.68 (4.00)	1.01
Optimism towards U.S. market (1 = the most optimistic towards U.S. market, 0 = the most optimistic towards a non-U.S. market)		0.72 (1.00)	0.45
Overconfidence (%)		3.20 (0.00)	17.09
Education			
Less than college	40.02%		
College	33.76%		
Post-Graduate	26.22%		
Investment		$199,643 ($55,000)	$254,061
$10,000 - $100,000	58.62%		
$100,000 - $200,000	16.45%		
$200,000 - $500,000	13.90%		
$500,000 - $1 million	6.49%		
More than $1 million	4.54%		
Income		$72,640 ($67,500)	$25,195
Less than $50,000	23.22%		
$50,000 - $100,000	46.07%		
More than $100,000	30.70%		
Gender			
Male	59.15%		
Female	40.85%		
Age		48.70 (48.00)	13.95
< 30	7.63%		
30 – 40	22.46%		
40 – 50	28.34%		
50 – 60	22.31%		
>= 60	19.26%		
Self-reported previous one year return (%)			
All surveys		2.09 (5.00)	21.02

Table III
Determinants of Investor Competence

Investor competence is measured as the response to the following survey question: "How comfortable do you feel about your ability to understand investment products, alternatives and opportunities?" The responses range from 1 (very uncomfortable) to 5 (very comfortable). An ordered logit regression is estimated. College and Post-Graduate are dummy variables which are set to 1 if an investor reports an education level of college and post-graduate respectively, and 0 otherwise. Male is a dummy variable, equal to 1 if the investor is male; 0 if the investor is female. Income is categorical. We take the mid-point of each category. The top category for income is "more than $100,000 per year." Income in this category is set to equal to $100,000. ***, **, * denote significance at 0.01, 0.05, and 0.10, respectively. Data are from the November 1996 survey.

	Estimate	Std Err
Intercept 5	-2.499***	0.202
Intercept 4	-0.893***	0.182
Intercept 3	1.022***	0.190
Intercept 2	2.669***	0.280
Male	0.762***	0.138
College	0.692***	0.165
Post-Graduate	0.909***	0.186
Income	0.005**	0.002
Pseudo R^2	0.115	
No. of observations	744	

Table IV
Trading Frequency

This table presents the distribution of trading frequency. Competence is estimated using investor characteristics that measure gender, education, and income. Overconfidence is defined as the forecast of investor's own portfolio return minus forecast of market return over the next 12 months. "Days between trading" is calculated at the mid-point of each response category. We test the effect of investor characteristics by comparing average number of days between trading at the lowest response value of a given variable with the average number of days between trading at higher response values. ***, **, * denote significance at 0.01, 0.05, and 0.10, respectively. Data are from June 1999 and April 2000 surveys.

	At least once a day	At least once a week	At least once a month	At least once a quarter	At least once a year	Average days between trading	No. of obs.
All investors	3.1%	11.6%	34.0%	75.7%	93.7%	93.7	670
Competence							
<= 4	2.9%	10.8%	27.5%	69.6%	91.9%	109.3	418
> 4	3.6%	13.1%	44.8%	85.7%	96.8%	67.9***	252
Overconfidence							
<= 3.2%	2.8%	9.5%	32.5%	72.8%	93.1%	100.4	422
> 3.2%	3.6%	15.3%	36.7%	80.7%	94.8%	82.3**	248
Gender							
Male	3.5%	13.4%	40.3%	82.0%	95.6%	77.6	434
Female	2.5%	8.5%	22.5%	64.0%	90.2%	123.4***	236
Education							
Less than college	3.6%	11.8%	25.6%	68.2%	89.7%	115.2	195
College	2.4%	11.5%	35.3%	78.2%	96.4%	85.4***	252
Post-Graduate	3.6%	11.7%	39.9%	79.4%	94.2%	84.5***	223
Age							
<30	3.0%	21.2%	47.0%	87.9%	97.0%	66	62.0
30 – 40	6.4%	12.3%	39.0%	84.5%	98.4%	70.3	187
40 – 50	2.5%	10.5%	28.5%	70.5%	92.5%	106.6***	200
50 – 60	1.6%	11.3%	35.5%	75.8%	93.6%	93.3**	124
>= 60	0.0%	6.4%	24.7%	60.2%	84.9%	136.4***	93
Income							
Less than $50,000	1.2%	4.7%	18.8%	56.5%	84.7%	145.7	85
$50,000 - $100,000	1.3%	9.0%	28.0%	71.7%	92.5%	105.1***	321
More than $100,000	6.1%	17.0%	46.2%	86.7%	98.1%	63.2***	264

Table V
Investor Competence and Trading Frequency

We estimate the impact of investor competence and other investor attributes on trading frequency using ordered logit regressions. The response variable is trading frequency. There are six categories, coded as following: category = 1 if trading frequency is "less than once a year"; category = 2 if trading frequency is "at least once a year, but not more than once a quarter"; category = 3 if trading frequency is "at least once a quarter, but not more than once a month"; category = 4 if trading frequency is "at least once a month, but not more than once a week"; category = 5 if trading frequency is "at least once a week, but not more than once a day"; category = 6 if trading frequency is "at least once a day." Competence is estimated using investor characteristics that measure gender, education, and income (see Table III). College and Post-Graduate are dummy variables that are set to 1 if an investor reports an education level of college and post-graduate respectively, and 0 otherwise. Male is a dummy variable, equal to 1 if the investor is male; 0 if the investor is female. Income is categorical. We take the mid-point of each category. The top category for income is "more than $100,000 per year." Income in this category is set to $100,000. MaleX is the residual of the following logit regression: regress Male onto Competence. CollegeX, Post-GraduateX, and IncomeX are calculated in the same manner. Intercepts are not reported. Standard errors are in parentheses. ***, **, * denote significance at 0.01, 0.05, and 0.10, respectively. Data are from June 1999 and April 2000 surveys.

	(1)	(2)	(3)
Competence	1.697***		1.525***
	(0.244)		(0.247)
Male		0.693***	
		(0.152)	
College		0.119	
		(0.180)	
Post-Graduate		0.156	
		(0.188)	
Income		0.019***	
		(0.003)	
Age		-0.026***	-0.026***
		(0.006)	(0.006)
MaleX			-0.185
			(0.609)
CollegeX			-0.629
			(0.554)
Post-GraduateX			-0.861
			(0.712)
IncomeX			0.013**
			(0.005)
Pseudo R^2	0.075	0.133	0.134
No. of obs	670	670	670

Table VI
Investor Competence, Overconfidence, and Trading Frequency

We investigate the impact of investor competence on trading frequency, controlling for overconfidence and other investor attributes. Ordered logit regressions are estimated. The response variable is trading frequency. There are six categories, coded as following: category = 1 if trading frequency is "less than once a year"; category = 2 if trading frequency is "at least once a year, but not more than once a quarter"; category = 3 if trading frequency is "at least once a quarter, but not more than once a month"; category = 4 if trading frequency is "at least once a month, but not more than once a week"; category = 5 if trading frequency is "at least once a week, but not more than once a day"; category = 6 if trading frequency is "at least once a day." Competence is estimated using investor characteristics that measure gender, education, and income (see Table III). Overconfidence is measured as (forecast of own portfolio return over the next twelve months – forecast of stock market return over the next twelve months). ForecastError is calculated in two steps. First, the absolute value of (forecast of overall return of the stock market over the next twelve months minus the realized return of the stock market over the next twelve months) is obtained. Then, the mean absolute forecast error of all respondents for the particular survey, i.e., June 1999 survey or April 2000 survey, is subtracted from the individual absolute forecast errors to arrive at ForecastError. College and Post-Graduate are dummy variables that are set to 1 if an investor reports an education level of college and post-graduate respectively, and 0 otherwise. Male is a dummy variable, equal to 1 if the investor is male; 0 if the investor is female. Income is categorical. We take the mid-point of each category. The top category for income is "more than $100,000 per year." Income in this category is set to $100,000. MaleX is the residual of the following logit regression: regress Male onto Competence. CollegeX, Post-GraduateX, and IncomeX are calculated in the same manner. Intercepts are not reported. Standard errors are in parentheses. Overconfidence and ForecastError are both winsorized at 0.01 and 0.99. ***, **, * denote significance at 0.01, 0.05, and 0.10, respectively. Data are from June 1999 and April 2000 surveys.

	(1)	(2)	(3)	(4)	(5)
Competence	1.671***		1.508***	1.770***	1.581***
	(0.244)		(0.247)	(0.249)	(0.252)
Overconfidence	1.517**	1.261	1.260		
	(0.767)	(0.773)	(0.772)		
ForecastError				0.011	0.008
				(0.008)	(0.008)
Male		0.673***			
		(0.153)			
College		0.124			
		(0.180)			
Post-Graduate		0.160			
		(0.188)			
Income		0.019***			
		(0.003)			
Age		-0.025***	-0.026***		-0.026***
		(0.006)	(0.006)		(0.006)
MaleX			-0.201		-0.151
			(0.609)		(0.609)
CollegeX			-0.622		-0.607
			(0.554)		(0.554)
Post-GraduateX			-0.853		-0.826
			(0.712)		(0.713)
IncomeX			0.013**		0.014**
			(0.005)		(0.005)
Pseudo R^2	0.080	0.137	0.129	0.078	0.135
No. of obs	670	670	670	670	670

Table VII
Home Bias

Percentage of investors who own foreign investments. Competence is estimated using investor characteristics that measure gender, education, and income. OptimismUS is estimated using investor characteristics that measure gender, education, age, and income. We test the effect of investor characteristics by comparing the decision to invest in foreign assets at the lowest response value of a given variable with the decision to invest in foreign assets at higher response values. ***, **, * denote significance at 0.01, 0.05, and 0.10, respectively. Data are from March 2002, June 2002 and September 2002 surveys. The total number of observations is 2,483.

	Own foreign investment	No. of obs.
All investors	36.3%	901
Competence		
<= 4	31.9%	560
> 4	47.0%***	341
OptimismUS		
<= 0.72	38.4%	437
> 0.72	34.5%**	464
Gender		
Male	39.1%	578
Female	32.2%***	323
Education		
Less than college	27.4%	272
College	37.9%***	328
Post-Graduate	48.1%***	301
Age		
<30	33.9%	64
30 – 40	43.0%**	233
40 – 50	38.8%	273
50 – 60	35.2%	194
>= 60	27.5%	137
Income		
Less than $50,000	24.8%	135
$50,000 - $100,000	36.4%***	435
More than $100,000	44.6%***	331

Table VIII
Investor Competence and Home Bias

We study the impact of investor competence and other investor attributes on home bias using logit regressions. The dependent variable is participation in foreign assets, equal to 1 if investor holds foreign assets, and 0 otherwise. Competence is estimated using investor characteristics that measure gender, education, and income. OptimismUS is estimated using investor characteristics that measure gender, education, age, and income. College and Post-Graduate are dummy variables that are set to 1 if an investor reports an education level of college and post-graduate respectively, and 0 otherwise. Male is a dummy variable, equal to 1 if the investor is male; 0 if the investor is female. Income is categorical. We take the mid-point of each category. The top category for income is "more than $100,000 per year." Income in this category is set to $100,000. MaleX is the residual of the following logit regression: regress Male onto Competence and OptimismUS. CollegeX, Post-GraduateX, ageX, and IncomeX are calculated the same way. Data are from March 2002, June 2002, and September 2002. Intercepts are not reported. Standard errors are in parentheses. ***, **, * denote significance at 0.01, 0.05, and 0.10, respectively.

	(1)	(2)	(3)	(4)
Competence	1.359***	1.233***		1.387***
	(0.145)	(0.138)		(0.148)
OptimismUS	-2.581***			-2.713***
	(0.813)			(0.829)
Male			0.190**	
			(0.089)	
College			0.308***	
			(0.104)	
Post-Graduate			0.708***	
			(0.112)	
Income			0.009***	
			(0.002)	
Age			-0.009***	
			(0.003)	
MaleX				-0.321
				(0.339)
CollegeX				-0.056
				(0.205)
Post-GraduateX				0.423
				(0.347)
IncomeX				0.004
				(0.005)
AgeX				-0.020
				(0.017)
Pseudo R^2	0.050	0.045	0.064	0.064
No. of obs	2483	2483	2483	2483

Table IX
Investor Competence and Realized Returns

The association between investor competence and realized returns is studied using OLS regressions. The dependent variable is an investor's self-reported return of the previous twelve months, measured in percentage. Competence is estimated using investor characteristics that measure gender, education, and income. OptimismUS is estimated using investor characteristics that measure gender, education, age, and income. Mar02 is a dummy variable, set to 1 if the data are from March 2002 survey, zero otherwise. June02 is defined similarly. Self-reported return of the previous twelve months is winsorized at 0.01 and 0.99. Data are from March 2002, June 2002, and September 2002. White (1980) standard errors are in parentheses. ***, **, * denote significance at 0.01, 0.05, and 0.10, respectively.

	(1)	(2)
Intercept	32.932***	25.716***
	(7.945)	(5.924)
Mar02	7.051***	7.081***
	(1.164)	(1.164)
June02	7.120***	7.126***
	(1.181)	(1.181)
Competence	-7.732***	-8.265***
	(1.373)	(1.555)
OptimismUS	-12.671	
	(9.744)	
Adjusted R^2	0.042	0.041
No. of obs	1723	1723

Figure I
Percentage of Participants that Choose Their Own Judgments over Matched Chance Lotteries

The horizontal axis is the self-rated probability of a participant's judgment being correct. The vertical axis is the percentage of participants that choose their own judgments over matched chance lotteries. This figure is adapted from Heath and Tversky (1991), Figure 4.

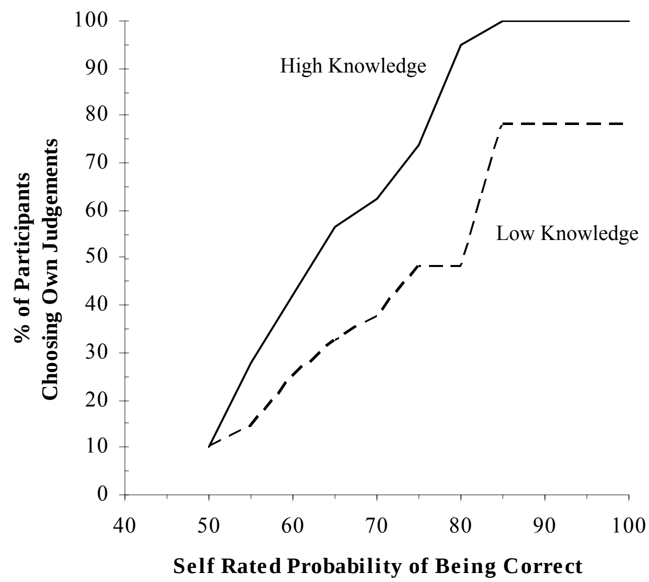

Figure II
Market Risk Exposure of Low Competence and High Competence Investors

The horizontal axis is the previous twelve months return of S&P500 index. The vertical axis is the mean portfolio returns for low and high competence investors for the same twelve months. Low competence is defined as competence less than or equal to 4.0; high competence is defined as competence greater than 4.0. ▲represents low competence investors, ♦ represents high competence investors. Data are from March 2002, June 2002, and September 2002.