

Investor Competence, Trading Frequency, and Home Bias

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People are more willing to bet on their own judgments when they feel skillful or knowledgeable. We investigate whether this “competence effect” influences trading frequency and home bias. We find that investors who feel competent trade more often and have more internationally diversified portfolios. We also find that male investors, and investors with larger portfolios or more education, are more likely to perceive themselves as competent than are female investors, and investors with smaller portfolios or less education. Our paper also contributes to understanding the theoretical link between overconfidence and trading frequency. Existing theories on trading frequency have focused on one aspect of overconfidence, i.e., miscalibration. Our paper offers a potential mechanism for the “better-than-average” aspect of overconfidence to influence trading frequency. In the context of our paper, overconfident investors tend to perceive themselves to be more competent, and thus are more willing to act on their beliefs, leading to higher trading frequency.

Key words: behavioral finance; investment; competence; ambiguity; stock trading frequency; home bias

History: Received June 25, 2007; accepted January 25, 2009, by Neal Stoughton (guest department editor), finance. Published online in *Articles in Advance* April 23, 2009.

1. Introduction

We argue that “investor competence” 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 make decisions based on their subjective probabilities, 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.

The competence effect posits that people’s willingness to act on their own judgments is affected by their subjective competence (Heath and Tversky 1991).¹ When people feel skillful or knowledgeable in an area, they are more willing to bet on their own judgments, and vice versa. 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 (1991) 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 subjective probabilities. It is likely that 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

¹ Fox and Tversky (1995) and Fox and Weber (2002) provide further evidence that self-perceived competence plays a role in the willingness to act on one’s own judgment. See Camerer and Weber (1992) for a review.

characteristics and self-rated competence. In most behavioral finance research, the underlying psychological bias is not observed directly, and therefore, these studies have to proxy for the bias. Our paper 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, income, and portfolio size. We find that male investors and investors with larger portfolios and more education are more likely to believe they are competent than are female investors and those with smaller portfolios and less education.

We also study the link between competence and investor behavior. Most empirical behavioral finance research studies one psychological bias to explain one type of investor behavior. Although these studies provide important insights, they do not directly investigate 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 toward addressing these issues. We study two types of investor behavior: 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.²

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 (French and Poterba 1991, Lewis 1999).³ 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 document that competence has a large economic effect. A one standard deviation increase in competence increases by about one-half the probability that an investor will trade frequently (e.g., weekly), and increases by nearly one-third the probability that an investor will invest in foreign assets.

We are careful to investigate alternative mechanisms that could account for similar effects. We control for the effect of overconfidence using two proxies: investor gender and the amount by which an investor thinks that he can beat the market. Our results suggest that overconfidence, although correlated with competence, does not subsume the competence effect. We acknowledge, however, that we do not have comprehensive measures for all aspects of overconfidence. Therefore, it is possible that certain aspects of investor overconfidence could partially explain our results on trading frequency. Nevertheless, even within the framework of overconfidence, our paper makes an important contribution.

In the existing theoretical literature on trading frequency, overconfidence is usually modeled as miscalibration, i.e., overestimating the precision of information about the value of a financial security (Kyle and Wang 1997, Odean 1998, Gervais and Odean 2001). This “miscalibration” leads to heterogeneity in investor opinion, which in turn causes trading (Varian 1989, Harris and Raviv 1993).⁴ Recent empirical studies, however, have shown that a second aspect of overconfidence, i.e., the “better-than-average” effect, is associated with trading frequency (Dorn and Huberman 2005, Glaser and Weber 2007). The theoretical link between the “better-than-average” effect and trading frequency has not been well established. Our paper offers a potential mechanism for this missing link. In the context of our paper, overconfident investors tend to perceive themselves to be more competent, and thus are more willing to act on their beliefs, leading to higher trading frequency.

With respect to home bias, the existing literature suggests that investor optimism toward home market could potentially drive home bias (Kilka and Weber

² Kumar and Lim (2008) argue that one psychological bias, narrow framing, is responsible for both the disposition effect and portfolio underdiversification.

³ A related strand of literature documents “home bias at home,” i.e., investors tend to demonstrate a preference for local stocks. See, for example, Coval and Moskowitz (1999), Benartzi (2001), Huberman (2001), and Huberman and Sengmuller (2004). Home bias at home has also been reported among Finnish (Grinblatt and Keloharju 2001), Swedish (Massa and Simonov 2006), and Chinese (Feng and Seasholes 2004) investors.

⁴ In the psychology literature, miscalibration can mean either “expected probability not equal to realized relative frequency” or “believing that the precision of a 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. See also Daniel et al. (1998, 2001).

Table 1 Survey Questions, from the UBS/Gallup Investor Survey

| | Survey questions | Data availability |
|---------------------------------|---|---|
| Trading frequency | In general, how often do you trade in the financial markets? | 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 12 months? | April 2000 February 2002 March 2002 May 2002 |
| | What overall rate of return do you think the stock market will provide investors during the coming 12 months? | June 2002 August 2002 September 2002 November 2002 |
| Optimism toward the 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 |

Source. UBS/Gallup investor survey. Data available from the Roper Center for Public Opinion Research, University of Connecticut.

2000, Strong and Xu 2003).⁵ In our analysis, the effect of competence on home bias is robust to the inclusion of optimism toward the home market in the empirical specification.

The competence effect is a psychological effect that can bias investor behavior. There also exists a rational avenue through which competence can influence investment decisions. An investor who perceives himself to be competent is likely to have less parameter uncertainty about his subjective distribution of future asset returns. In other words, he is more sure about the mean and variance of his signal about future asset returns. Similar to the irrational competence effect described by Heath and Tversky (1991) this low parameter uncertainty would make a competent investor more willing to act on his information.

The rest of this paper is organized as follows. Section 2 discusses the data. In §3, we discuss our measures of investor competence and optimism toward the U.S. market. Section 4 presents the empirical analysis. Some concluding remarks are offered in §5.

2. Data Sources

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 investments 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 it 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 by Odean (1999), and the annual asset turnover is 16%, less than one-fourth of the turnover reported by 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 aggregate investment portfolio decisions.

The survey questions that are of particular interest to us are listed in Table 1. In the April 2000 and June 1999 surveys, respondents are asked to report their trading frequencies. (Because the June 1999 survey does not provide information about an investor's portfolio size, it is not included in the analysis reported in this paper. In an unreported

⁵ An alternative explanation for home bias is information costs (Coval and Moskowitz 2001, Vissing-Jørgensen 2004). However, several studies present evidence that cannot be explained by the information cost argument (Benartzi 2001, Huberman 2001). See Lewis (1999) for a review of other potential explanations for home bias.

Table 2 Investor Characteristics

| | Percent (%) | Mean (median) | Std. dev. |
|--|-------------|-------------------------|-----------|
| Competence (1 = low, 5 = high) | | 3.68 (4.00) | 1.01 |
| Optimism toward U.S. market (1 = the most optimistic toward U.S. market, 0 = the most optimistic toward a non-U.S. market) | | 0.72 (1.00) | 0.45 |
| Overconfidence (%) | | 2.30 (0.00) | 24.28 |
| Education | | | |
| Less than college | 40.14 | | |
| College | 33.60 | | |
| Postgraduate | 26.27 | | |
| Investments | | \$204,332 (\$55,000) | \$256,787 |
| \$10,000–\$100,000 | 57.27 | | |
| \$100,000–\$200,000 | 16.99 | | |
| \$200,000–\$500,000 | 14.35 | | |
| \$500,000–\$1 million | 6.71 | | |
| More than \$1 million | 4.68 | | |
| Income | | \$72,663 (\$87,500) | \$25,281 |
| Less than \$50,000 | 23.32 | | |
| \$50,000–\$100,000 | 45.69 | | |
| More than \$100,000 | 30.99 | | |
| Gender | | | |
| Male | 59.10 | | |
| Female | 40.90 | | |
| Age | | 48.87 (48.00) | 13.97 |
| <30 | 7.42 | | |
| 30–40 | 22.19 | | |
| 40–50 | 28.27 | | |
| 50–60 | 22.55 | | |
| ≥60 | 19.57 | | |
| Self-reported previous one-year return (%) | | | |
| All surveys | | –0.74 (3.00) | 19.99 |

Notes. Optimism toward 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 toward the U.S. market is set to 1 if an investor is the most optimistic toward the U.S. market, and set to 0 otherwise. Overconfidence is defined as the margin by which an investor thinks that his own portfolio return will beat the market return over the next 12 months. Overconfidence is calculated as follows: (forecast of own portfolio return over the next 12 months) minus (forecast of stock market return over the next 12 months). Data are from the following surveys: November 1996, April 2000, February 2002, March 2002, May 2002, June 2002, August 2002, September 2002, and November 2002. The total number of observations is 7,218.

analysis, we modify our model to include the June 1999 data in the analysis, and our results are qualitatively unchanged.) The responses to the trading frequency question 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 2 reports the characteristics of the investors surveyed by UBS/Gallup. The investors are, on

average, 48.9 years old, with a median annual income of \$87,500. These numbers are comparable to those of Barber and Odean (2001), whose sample of investors are, on average, 50 years old, with a median annual income of \$75,000. The investors in our sample are well educated: 60% have finished college, and 26.3% have postgraduate education.

3. Measuring Competence and Optimism Toward the U.S. Market

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 3.68.

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 appears only 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. 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. Using ordered logit regressions, we model competence as a function of investor characteristics such as gender, education, age, income, and total investments. Our proposed model is reported in Table 3, panel A, column 2. This model includes four characteristics: gender, education, income, and total investments. 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 a *p*-value of 0.50, whereas the deviance goodness-of-fit test has a *p*-value of 0.97. Both of these tests fail to provide evidence against the specification. As to the predictive power of the model, for the November 1996 survey, the correlation between the observed competence and *competence* constructed from the model is 0.34, with statistical significance of less than 0.001. Using this model, constructed *competence* is calculated for the rest of the surveys. In these surveys, constructed *competence* has a mean of 3.78, and standard

Table 3 Determinants of Investor Competence and Optimism Toward the U.S. Market

| | | Panel A | | |
|---------------------|--|----------------------|----------------------|---------------------|
| | | <i>Competence</i> | | <i>OptimismUS</i> |
| | | (1) | (2) | (3) |
| Intercept 5 | | -2.499*** (0.202) | -2.515*** (0.202) | |
| Intercept 4 | | -0.893*** (0.182) | -0.884*** (0.182) | |
| Intercept 3 | | 1.022*** (0.190) | 1.037*** (0.191) | |
| Intercept 2 | | 2.669*** (0.280) | 2.684*** (0.280) | |
| Intercept | | | | -0.342 (0.225) |
| <i>Male</i> | | 0.762*** (0.138) | 0.729*** (0.139) | 0.104 (0.084) |
| <i>College</i> | | 0.692*** (0.165) | 0.704*** (0.166) | 0.031 (0.102) |
| <i>Postgraduate</i> | | 0.909*** (0.186) | 0.825*** (0.188) | -0.163 (0.107) |
| <i>Income</i> | | 0.546** (0.259) | 0.279 (0.271) | 0.380** (0.200) |
| <i>Investments</i> | | | 0.116*** (0.031) | 0.005 (0.019) |
| <i>Age</i> | | | | 0.018*** (0.003) |
| <i>Opindex1</i> | | | | 0.158*** (0.051) |
| <i>Opindex2</i> | | | | 0.481*** (0.056) |
| Pseudo R^2 | | 0.115 | 0.131 | 0.084 |
| No. of observations | | 744 | 744 | 3,194 |

| Panel B. Correlation matrix | | | | | | | | | |
|----------------------------------|----------------------------------|----------------------------------|-----------------------|----------------------|----------------------|----------------------|----------------------|----------------------|----------------------|
| | Constructed <i>Competence</i> | Constructed <i>OptimismUS</i> | <i>Overconfidence</i> | <i>Ability</i> | <i>Male</i> | <i>Postgraduate</i> | <i>Income</i> | <i>Investments</i> | <i>Age</i> |
| Constructed <i>Competence</i> | 1 | 0.200*** (0.000) | 0.036** (0.040) | -0.130*** (0.000) | 0.620*** (0.000) | 0.451*** (0.000) | 0.503*** (0.000) | 0.576*** (0.000) | -0.022* (0.063) |
| Constructed <i>OptimismUS</i> | | 1 | 0.002 (0.901) | 0.047** (0.015) | 0.219*** (0.000) | -0.089*** (0.000) | 0.132*** (0.000) | 0.208*** (0.000) | 0.362*** (0.000) |
| <i>Overconfidence</i> | | | 1 | -0.129*** (0.000) | 0.019 (0.280) | -0.009 (0.615) | 0.044** (0.012) | 0.047*** (0.007) | -0.021 (0.219) |
| <i>Ability</i> | | | | 1 | -0.071*** (0.000) | -0.097*** (0.000) | -0.067*** (0.000) | -0.055*** (0.002) | -0.073*** (0.000) |
| <i>Male</i> | | | | | 1 | 0.063*** (0.000) | 0.151*** (0.000) | 0.083*** (0.000) | -0.025** (0.037) |
| <i>Postgraduate</i> | | | | | | 1 | 0.226*** (0.000) | 0.176*** (0.000) | 0.003 (0.830) |
| <i>Income</i> | | | | | | | 1 | 0.319*** (0.000) | -0.203*** (0.000) |
| <i>Investments</i> | | | | | | | | 1 | 0.221*** (0.000) |
| <i>Age</i> | | | | | | | | | 1 |

Notes. 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). *OptimismUS* is measured as the response to the following survey 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." *OptimismUS* is set to one if the investor is the most optimistic toward the U.S. market, and 0 otherwise. In panel A, ordered logit regressions are performed. *College* and *Postgraduate* are dummy variables that are set to 1 if an investor reports an education level of college or postgraduate 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 midpoint of each category. The top category for income is "more than \$100,000 per year." Income in this category is set to \$100,000. Income is measured in units of \$100,000. *Investments* measures the investor's total portfolio size. *Investments* is categorical. We take the midpoint of each category. The top category for investments is "more than \$1,000,000." Investments in this category is set to \$1,000,000. Investments is measured in units of \$100,000. *Opindex1* measures an investor's sentiment toward fulfilling his personal investment goals. *Opindex2* measures an investor's sentiment toward the general market environment in the United States. Both *Opindex1* and *Opindex2* range from -2 to 2, with -2 being the most pessimistic, and 2 being the most optimistic. The data for the *Competence* model are from the November 1996 survey. The data for the *OptimismUS* model are from the February 2002, May 2002, August 2002, and November 2002 surveys. Standard errors are in parentheses. Panel B reports the correlation matrix of investor demographics and *Competence* and *OptimismUS* constructed from the models reported in Table 3, panel A, columns 2 and 3, respectively. *Overconfidence* is calculated as (forecast of own portfolio return over the next 12 months) minus (forecast of stock market return over the next 12 months). *Ability* is calculated in two steps. First, the absolute value of (forecast of overall return of the stock market over the next 12 months minus the realized return of the stock market over the next 12 months) is obtained. Then, the mean absolute forecast error of all respondents for the particular survey is subtracted from the individual absolute forecast errors to arrive at *Ability*. *p*-values are in parentheses.

***, **, *Significant at 0.01, 0.05, and 0.10, respectively.

deviation of 0.35. In comparison, in the November 1996 survey, the actual reported competence has a mean of 3.68 and standard deviation of 1.01.⁶ A paired rank sum test of constructed *competence* and actual reported competence yields a *p*-value of 0.63, failing to reject that the two variables have the same distribution.

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. As shown in Table 3, panel A, column 2, the estimated coefficients indicate that investor competence increases with education. For example, consider an average investor in our sample, a male with an annual income of \$72,663 and total investments of \$204,332. If his education level were to increase from college to postgraduate, the predicted *competence* for this investor would increase from 4.01 to 4.07. In other words, higher education makes a person feel competent, which might lead to higher perceived competence in all domains, including financial decisions. Investor competence also increases with the size of the investor's total portfolio. For a typical male investor with college education and average income, if his investments were to increase by one standard deviation from \$204,332 to \$461,119, his *competence* would increase from 4.01 to 4.14. Panel A, column 2 also shows that male investors are more likely to feel competent than are female investors. Comparing a college-educated female investor, with average income and investments, to a male investor with the same demographics, the gender difference accounts for an increase of 0.39 in predicted investor *competence*, from 3.64 to 4.01.

Kilka and Weber (2000) find that people are more optimistic toward 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 toward the U.S. market.

⁶ The standard deviation of constructed competence is naturally lower because constructed competence represents the expected value from the predictive model. With this model, for any investor, the predicted probability of competence being equal to any interger value between 1 and 5 is always positive. Competence constructed from this model is always greater than 1 and less than 5. Therefore, the standard deviation of the constructed competence is less than that of the reported competence in the November 1996 survey.

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 toward the U.S. market, and zero otherwise. Overall, 72% of investors are more optimistic toward the U.S. market than toward financial markets in other regions of the world.

Because the optimism question is not asked in March 2002, June 2002, or September 2002 (the surveys that address foreign investing and home bias), we do not have a direct measure for *OptimismUS* for these surveys. Therefore, we construct an empirical model of optimism toward the U.S. market in the same manner as we did for investor competence. We start by investigating the determinants of investor optimism toward 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, income, portfolio size, investor sentiment toward fulfilling personal investment goals, and sentiment toward the market environment in the United States. Then for all other surveys, we construct predicted optimism toward the home market for each investor, using his individual characteristics and the coefficients obtained from this regression. The model for *OptimismUS* is reported in Table 3, panel A, column 3. Not surprisingly, the most significant explanatory variables in this model are the two sentiment variables. Investors with favorable sentiments toward the market environment in the United States tend to be more optimistic toward the U.S. market than toward the stock markets in other regions of the world.

In Table 3, panel B, we report a correlation matrix that includes constructed investor competence and other variables of interest.

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

4.1. 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 the Survey of Consumer Finance, Vissing-Jørgensen (2004) finds that wealthier households tend to trade more frequently. Therefore, we control for gender, age, and income when studying trading frequency.

Table 4 Trading Frequency

| | 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 | 3.8 | 12.4 | 36.8 | 77.0 | 94.7 | 88.7 | 475 |
| <i>Competence</i> | | | | | | | |
| ≤4 | 3.1 | 8.9 | 28.3 | 68.9 | 92.2 | 110.0 | 293 |
| >4 | 4.9 | 18.1 | 50.5 | 90.1 | 98.9 | 54.5*** | 182 |
| <i>Overconfidence</i> | | | | | | | |
| ≤2.3% | 3.9 | 10.3 | 36.7 | 74.4 | 93.2 | 95.7 | 281 |
| >2.3% | 3.6 | 15.5 | 37.1 | 80.9 | 96.9 | 78.7* | 194 |
| Gender | | | | | | | |
| Male | 4.3 | 14.8 | 43.4 | 84.9 | 96.7 | 69.8 | 304 |
| Female | 2.9 | 8.2 | 25.2 | 63.2 | 91.2 | 122.4*** | 171 |
| Education | | | | | | | |
| Less than college | 3.9 | 10.9 | 25.8 | 68.0 | 89.8 | 115.5 | 128 |
| College | 2.8 | 11.1 | 35.6 | 77.8 | 96.7 | 85.6*** | 180 |
| Postgraduate | 4.8 | 15.0 | 46.7 | 83.2 | 96.4 | 71.6*** | 167 |
| Age | | | | | | | |
| <30 | 5.6 | 22.2 | 52.8 | 91.7 | 100.0 | 48.9 | 36 |
| 30–40 | 6.9 | 13.9 | 40.8 | 85.4 | 98.5 | 67.7 | 130 |
| 40–50 | 3.7 | 11.8 | 33.8 | 75.0 | 95.6 | 92.4*** | 136 |
| 50–60 | 2.1 | 11.5 | 37.5 | 77.1 | 94.8 | 88.5*** | 96 |
| ≥60 | 0.0 | 7.8 | 27.3 | 59.7 | 84.4 | 136.7*** | 77 |
| Income | | | | | | | |
| Less than \$50,000 | 1.9 | 3.9 | 21.2 | 59.6 | 90.4 | 131.8 | 52 |
| \$50,000–\$100,000 | 1.0 | 7.7 | 29.0 | 70.5 | 91.8 | 107.8 | 207 |
| More than \$100,000 | 6.9 | 18.9 | 48.2 | 87.5 | 98.6 | 60.1*** | 216 |

Notes. This table presents the distribution of trading frequency. *Competence* is estimated using investor characteristics that measure gender, education, income, and total investments (see Table 3, panel A, column 2). *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 midpoint 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. Data are from the April 2000 survey.

***, **, *Significant at 0.01, 0.05, and 0.10, respectively.

Table 4 reports univariate relations between trading frequency, investor competence, and other characteristics. Recall that in §1, 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 4 are consistent with this hypothesis. We observe a significant shift in the distribution of trading frequency as investor competence changes. When constructed *competence* is less than or equal to 4.0, 28.3% of investors trade at least once a month. When constructed *competence* is greater than 4.0, 50.5% of investors trade at least once a month. Overall, the average number of days between trading for all investors is 88.7 days. For those investors with constructed *competence* less than or equal to 4.0, the average number of days between trading is 110.0 days. In contrast, for those investors with constructed *competence* greater than 4.0, the average number of days between trading is only 54.5 days. This large difference in days between trading is both economically and statistically significant, and is con-

sistent with more competent investors trading more frequently.⁷

In Table 5, 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."

⁷One potential concern is "self-reporting" bias; e.g., an investor who reports high trading frequency may be reluctant to admit his lack of expertise in trading. A related concern is the endogeneity of competence. High competence may be a result of high trading frequency, because those investors who trade more frequently can become more familiar with the market through their trading activities. In our analysis, however, the survey with the competence question does not overlap the surveys that investigate trading frequency or home bias, and different investors respond to the different surveys. Therefore, the possibilities of "self-reporting" bias and the endogeneity issue appear to be small, and should not drive our trading frequency or home bias results.

Table 5 Investor Competence and Trading Frequency

| | (1) | (2) | (3) | (4) | (5) | (6) |
|-----------------------|---------------------|----------------------|---------------------|----------------------|---------------------|----------------------|
| <i>Competence</i> | 1.636*** (0.224) | 2.059*** (0.518) | 1.603*** (0.224) | 1.990*** (0.519) | 1.710*** (0.228) | 2.093*** (0.518) |
| <i>Overconfidence</i> | | | 1.292* (0.768) | 0.881 (0.776) | | |
| <i>Ability</i> | | | | | 0.011 (0.008) | 0.008 (0.008) |
| <i>Male</i> | | -0.038 (0.240) | | -0.027 (0.240) | | -0.022 (0.240) |
| <i>College</i> | | -0.661** (0.266) | | -0.632** (0.267) | | -0.658** (0.266) |
| <i>Postgraduate</i> | | -0.778*** (0.299) | | -0.744** (0.300) | | -0.770** (0.299) |
| <i>Income</i> | | 1.189*** (0.394) | | 1.214*** (0.394) | | 1.202*** (0.394) |
| <i>Age</i> | | -0.034*** (0.006) | | -0.033*** (0.006) | | -0.033*** (0.006) |
| Pseudo R^2 | 0.083 | 0.155 | 0.087 | 0.156 | 0.086 | 0.156 |
| No. of obs. | 475 | 475 | 475 | 475 | 475 | 475 |

Notes. 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 follow: 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, income, and total investments (see Table 3, panel A, column 2). *Overconfidence* is measured as (forecast of own portfolio return over the next 12 months minus forecast of stock market return over the next 12 months). *Ability* is the absolute value of (forecast of overall return of the stock market over the next 12 months minus the realized return of the stock market over the next 12 months). *Ability* is de-meant to take out the effect of market conditions. *College* and *Postgraduate* are dummy variables that are set to 1 if an investor reports an education level of college or postgraduate, 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 midpoint of each category. The top category for income is “more than \$100,000 per year.” Income in this category is set to \$100,000. Income is measured in units of \$100,000. Intercepts are not reported. Standard errors are in parentheses. Data are from the April 2000 survey.

***, **, *Significant at 0.01, 0.05, and 0.10, respectively.

In Table 5, we focus on the coefficients for the variable *Competence*, i.e., the fitted response to the investment knowledge question, “How comfortable do you feel about your ability to understand investment products, alternatives and opportunities?”

The regression results in the first column of Table 5 suggest that the effect of competence on trading frequency is positive and highly significant, indicating that trading frequency increases with investor competence. The effect of competence is very large in magnitude. When constructed *competence* increases by one standard deviation, from its mean of 3.78 to 4.12, the probability of an investor trading more than once per week increases from 9.9% to 16.1%.

Next we introduce investor demographics as control variables: gender, education, age, and income. As shown in Table 5, column 2, after controlling for investor demographics, the coefficient for constructed competence remains positive and highly significant. Interestingly, the coefficient for *Male* 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 perceived investor competence.

Some economists posit that raising incentives may attenuate the degree of psychological bias demonstrated by individuals. However, recent metastudies show that, when the task at hand is a judgment or decision task, incentives do not reduce the degree of bias demonstrated by the subject. In some cases, higher incentives are even associated with higher degrees of bias (Jenkins et al. 1998, Camerer and Hogarth 1999). In unreported regressions, we split the sample into two subsamples based on the investment/income ratio to control for potentially different incentives. The effect of investor competence is positive and highly significant for both the high-incentive and the low-incentive subsamples.

There exists a large and influential literature that studies the effect of overconfidence on trading fre-

quency. 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. Recent studies show that the “better-than-average” aspect of overconfidence is associated with higher trading frequency (Dorn and Huberman 2005, Glaser and Weber 2007). In Table 5, column 2, 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 Table 5, columns 3 and 4, 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 12 months minus his forecast of the stock market return over the next 12 months. In other words, our *Overconfidence* variable in Table 5 measures the degree to which an investor thinks that he could “beat the market.” As shown in Table 2, on average, an investor forecasts his own portfolio return to be 2.3% higher than the market return over the next 12 months. The correlation between constructed competence and this measure of overconfidence is only 0.036. Therefore, this measure of overconfidence is statistically distinct from the competence effect that we focus on in this paper. As shown in Table 5, column 3, 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 5, column 1. Better-than-average overconfidence is positively and significantly related to trading frequency in column 3, though insignificant when demographics enter the specification (column 4).

So far, we have shown that investor competence is a significant determinant of trading frequency, controlling for two different proxies of overconfidence. In Table 5, columns 5 and 6, we control for an investor’s ability. In the UBS surveys, investors are asked to forecast the stock market return over the next 12 months. We use the accuracy of these forecasts, called *Ability* in Table 5, as a measure of an investor’s true ability. It is calculated as the absolute value of the forecasted minus the realized return over the next 12 months. In both columns, the coefficient estimate for *Ability* is small in magnitude and statistically insignificant, whereas the coefficient estimate for constructed

competence remains positive and highly statistically significant.

There exist several aspects of overconfidence, i.e., miscalibration, illusion of control, and better than average. We controlled for the better-than-average effect in Table 5. Is it possible that miscalibration or illusion of control explain our results? The UBS survey does not offer good measures for an investor’s degree of miscalibration or illusion of control. We cannot directly control for these two aspects of overconfidence in our regressions. The existing literature provides some clues on this issue. Glaser and Weber (2007) show that an investor’s miscalibration and illusion-of-control scores are not associated with investor demographics such as gender, age, and portfolio size. Similarly, Biais et al. (2005) and Deaves et al. (2009) show that miscalibration is not associated with gender. Because our measure of investor competence is constructed from these investor demographics, it seems unlikely that our constructed competence is highly correlated with an investor’s miscalibration or illusion of control. Therefore, it seems unlikely that these two aspects of overconfidence drive our results. The above being said, because our sample is different from the samples used in these studies, it is difficult to refute these alternative explanations definitively.

The results in Tables 4 and 5 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.

4.2. Investor Competence and Home Bias

In the March 2002, June 2002, and September 2002 surveys, investors report their foreign asset holdings (see Table 1). We use these data to investigate the relation between investor competence and home bias.

Table 6, panel A, reports univariate relations between home bias and investor competence, optimism toward the U.S. market, and education. Ideally, to test the association between investor competence and home bias, we would like to measure an investor’s competence toward investing in foreign assets. Because this measure is not available, we will use an investor’s overall competence, because this general measure of competence is likely to be highly correlated with an investor’s competence with respect to investing in foreign assets.⁸ For instance, in the August 1997, March 1998, and September 1998 surveys, investors are asked to rate the risk of international mutual funds. For those investors

⁸ We thank Chip Heath for suggesting that competence in foreign assets is likely to be correlated with overall competence, and therefore overall competence is a reasonable measure for this experiment.

Table 6 Investor Competence and Home Bias

| Panel A | | | | | | | | |
|------------------------------------|---------------------|---------------------|----------------------|----------------------|-------|-----------|---------|--------------|
| | All | Competence | | OptimismUS | | Education | | |
| | | ≤4 | >4 | ≤0.72 | >0.72 | <College | College | Postgraduate |
| <i>Own foreign investments (%)</i> | 37.5 | 33.1 | 51.6*** | 37.7 | 37.3 | 28.6 | 38.6*** | 49.6*** |
| Panel B | | | | | | | | |
| | (1) | (2) | (3) | (4) | | | | |
| <i>Competence</i> | 1.233*** (0.135) | 1.250*** (0.128) | 1.630*** (0.352) | 1.644*** (0.356) | | | | |
| <i>OptimismUS</i> | −0.507 (0.418) | | 0.368 (0.480) | −1.107 (2.841) | | | | |
| <i>Male</i> | | | −0.473*** (0.161) | −0.469*** (0.175) | | | | |
| <i>College</i> | | | −0.329* (0.171) | −0.329* (0.175) | | | | |
| <i>Postgraduate</i> | | | 0.003 (0.004) | −0.063 (0.209) | | | | |
| <i>Income</i> | | | 0.352 (0.230) | 0.512 (0.315) | | | | |
| <i>Age</i> | | | −0.014*** (0.004) | −0.010 (0.010) | | | | |
| <i>Northeast</i> | | | | 0.042 (0.129) | | | | |
| <i>West</i> | | | | −0.348*** (0.132) | | | | |
| <i>South</i> | | | | −0.328*** (0.118) | | | | |
| <i>Opindex1</i> | | | | −0.077 (0.104) | | | | |
| <i>Opindex2</i> | | | | 0.249 (0.270) | | | | |
| Pseudo R ² | 0.051 | 0.054 | 0.074 | 0.086 | | | | |
| No. of obs. | 2,313 | 2,313 | 2,313 | 2,313 | | | | |

Notes. Panel A presents the percentages of investors who own foreign investments. We test the effect of investor characteristics by comparing the percentage of investors that own foreign assets at the lowest response value of a given variable with the percentage of investors that own foreign assets at higher response values. In panel B, 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, income, and total investments. *OptimismUS* is estimated using investor characteristics that measure gender, education, age, income, total investments, and optimism indexes. *College* and *Postgraduate* are dummy variables that are set to 1 if an investor reports an education level of college or postgraduate 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 midpoint of each income category. The top category for income is “more than \$100,000 per year.” Income in this category is set to \$100,000. Income is measured in units of \$100,000. *Northeast*, *West*, and *South* are dummy variables that indicate whether an investor is located in that geographical region or not. *Opindex1* and *Opindex2* measure investor sentiments toward fulfilling his personal investment goals, and the general market environment, respectively. Data are from March 2002, June 2002, and September 2002. Intercepts are not reported.

***, **, *Significant at 0.01, 0.05, and 0.10, respectively. Standard errors are in parentheses.

with constructed competence less than 4, 17.4% responded “Don’t know.” In comparison, only 8.6% of investors with constructed competence greater than 4 responded “Don’t know” to this question. In other words, investors with higher general competence exhibit signs of higher perceived competence toward international assets.

There is significant home bias in our sample. Overall, 37.5% of all investors hold foreign assets. The

remaining 62.5% do not own any foreign assets. For those investors with constructed *competence* less than or equal to 4.0, only 33.1% hold foreign assets. In comparison, among investors with constructed *competence* greater than 4.0, 51.6% 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 Table 6 also permit the analysis of optimism toward the U.S. market. In our sample, when fitted *OptimismUS* is less than its average value of 0.72, 37.7% of investors choose to hold foreign assets. In comparison, when *OptimismUS* is greater than 0.72, 37.3% of investors choose to invest in international markets. Existing studies suggest that home bias is caused by optimism toward the home market (Kilka and Weber 2000, Strong and Xu 2003). Our results are consistent with these studies, although the magnitude of the effect is quite small.

Multivariate logit regression results are reported in Table 6, panel B. The response variable is a dummy variable, set to 1 if an investor holds foreign assets. We control for investor demographics and optimism toward the home market, constructed using the model reported in Table 3, panel A, column 3.⁹ The coefficients for constructed investor competence are positive and highly statistically significant, indicating that high-competence investors are more likely to hold foreign assets. 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. The coefficient estimates in panel B, column 2, suggest that, when investor competence increases by one standard deviation from 3.78 to 4.12, the likelihood of an investor holding foreign assets increases from 37.4% to 47.7%. Alternatively, if investor competence increases to its maximum of 5, the probability that an investor holds foreign assets increases to 73.3%. 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 remain when we control for other investor characteristics, including gender, education, income, age, geographical location, the investor's sentiment toward fulfilling his own

investment goals, and sentiment toward the general market environment in the United States. The third and fourth columns of Table 6, panel B, report the effect of *Competence* on home bias, with *OptimismUS* and the other 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.

The results reported in Table 6, column 4, also show that geographical location is an important determinant of an investor's likelihood to hold foreign assets. The UBS surveys identify four regions of the country: Midwest, Northeast, West, and South. Our analysis shows that, controlling for other investor characteristics, including income and education, investors located in the South and the West regions are less likely to hold foreign assets than northeastern or midwestern investors.

In unreported regressions, we split the sample into two subsamples based on the investment/income ratio. The effect of investor competence is positive and highly significant for both the high-incentive and the low-incentive subsamples.

Our competence model is based on the November 1996 survey, whereas the surveys containing the home bias question are conducted in 2002. Investor sentiment in 1996 could be different from the sentiment in 2002, and potentially influence our results. To address this concern, we study the response to the following survey question in November 1996: "Do you own any international or global mutual funds that invest outside of the U.S.?" Studying this question offers the added benefit that, in this survey, we can use actual reported competence, instead of the constructed values, as an explanatory variable. Similar to the results reported in Table 6, we find that, controlling for investor demographics, investors who report higher competence are more likely to invest in international mutual funds.

An alternative explanation for home bias is the information story. For example, if the *Competence* variable captures an investor's information advantage, instead of perceived knowledge and 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

⁹One might think that an investor's optimism toward the U.S. market is affected by the current performance of the U.S. market, as well as by 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 the S&P 500 index or the University of Michigan's consumer sentiment index. Our results are qualitatively unchanged.

subjectively perceived knowledge instead of true information, then there is no reason for it to be positively associated with realized abnormal returns.¹⁰

In an unreported analysis (available upon request), we regress the average excess returns of high- and low-competence investors on the excess returns of the S&P 500 index and the Morgan Stanley Capital International World Index (excluding the U.S. market). If high-competence investors have better information or skill, then we would expect them to achieve higher alphas. Contrary to this prediction, our results show that the alphas of high- and low-competence investors are not statistically different. Moreover, the market risk loadings of the two groups of investors are not statistically different either. This evidence suggests that it is unlikely that our investor competence variable is simply capturing an information or risk effect.

5. 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 larger portfolios or more education, are more likely to perceive themselves as competent than are investors who are female, have smaller portfolios, or have 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 feels 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. Overall, the competence effect identified in our analysis is economically important and robust to the influence of overconfidence, optimism, and information advantage.

Acknowledgments

The authors thank Itzhak Ben-David, Alon Brav, Jennifer Conrad, Craig Fox, Simon Gervais, John Lynch, Terry Odean, John Payne, seminar participants at Duke University, and especially Chip Heath for helpful comments. They appreciate the detailed comments of the associate editor and two referees.

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¹⁰ Ideally, to test the link between our competence measure and true information, we would like to use future abnormal returns, realized after we measure investor competence. Because such returns are not available in our data due to lack of details on investor portfolio holdings, we study realized portfolio returns over the 12 months prior to the survey.

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