Superior Information or a Psychological Bias? A Unified Framework with Cognitive Abilities Resolves Three Puzzles*

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November 12, 2007

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ABSTRACT

We show that a portfolio choice framework with cognitive abilities resolves three recent puzzles identified in the retail investor literature: portfolio concentration, excess trading, and local bias. In all three instances, portfolio decisions could be induced by superior information or a psychological bias. Using imputed cognitive ability measures and both investor-level and aggregated stock-level tests, we show that high cognitive ability investors hold concentrated portfolios, trade actively, and prefer to hold local stocks due to an informational advantage. Consequently, they earn higher risk-adjusted returns. In contrast, the decisions of low cognitive ability investors reflect psychological biases (overconfidence and familiarity), which leads to lower risk-adjusted performance. Overall, both behavioral and rational explanations for the three puzzles are supported empirically, but they apply to low and high cognitive ability investor groups, respectively.

THE RECENT LITERATURE ON RETAIL INVESTORS has identified three puzzles. The first puzzling finding is that retail investors hold concentrated portfolios with only a handful of stocks (e.g., Barber and Odean (2000)). It is not entirely clear whether certain investors hold few stocks because they are relatively unsophisticated and exhibit stronger behavioral biases (Goetzmann and Kumar (2005)), exhibit a preference for skewness (Mitton and Vorkink (2007)), or because they are resourceful and are able to gather better information about those stocks (Ivković, Sialm, and Weisbenner (2007)).

Second, retail investors trade actively and excess trading could be induced by behavioral biases. For instance, overconfident investors who either over-estimate the quality of their private information or their ability to interpret that information would trade excessively (Odean (1999), Barber and Odean (2000)). Alternatively, excess trading might reflect contrarian trading (Grinblatt and Keloharju (2001b)), perceived competence (Graham, Harvey, and Huang (2006)), a desire to seek sensation (Grinblatt and Keloharju (2006)), or for pure entertainment reasons (Dorn and Sengmueller (2006)). But in addition to these behavioral determinants of trading, aggressive trading by investors could also reflect their attempts to exploit their superior, time-sensitive private information (e.g., Kyle (1985), Admati and Pfleiderer (1988), Holden and Subrahmanyam (1992), Wang (1994)). In this setting, active trading could be optimal and need not be excessive.

Third, retail investors exhibit a local bias, i.e., a disproportionately large proportion of their equity portfolios are invested in geographically proximate stocks. This preference for local stocks could be induced by familiarity, where they invest in local stocks because they are familiar with them and are not necessarily better informed (e.g., Huberman (2001), Grinblatt and Keloharju (2001a), Zhu (2002)). But those preferences could also be driven by superior information about local stocks (e.g., Bodnaruk (2003), Ivković and Weisbenner (2005), Massa and Simonov (2006)).

Because of multiple competing explanations, there has been considerable debate about the underlying mechanisms that induce investors to hold concentrated portfolios, trade actively, and hold local stocks. In this study, we introduce cognitive abilities in the portfolio choice framework and examine whether this extended framework provides a unified explanation for the three puzzles. Our main idea is simple and fairly intuitive. We conjecture that the investment decisions of investors with higher cognitive abilities would be driven by superior information, while the decisions of investors with lower cognitive abilities are more likely to reflect behavioral biases. This conjecture is motivated by recent research in behavioral economics (e.g., Frederick (2005), Benjamin, Brown, and Shapiro (2006), Dohmen, Falk, Huffman, and Sunde (2007)), which finds that lower levels of cognitive abilities are associated with more "anomalous" preferences (e.g., greater level of impatience and stronger short-stakes risk aversion).

Thus, when high cognitive ability investors hold concentrated portfolios, trade aggressively, or exhibit a greater propensity to hold local stocks, their decisions are more likely to be induced by superior information about those stocks, which should generate higher risk-adjusted returns. There are several reasons why high cognitive ability investors could possess an informational advantage. Those investors are likely to be more attentive, might have access to better information networks (e.g., due to their superior social networks), might exhibit greater skill in gathering information, and might even be better at interpreting the acquired information. High cognitive ability investors might also possess superior learning abilities because of their stronger memory and superior analytical and numerical abilities (Kezdi and Willis (2006)). Consequently, they are more likely to follow adaptive strategies, where they learn from their past mistakes and experiences and change their investment strategies when they are not successful.

In contrast, in all three instances, the decisions of low cognitive ability investors are more likely to be induced by behavioral biases, which would generate lower realized returns. When low cognitive ability investors hold fewer stocks, it is likely to be due to their lack of sophistication and improper understanding of the benefits of diversification. Similarly, their active trading might be induced by overconfidence. And they would overweight local stocks not because of an informational advantage, but just because they are more familiar with them or have a perception of information.

To empirically test the main hypothesis, we need direct measures of people's cognitive abilities and detailed accounts of their investment decisions. Unfortunately, it is difficult to obtain direct measures of people's cognitive abilities. It is even more difficult to obtain details of people's investment decisions and estimates of their cognitive abilities simultaneously. Therefore, we follow the standard imputation methodology that is often used to link data from multiple sources (e.g., Skinner (1987), Ziliak (1998), Browning and Leth-Petersen (2003)).

Using a relatively unique data set that contains direct and multiple measures of the cognitive abilities of a representative sample of European households, we estimate a regression model and identify the key demographic characteristics that are known to be correlated with cognitive abilities. We employ this empirical model out-of-sample to predict the cognitive abilities of a sample of individual investors at a large U.S. brokerage house. The cognitive abilities of those investors are not observed but detailed information about their demographic characteristics and stock investment decisions are available.[1] This approach is similar to Graham, Harvey, and Huang (2006), who use investor characteristics to estimate

[1]Christelis, Jappelli, and Padula (2007) employ the European data to examine whether higher cognitive abilities increase stock market participation rates. The retail investor data have been used in several studies including Odean (1998a, 1999), Barber and Odean (2000, 2001), and more recently in Ivković and Weisbenner (2005), Ivković, Poterba, and Weisbenner (2005), Graham and Kumar (2006), Lim (2006), Zhu (2006), Barber and Odean (2007), and Ivković, Sialm, and Weisbenner (2007).

a model of perceived competence and optimism. They estimate the models in one setting and use the predicted values of competence and optimism from this model in another setting in which competence and optimism measures are unavailable.

We find that just a handful of demographic characteristics are able to explain a significant proportion of the cross-sectional variance in people's cognitive abilities. In particular, age, education, and social network proxy are the three strongest determinants of cognitive abilities. The in-sample correlation between the actual and the model predicted cognitive ability measures is about 0.66, which translates into an impressive adjusted R^2 of 44%.

Using the imputed cognitive ability measures for the investors in the brokerage data set, we examine the characteristics of investors across cognitive ability quintiles. We find that many characteristics such as wealth, gender, investment experience, and mutual fund holdings do not vary with cognitive ability. But high ability investors are younger, have significantly higher incomes, and tend to live in urban regions. Examining investors' stock preferences, we find that high cognitive ability investors tilt their portfolios toward S&P500 stocks and also hold stocks with greater systematic risk and higher average returns. In contrast, low ability investors exhibit a stronger preference for stocks with high idiosyncratic volatility that are known to earn low average returns (Ang, Hodrick, Xing, and Zhang (2006)). Examining the relation between cognitive abilities and behavioral biases, we find that high cognitive ability investors trade actively, hold more concentrated portfolios, and exhibit stronger preference for local stocks. Perhaps more surprisingly, high cognitive ability investors exhibit stronger disposition effect, but they do not underperform due to this bias.

Next, we examine the performance of high and low cognitive ability investors, conditional upon the degree of their behavioral biases. We find that the performance differential between high and low cognitive ability investors is indistinguishable from zero when both groups hold relatively diversified portfolios, trade infrequently, and do not tilt their portfolios toward local stocks. But during the six-year sample period, investors with higher predicted cognitive abilities earn about 5% higher risk-adjusted, annual return when they hold concentrated portfolios, hold local stocks, or when they trade aggressively. The performance differential is also economically significant (about 3%) when we only compare investors' local investments.

Using the Daniel, Grinblatt, Titman, and Wermers (1997) performance decomposition methodology, we find that a significant part of this performance differential is due to the superior stock selection abilities of high cognitive ability investors. Furthermore, the superior skill is concentrated among stocks that have greater information asymmetry (non-S&P 500 stocks) and/or are harder-to-value (growth stocks or stocks with high idiosyncratic volatility). Taken together, the conditional performance results indicate that the "bias" of high cognitive ability investors are induced by superior information.

For greater accuracy and robustness, we conduct portfolio-based tests. We compute the average cognitive ability of the stockholders of each stock and sort stocks based on the cognitive abilities of their investor clienteles. Because the stock-level cognitive ability measures are persistent, we are able to extend the sample beyond the relatively short six-year period. With the extended sample (1980-2005), we find that stocks with "smarter" investor clientele earn higher returns than stocks that attract a "dumb" investor clientele. The annualized, risk-adjusted cognitive ability spread is about 4-5% and the spread is even larger when the high cognitive ability clientele holds concentrated portfolios, trades more actively, or prefers local stocks. Furthermore, the spread is persistent and remains economically significant even three years after the portfolio formation date. This evidence indicates that the return spread reflects the information exploited by high cognitive ability investors, rather than mispricing that eventually gets corrected.

Collectively, these results are strongly consistent with our main conjecture. As predicted, the investment decisions of low cognitive ability investors reflect behavioral biases, while the investment decisions of high cognitive ability investors are induced by superior information. We find empirical support for both behavioral and information-based explanations for portfolio concentration, excess trading, and local bias. But the two explanations are applicable to two distinct groups of investors, and cognitive abilities define the boundary between the two groups.

The rest of the paper is organized as follows. In the next section, we estimate an empirical model of cognitive abilities. In Section II, we examine whether the investment style varies with cognitive abilities. In Section III, we show that in three distinct settings, investors' cognitive abilities determine whether their portfolio decisions are induced by superior information or psychological biases. In Section IV, we conduct empirical tests at the stock-level to gather additional support for our main hypothesis. We briefly discuss the implications of our research in Section V and conclude in Section VI.

I. An Empirical Model of Cognitive Abilities

To begin, we estimate an empirical model of cognitive abilities. We consider several regression specifications, where one of the direct measures of cognitive abilities is the dependent variable. The independent variables are the main determinants of cognitive abilities identified in the psychological literature.

A. SHARE and HRS

We use data from two sources to estimate the cognitive abilities model. Our first data source is the 2005 wave of the Survey of Health, Aging, and Retirement in Europe (SHARE). The survey is administered in 11 European countries to individuals who are at least 50 years old.[2] The SHARE data contain three direct and standardized measures of cognitive abilities: (i) verbal ability, (ii) quantitative ability, and (iii) memory. The ability measures are constructed based on responses from a paper-based survey. The three cognitive measures are positively correlated, but the maximum correlation is below 0.50. Using these measures, we obtain a composite (equal-weighted) measure of cognitive ability of each household.

The SHARE data also contain demographic variables like age, income, wealth, education, gender, and a social network proxy. The social network proxy is defined as the average level of social activities undertaken by a household, which includes sports, political and community activities, and religious activities. The assumption is that people who engage in more social activities would have larger social networks.

We use the SHARE data set to estimate the model because it contains more accurate measures of cognitive abilities and social networks. But for robustness, we also consider the 2004 wave of the Health and Retirement Study (HRS) data. Like the SHARE data, the HRS data contain information about the health and financial status for a sample of U.S. households who are over the age of 50.[3] The more recent waves of the HRS contain measures of verbal ability, quantitative ability, and memory, and we use them to obtain an

[2] The SHARE data are available at `http://www.share-project.org/`. See Christelis, Jappelli, and Padula (2007) for additional details.

[3] The HRS data are available at `http://hrsonline.isr.umich.edu/`. See Hong, Kubik, and Stein (2004) or Campbell (2006) for additional details.

equal-weighted measure of cognitive ability of each household.

B. The Empirical Model

The cognitive abilities regression estimates are reported in Table I. To ensure that extreme values are not affecting our results, we winsorize all variables at their 0.5 and 99.5 percentile levels. To facilitate comparisons of coefficient estimates within and across regression specifications, we standardize both the dependent and the independent variables so that each variable has a mean of zero and a standard deviation of one. In the first three columns, we present the estimates for the verbal, quantitative, and memory measures of cognitive ability. In the fourth column, the dependent variable is an equal-weighted measure of the three cognitive abilities. In the last column, for robustness, we report the model estimates, where the dependent variable is the first principle component of the three cognitive ability measures.[4] This test is designed to examine whether some weighted combination of the three cognitive measures is a better proxy of cognitive abilities.

We find that the coefficient estimates are very similar across the various cognitive ability measures, including the first principal component measure. Examining the coefficient estimates, we find that, consistent with the psychological evidence, cognitive abilities decline with age, and are positively associated with education and the size of the social network. The estimates of wealth and income are also significantly positive, although their magnitude is low. Also, the cognitive abilities are lower for individuals who are older (age > 70).

While we use country fixed effects in the estimation, the coefficient estimates are very similar without the country fixed effects, although the adjusted R^2 drops to 0.371. We also obtain qualitatively similar results when the dependent variable is the composite cognitive ability measure obtained using the HRS data (see the last column in Table I). One exception is the coefficient estimate of the social network proxy, which is considerably weaker. This evidence is not very surprising because the social network proxy (church attendance) is inferior to the social network proxy available in the SHARE data.

The strong positive relation between cognitive ability and education is intuitive and consistent with the evidence from previous studies that find a high correlation (over 0.60) be-

[4] The first principal component explains 63.10% of the total variance in the cognitive ability measures.

tween education level and cognitive ability (e.g., Brown and Reynolds (1975), Barber (2005), Zagorsky (2007)). The relatively weaker relation between cognitive ability and income (and wealth) is also consistent with the previous evidence. Overall, the cognitive ability regression estimates indicate that education, age, and social network are the three strongest correlates of cognitive abilities.

C. *How Valuable is the Empirical Model of Cognitive Abilities?*

It is remarkable that just a handful of demographic variables can explain a significant proportion of the cross-sectional variation in people's cognitive abilities. The adjusted R^2 of our cognitive abilities model is an impressive 44%. Nevertheless, we conduct several tests to examine whether the imputed cognitive abilities obtained using the empirical model are appropriate.

First, we examine the in-sample correlation between the actual and the predicted values of cognitive abilities. The correlation is 0.658, which is significantly higher (almost twice) than the correlations between the actual and predicted values observed in other studies that follow the imputation methodology similar to ours (e.g., Graham, Harvey, and Huang (2006)). Second, we aggregate the imputed cognitive ability measures of our sample of individual investors (see Section II.A) at the state level and compute the correlation with state IQ estimates (Kanazawa (2006)). While the state level IQ estimates are noisy, somewhat controversial, and do not match with our sample period, it is comforting to know that the correlation between our state level cognitive ability estimates and the IQ estimates from other studies is significantly positive (correlation = 0.207, t-stat = 2.148).

Last, we conduct randomization tests to show that the choice of independent variables and their coefficient estimates in the empirical model of cognitive abilities capture valuable information for identifying skilled investors. The randomization tests are conducted as follows. We consider all the independent variables used in the empirical model and assign them a coefficient randomly chosen from the set $(-1, +1)$.[5] Using the model with randomized coefficients, we obtain imputed cognitive ability measures for all investors in the

[5] We find very similar results when we conduct alternative randomization tests, where we maintain the signs of the coefficient estimates in the model, but randomize their magnitudes.

brokerage sample. We sort investors into five quintiles using the imputed ability measures and compute the performance differential between the high (quintile 5) and low (quintile 5) cognitive ability categories. The quintile performance is the sample-period, equal-weighted average performance of all investors in the group. The performance measure used is the characteristic-adjusted returns computed using the Daniel, Grinblatt, Titman, and Wermers (1997) methodology.

We repeat the procedure 1500 times and generate a distribution of the annualized performance differential between the high and the low cognitive ability categories (see Figure 1). We find that the actual performance differential of 2.31% (see Section III.A) is in the extreme right tail of the empirical distribution. Only two observations in the empirical distribution are above the actual performance differential. Thus, we can easily reject the null hypothesis (p-value = 0.001) that the estimated model of cognitive abilities does not contain useful information about the investment abilities of investors.

D. *Cognitive Abilities or Perceived Competence?*

The coefficient estimate of education is strong in our cognitive abilities model as well as the perceived competence model estimated in Graham, Harvey, and Huang (2006). Furthermore, both high competence and high cognitive ability investors exhibit a greater propensity to invest in foreign securities (see Section II.B). Thus, one might be concerned that our imputed cognitive ability measure is a proxy for investor competence. There are several reasons why this is unlikely to be the case.

First, investors with greater competence trade more often and hold larger portfolio. But we find that high cognitive ability investors unconditionally do not trade more frequently (see Table IV) and hold somewhat smaller portfolios (see Table II). Second, age is one of the main determinants of cognitive ability, but investor competence is unrelated to age. Third, the performance differential between the high and the low competence investors is not statistically significant. But we find that high cognitive ability investors earn significantly higher risk-adjusted returns than low cognitive ability investors (see Section III.A). These comparisons indicate that while certain aspects of competence and cognitive ability might be related, these are two distinct investor attributes.

II. Cognitive Abilities and Investment Style

A. Cognitive Ability Measures of Individual Investors using Imputation

In this section, we examine the extent to which cognitive abilities influence the investment style of U.S. individual investors. For this exercise, we use the model of cognitive abilities reported in Table I and obtain imputed values of cognitive abilities of individual investors at a large U.S. discount brokerage house. A key advantage of our imputation methodology, which links data from two distinct sources, is that it is immune to potential concerns about data-mining and endogeneity. Unlike most studies on retail investors, we do not estimate investment skill using investors' portfolio decisions. Instead, we obtain investors' ability estimates *ex ante* using only their demographic characteristics.

Specifically, we use the coefficient estimates in the "Avg" column of Table I and the demographic characteristics of brokerage investors to predict their cognitive abilities. We use the SHARE model for this exercise because it is more reliable and yields estimates that are closer to the psychological evidence. Nevertheless, our results are very similar when we use the HRS model ("Avg2" column).[6] Using the imputed cognitive ability measures and the observed portfolio holdings and trades of brokerage investors, we evaluate various dimensions of their stock investment decisions.

B. Individual Investor Database and Other Data Sources

The brokerage data contain the monthly positions and all trades of a sample of individual investors for the 1991 to 1996 time period. There are 77,995 households in the retail database. These investors hold common stocks and trade a variety of other securities including mutual funds, options, American depository receipts (ADRs), etc. In this study, we focus on the investment behavior of 62,387 investors who have traded common stocks. An average investor holds a four-stock portfolio (median is three) with an average size of $35,629 (median is $13,869). For a subset of households, demographic information such as age, income,

[6] This is not surprising because the correlation between the cognitive ability measures obtained using the SHARE and the HRS data is 0.933.

wealth, occupation, marital status, gender, etc. is available, where most of the demographic information is self-reported. Further details on the investor database are available in Barber and Odean (2000).

The brokerage data are quite appropriate for examining the effects of cognitive abilities because unlike a full-service brokerage, where investors are likely to be strongly influenced by advice from the brokerage firm, investors in our sample manage their portfolios themselves. In this setting, it would be easier to detect the effects of cognitive abilities. Furthermore, the brokerage sample is tilted towards relatively more affluent investors.[7] Thus, the low cognitive ability investors in our sample are likely to have higher cognitive ability than the typical low cognitive ability investor. This evidence suggests that the relation between cognitive abilities and investment decisions we find is likely to be stronger in a more representative sample that contains a larger proportion of low cognitive ability individuals.

We enrich the individual investor data using the zip code level Census data and regional social network measures. Specifically, we use the 1990 U.S. Census data to infer the education level of an investor.[8] Investors who live in more educated zip codes are assumed to be more educated, where the proportion of the zip code population that holds a bachelor's or higher degree is used to identify the educational status of that zip code. To estimate the size of the social network of an investor, we obtain a sociability index for each county. This index is a composite measure of social capital that includes measures such as interactions with friends, trust, and membership in social organizations.[9] We assume that investors who live in more sociable counties have relatively larger social networks.

Several other standard data sets are used in this study. For each stock in the sample, we obtain the quarterly cash dividend payments, monthly prices, returns, and market capitalization data from the Center for Research on Security Prices (CRSP) and quarterly book value of common equity data from COMPUSTAT. We obtain the monthly time-series of the three Fama-French factors and the momentum factor from Professor Kenneth French's

[7]The mean net worth of investors in our sample is $268,909 (median is $100,000), which is considerably higher than the mean net worth (= $106,399) of households in the 1995 Survey of Consumer Finances (Poterba (2001)).

[8]The U.S. Census data are available at `http://www.census.gov/main/www/cen1990.html`.

[9]The data are described in Putnam (2000) and are available at `http://www.bowlingalone.com.` Ivković and Weisbenner (2007) use the data to examine whether the stock holdings of individual investors in more sociable regions exhibit stronger correlations. We thank Zoran Ivković for making us aware of this data set.

data library. Last, we obtain characteristic-based performance benchmarks from Professor Russell Wermers' web site.[10]

C. Cognitive Abilities and Investor Characteristics

Table II presents several measures of portfolio and investor characteristics for cognitive ability sorted investor categories. We find that many characteristics such as gender, investment experience, and mutual fund holdings do not vary significantly with cognitive ability. However, there are significant differences between the low and high cognitive ability investors along other important dimensions.

For instance, a very large proportion (about 46%) of high ability investors live in urban regions (within 100 miles of the top twenty metropolitan regions in the U.S.). In contrast, only about 17% of low cognitive ability investors are located in urban areas. Moreover, we find that high cognitive ability investors are not wealthier than low cognitive ability investors, but they earn significantly higher income in comparison to low cognitive ability investors ($126,342 versus $58,684).[11] We also find that high cognitive ability investors exhibit a greater propensity to invest in foreign stocks, a weaker propensity to hold high dividend yield stocks, and are more likely to trade options or engage in short-selling. Overall, these summary statistics indicate that high cognitive ability investors are more likely to adopt relatively sophisticated investment strategies.

D. Cognitive Abilities and Stock Preferences

To examine whether stock preferences vary with cognitive abilities, we estimate stock-level Fama-MacBeth regressions. For this analysis, first, we sort investors into quintiles using their imputed cognitive ability measures. Investors in quintile one (five) are identified as low

[10] The risk factors are obtained from `http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/` and the performance benchmarks for computing characteristic-adjusted returns are obtained from `http://www.smith.umd.edu/faculty/rwermers/ftpsite/Dgtw/coverpage.htm`.

[11] Because income is one of the correlates of cognitive ability and it has a positive sign in the empirical model, we expect income to increase across the cognitive ability quintiles. However, the dramatic difference between the low and the high cognitive ability quintiles cannot to be attributed to the small, positive coefficient estimate of income in the model. Moreover, the income pattern across the cognitive ability quintiles is very similar when we do not use income to predict investors' cognitive abilities.

(high) cognitive ability investors. Next, by combining the portfolios of all investors within a group, we construct an aggregate group portfolio for both low and high cognitive ability investor categories. Last, we estimate Fama-MacBeth regressions, where the excess weight assigned to a stock in the aggregate group portfolio is the dependent variable and various stock characteristics are used as independent variables.

The excess portfolio weight allocated to stock i in month t is given by: $EW_{ipt} = \frac{w_{ipt} - w_{imt}}{w_{imt}} \times 100$, where, w_{ipt} is the actual weight assigned to stock i in group portfolio p in month t and w_{imt} is the weight of stock i in the aggregate market portfolio in month t. The set of independent variables include: (i) market beta, which is estimated using the previous six months of daily returns data, (ii) firm size, (iii) book-to-market ratio, (iv) past one-month stock return, (v) past twelve-month stock return, (vi) stock price, (vii) idiosyncratic volatility, which is the variance of the residual obtained by fitting a four-factor model to the daily stock returns in the previous six months, (viii) firm age, (ix) an S&P500 dummy which is set to one if the stock belongs to the S&P500 index, and (x) a dividend paying stock dummy, which is set to one if the stock is a dividend paying stock during the previous year.

We follow the Pontiff (1996) methodology to correct the Fama-MacBeth standard errors for serial correlation. To ensure that extreme values are not affecting our results, we winsorize all variables at their 0.5 and 99.5 percentile levels. To facilitate comparisons of coefficient estimates within and across regression specifications, we standardize both the dependent and the independent variables so that each variable has a mean of zero and a standard deviation of one.

The Fama-MacBeth regression estimates are presented in Table III. Specification (1) reports the estimates for low cognitive ability investors, specification (2) reports the estimates for high cognitive ability investors, and specification (3) shows the estimates for the difference. The most salient result in the table is that high cognitive ability investors hold stocks with higher systematic risk that yield higher average returns. In contrast, low cognitive ability investors exhibit a strong preference for high idiosyncratic volatility stocks, which are known to earn low average returns (Ang, Hodrick, Xing, and Zhang (2006)). The second salient finding is that high cognitive ability investors exhibit a stronger preference for non-dividend paying stocks. They also tilt their portfolios toward S&P500 stocks and exhibit a relatively weaker preference for small, low priced, and value stocks. However, these preference differences are not strong. Overall, the stock-level Fama-MacBeth regression estimates indicate that low and high cognitive ability investors have distinct stock preferences.

E. Cognitive Abilities and Behavioral Biases

In this section, we examine whether investors' cognitive abilities influence their propensities to exhibit different types of behavioral biases. First, we measure portfolio concentration using the sample period average number of stocks in the portfolio, the average correlation among the stocks in the portfolio, and the normalized portfolio variance (the ratio of portfolio variance and the average correlation of stocks in the portfolio). Second, we measure trading activity using the monthly turnover measure (the average of buy and sell turnover rates) and the average stock holding period. Last, to capture investors' propensity to invest in local stocks, we obtain the local bias (LB) measure, defined as, $LB = 1 - D_{act}/D_{portf}$, where D_{act} is the distance between an investor's location and her stock portfolio and D_{portf} is the average distance between an investor's location and other characteristic-matched portfolios not held by the investor. We also measure local bias as the proportion of total equity portfolio that is invested in stocks that are located within 250 miles of investor's location.[12]

In addition to these three biases that are the focus of this study, we consider other biases identified in the recent individual investor literature. Specifically, we compute: (i) Odean's (1998b) disposition effect measure, which is the difference in the proportion of winners realized and the proportion of losers realized, (ii) narrow framing, which is an adjusted measure of trade clustering (Kumar and Lim (2007)), (iii) an overconfidence dummy, which is set to one for investors who are in the highest portfolio turnover quintile but lowest performance quintile, and (iv) portfolio weight in "lottery-type" stocks (i.e., stocks that have high idiosyncratic volatility, high idiosyncratic skewness, and low prices), as defined in Kumar (2006).

Table IV reports the average bias measures for cognitive ability sorted investor categories (quintiles). We find that high cognitive ability investors hold more concentrated portfolios, trade somewhat more actively, and exhibit stronger preference for local stocks. For instance,

[12] See Coval and Moskowitz (2001), Zhu (2002), Ivković and Weisbenner (2005) for additional details on the local bias measure.

low cognitive ability investors hold an average of 5.18 stocks, while high cognitive ability investors hold an average of 4.37 stocks. Similarly, the average proportion of local stocks in the portfolios of high cognitive ability investors is 13.28% and the portfolios of low cognitive ability investors contain an average of 9.73% local stocks. The monthly turnover rates do not vary significantly across the cognitive ability quintiles, but high cognitive ability investors hold a stock for 20 fewer days (334 days versus 354 days).

Among the other biases, we find that overconfidence and gambling propensity do not vary significantly with cognitive abilities. But high cognitive ability investors exhibit less clustered trades, which indicates that they are more likely to frame their investment decisions narrowly (Kahneman and Lovallo (1993), Barberis, Huang, and Thaler (2006), Kumar and Lim (2007)). Most surprisingly, high cognitive ability investors exhibit a greater propensity to sell their winners and are more reluctant to sell their losers. Consequently, they exhibit stronger disposition effect.

At first glance, the evidence that investors with high cognitive abilities are more likely to frame their investment decisions narrowly and exhibit stronger disposition effect appear puzzling because both behaviors are associated with lower average performance (e.g., Odean (1998b)). However, we show later in the paper (see Section III.H) that, in spite of the higher bias levels, the underperformance induced by these biases are lower for high cognitive ability investors. In sum, the average bias estimates for cognitive ability sorted investor quintiles indicate that high cognitive ability investors exhibit stronger biases. In the next two sections, we conduct several tests to better understand this seemingly puzzling result.

III. Cognitive Abilities and the Three Puzzles

Our main conjecture is that a portfolio choice framework with cognitive abilities would be able to resolve the three puzzles identified in the retail investor literature. The key identification strategy focuses on the bias-performance interaction, conditional upon the level of cognitive ability. We assume that if portfolio distortions reflect a bias, the realized portfolio performance would be lower. In contrast, if those distortions are induced by superior information, investor portfolios would earn abnormal risk-adjusted returns.

Specifically, we conjecture that when investors hold well-diversified portfolios, trade less frequently and follow buy-and-hold type strategies, and do not tilt their portfolios toward local stocks, having high cognitive abilities might not yield significant advantages. But, differences in cognitive abilities could significantly influence performance when investors ignore the normative prescriptions of portfolio theory and hold concentrated portfolios, trade actively, and overweight local stocks. In particular, high cognitive ability investors with superior information would be able to generate high risk-adjusted returns from those portfolio distortions, while the portfolios of low ability investors would significantly under-perform because their distortions are more likely to reflect behavioral biases.

A. *Cognitive Abilities and Portfolio Performance*

Before presenting the bias-conditional performance estimates, we report the performance differential between the high and the low cognitive ability investors without conditioning on the degree of behavioral bias. These estimates serve as appropriate benchmarks and allow us to better interpret the conditional performance estimates.

We find a positive relation between cognitive ability and portfolio performance. The annual raw, characteristic-adjusted, and risk-adjusted (four-factor alpha) performance differentials between the high and lowest cognitive ability investor categories are 2.36%, 2.22% (t-stat = 2.909), and 2.31% (t-stat = 2.310), respectively. This evidence is consistent with previous evidence that finds that certain subset of individual investors might have information (e.g., Coval, Hirshleifer, and Shumway (2005), Ivković and Weisbenner (2005), Ivković, Sialm, and Weisbenner (2007)). The novel aspect of our findings is that we are able to identify superior performing investors on an *ex ante* basis using their demographic characteristics and without examining their investment decisions or realized portfolio performance.

B. *Superior Information or a Psychological Bias?*

In this section, to gather support for our main conjecture, we compute investors' realized risk-adjusted portfolio performance measures, conditional upon the degree of distortion in their portfolio decisions. We focus on three investment decisions that might reflect a bias or could be induced by superior information: (i) the decision to hold a concentrated portfolio (portfolio with only a handful of stocks), (ii) the decision to trade actively, and (iii) the decision to tilt the portfolio toward local stocks. We sort investors independently using their imputed cognitive ability measures and three portfolio distortion measures. Then, for each of the three portfolio distortion measures, we compute the average portfolio performance of high and low cognitive ability investors when the distortion is low (bottom quintile) and high (top quintile).

Figure 2 shows the bias-conditional portfolio performance for low and high cognitive ability investor groups. Consistent with our conjecture, we find that when portfolio distortions are low, high cognitive ability investors earn an average of only 1% higher annualized, characteristic-adjusted returns than low cognitive ability investors. But when portfolio distortions are significant, high cognitive ability investors outperform low cognitive ability investors by more than 5%. This evidence indicates that the large portfolio distortions by high cognitive ability are likely to be induced by information rather than psychological biases. Because low cognitive ability investors earn negative characteristic-adjusted returns, the evidence also indicates that the large portfolio distortions by those investors are more likely to be induced by psychological biases.

To examine the interactions among behavioral biases, performance, and cognitive ability more accurately, we estimate an investor-level cross-sectional regression, where the dependent variable is an investor's sample-period characteristic-adjusted performance. The independent variables include the imputed value of cognitive ability, measures of the three behavioral biases (see Section II.D for definitions), and interactions among these variables. Our main focus is on the cognitive ability-bias interaction terms.

To define the interaction terms, we define a high (low) ability dummy, which is set to one for investors in the highest (lowest) cognitive ability quintile. The high and low bias dummy variables are defined in an analogous manner. The regression specification also includes the known determinants of portfolio performance as control variables: portfolio size (size of the investor portfolio when she enters the sample), portfolio dividend yield, investment experience (the number of days between the account opening date and December 31, 1996), and gender. The high and low dummy measures used to define the interaction terms are additional control variables. For brevity, the coefficient estimates of the control variables are suppressed. We use robust, clustered standard errors (except in specification (4)) to account for potential cross-sectional dependence within zip codes.

The regression estimates are reported in Table V. Consistent with the evidence from previous section, we find that investors with higher cognitive abilities earn higher characteristic-adjusted returns. Furthermore, both portfolio turnover and local bias variables have positive coefficient estimates, which indicate that the two biases might have an information-based explanation. The positive estimate of the local bias variable is consistent with the evidence in Ivković and Weisbenner (2005). More importantly, consistent with the sorting results reported in Figure 2, we find that the portfolio performance is lower (higher) when investors have low (high) cognitive abilities and exhibit stronger behavioral biases. The three high ability $\times$ high bias interactions have significantly positive estimate, while the low ability $\times$ low bias interactions have significantly negative estimates.

Because the cognitive ability measure is obtained using a regression model and is subject to potential measurement error, for robustness, in column (4), we report the estimates from errors-in-variables regression (Kmenta (1997)). In this specification, we assume that the reliability ratio of variables that include the cognitive ability proxy is the adjusted R^2 (= 0.441) of the cognitive abilities model in Table I. The results indicate that the coefficient estimates of all ability-bias interactions are still statistically significant. The coefficient estimates of most other variables are similar to the baseline estimates. The notable exception is the cognitive ability measure whose coefficient estimate becomes significantly stronger.

C. Which Cognitive Ability Determinants are More Important?

The imputed cognitive ability measures represent a linear combination of investor characteristics such as education, age, social network, and income. Therefore, the bias-conditional performance differential between low and high cognitive ability investors would also be some combination of these investor characteristics. To identify what proportion of the performance differential could be attributed to these investor characteristics, we estimate the bias-conditional performance differentials when one or more of the cognitive ability determinants are used to proxy for cognitive abilities.

The results are summarized in Table VI, Panel A. Similar to the results plotted in Figure

2, we report the annualized, characteristic-adjusted performance differential between high (quintile 5) and low (quintile 1) cognitive ability investor categories, conditional upon the level of behavioral bias. When only income is used to define the cognitive ability proxy, the performance differentials are positive (about 2%) when the biases are stronger. The evidence is similar, although somewhat weaker, when social network proxy is used. In both instances, the estimates are statistically significant only at the 10% level. With education and age variables, the performance differential estimates are stronger (about 2.75%) and the statistical significance improves.

When we consider an equal-weighted linear combination of only income, education, age, and social network, with a negative sign on age, the performance differentials are higher and around 3.25%.[13] This evidence indicates that the simple linear combination of these variables is a better proxy for cognitive abilities. As expected, the imputed cognitive ability measures obtained from the empirical model delivers the strongest result. The annualized characteristic-adjusted performance differential is about 5.75% and all three estimates are significant at the 5% level. This evidence indicates that, while the cognitive ability determinants have some independent ability to discriminate between skilled and unskilled investors, the imputed values of cognitive abilities have considerably higher discriminatory power.

To further demonstrate that the imputed values of cognitive abilities have greater ability to discriminate between skilled and unskilled investors, we examine the bias-conditional performance differential for a factor that is a known determinant of portfolio performance, namely, investment experience. We find that investors with greater experience outperform low experience investors by about 1.5% when the degree of behavioral biases are *low*. However, when biases are high, the performance differentials are not statistically different from zero. This evidence indicates that any measure of investor sophistication that is known to influence portfolio performance would not generate positive bias-conditional performance differentials. The discriminatory ability of the cognitive ability measure is unique.

[13]We obtain the equal-weighted, linear combination after standardizing (the mean is set to zero and the standard deviation is one) those four variables.

D. Additional Robustness Checks to Entertain Alternative Explanations

Our performance differential estimates are robust and we attribute them to investors' cognitive abilities. In this section, to ensure that our evidence is robust to these alternative interpretations, we re-estimate the bias-conditional performance differentials for several sub samples. The results are summarized in Table VI, Panel B.

In the first test, we attempt to rule out the possibility that our estimates primarily reflect the "old and retired" effect. The concern is that older investors with the bulk of their retirement money elsewhere are more likely to use the brokerage accounts as their "play money" accounts. When we compute the bias-conditional performance estimates for low and high cognitive ability investors after excluding investors with age above 60, the estimates (Row 1) are very similar to the full sample results shown in Panel A (Row 6).[14] Thus, it is unlikely that the large performance differentials reflect mainly the unique behavior of old and retired investors.

Second, to formally examine the "play money" hypothesis, we obtain the bias-conditional performance estimates only for investors who hold larger portfolios (portfolio size > \$25,000).[15] The evidence (Row 2) indicates that the performance differentials between the high and the low cognitive ability investors are still positive and economically significant. The estimates are larger for portfolio concentration and local bias (= 6.28% and 6.25%, respectively) measures, but the differential is significantly positive (= 4.65%) even for the portfolio turnover measure.

Third, given the greater concentration of high cognitive ability investors in urban areas (see Table II), we examine whether investor's location influences the bias-conditional performance differentials. We find that high cognitive ability investors perform better in urban regions, perhaps due to the better quality of the information environment in urban regions. However, high cognitive ability investors are able to outperform low cognitive ability even in rural regions. Additionally, in untabulated results, we find that the performance of low cognitive ability investors are similar in both rural and urban settings. Thus, they are unable to take advantage of potentially superior information environments in urban regions.

In the fourth test, we ensure that our results do not reflect the superior performance

[14]The results are similar if we use an age cutoff of 65 years.

[15]The results are not sensitive to the choice of the portfolio size cutoff used to define larger portfolios.

of insiders. To exclude potential insiders, we adopt an approach similar to Ivković, Sialm, and Weisbenner (2007) and exclude portfolios with only one stock. We re-estimate the bias-conditional performance differentials and find that the results are essentially unchanged (see Row 5). In untabulated results, we find that the estimates are very similar if we exclude only those one-stock portfolios that contain a local stock or a stock that is not traded actively.

Overall, the sub sample estimates indicate that several plausible alternative explanations for our economically significant results do not have much empirical support. So far, the most plausible explanation for the large performance differentials is still that the portfolio distortions of high cognitive ability investors are induced by superior information, and psychological biases induce distortions in the portfolios of low cognitive ability investors.

E. Cognitive Abilities and Performance of Local Investments

To get additional insights into the mechanisms through which high cognitive ability investors generate economically significant risk-adjusted returns, we examine the performance of the "local" component of investor portfolios. Stocks that are within a 250 mile radius of the investor's location are considered local.[16]

The performance estimates (equal-weighted average) of local portfolios of cognitive ability sorted investor groups are reported in Table VII. In Panel A, we report the actual and expected performance and characteristics of local portfolios, and in Panel B, we report the average k-day buy-sell return differential ($PTBSD$) estimates. The expected local performance for an investor is the average monthly return of characteristic (size, B/M, and past 12-month returns) matched local stocks that are not in the investor's portfolio, i.e., the set of local stocks that the investor could have held but chooses not to hold. The $PTBSD$ for an investor portfolio is defined as the difference in the k-day returns following local buy and local sell trades executed by the investor.

The local performance estimates indicate that high cognitive ability investors outperform low cognitive ability investors by 3.35% (0.279×12) annually on a risk-adjusted basis. High cognitive ability investors also outperform investor-specific local performance benchmarks. For the high cognitive ability investors, the annual average performance differential relative

[16]The results are stronger when we use a 100 mile radius to identify local stocks.

to the local benchmarks is 3.54% (0.295×12). In contrast, the low cognitive ability investors mildly under-perform the investor-specific local performance benchmarks.

When we use an alternative performance measure and compare the average k-day post-trade buy-sell return differential ($PTBSD$) measures of low and high cognitive ability investor categories, the results are similar. The high cognitive ability investors have positive $PTBSD$ estimates, the low cognitive ability investors have negative $PTBSD$ estimates, and the difference is statistically significant. Overall, the local performance estimates provide further support to the conjecture that high cognitive ability investors are able to generate higher risk-adjusted returns from their local investments due to superior local information.

F. DGTW Performance Decomposition

To get further insights into the mechanisms that allow high cognitive ability investors to generate higher returns, we use the Daniel, Grinblatt, Titman, and Wermers (1997) and Wermers (2003) decomposition to estimate the three components of portfolio performance: characteristic selectivity (CS), characteristics timing (CT), and average style (AS). A positive estimate for CS reflects stock selection ability within the style portfolios, while a positive CT estimate provides evidence of style timing.

We conduct independent double sorts and group investors into 25 categories based on their imputed cognitive ability measures and one of the behavioral bias measures. As before, three biases are considered: portfolio concentration, portfolio turnover, and local bias. We compute the CS, CT, and AS measures for each of the 25 bias-ability categories. The annualized performance measures are presented in Table VIII, Panel A, where for brevity, we only report the estimates for the four extreme bias-ability categories.

The DGTW performance estimates indicate that, when the behavioral bias is low (i.e., portfolio distortions are small), both the low and the high cognitive ability investors have negative CS and CT estimates, and the differences are economically small. The AS differences are also small and economically insignificant. But when the level of behavioral bias is high (i.e., portfolio distortions are large), high cognitive ability investors exhibit superior stock-picking abilities. The CS estimates for low cognitive ability investors are negative, the CS estimates for high cognitive ability investors are positive and economically significant

(2.78%, 3.72%, and 2.57%), and the differences between the estimates for the two groups are significantly positive.

Examining the CT estimates for the low and the high cognitive ability investor categories, we find that CT estimates are negative for both categories. Thus, when behavioral bias is high, both high and low cognitive ability investors lack characteristic timing abilities. However, the low cognitive ability investors have more negative CT estimates and exhibit worse timing abilities. For the three biases (portfolio concentration, portfolio turnover, and local bias), the annual CT estimates for the low cognitive ability category are -2.38%, -1.80%, and -1.56%, respectively. The corresponding CT estimates for the high cognitive ability category are -0.33%, -0.86%, and -0.35%, respectively.

When the bias level is high, we also find that the AS estimates for the high cognitive ability investors are higher than those for the low cognitive ability investors. The annual AS differentials corresponding to portfolio concentration, portfolio turnover, and local bias are 4.99%, 5.50%, and 4.78%, respectively. In sum, the DGTW performance estimates indicate that high cognitive ability investors are able to generate superior returns through appropriate style selection, their better stock selection abilities within those styles, and their relatively less inferior characteristic timing skills.

G. Information Asymmetry and Stock Selection Ability

If high cognitive ability investors are better at exploiting their superior information, they would be more effective among stocks with greater information asymmetry. It is less likely that those investors would have better information about widely followed stocks, such as the stocks that belong to the S&P500 index. To investigate whether the stock selection abilities of high cognitive ability investors vary with information asymmetry, we consider three proxies for information asymmetry: (i) membership in the S&P 500 index, (ii) idiosyncratic volatility (the variance of the residual obtained by fitting a four-factor model to the daily stock returns in the previous six months), and (iii) book-to-market (B/M) ratio. For the four extreme bias-ability categories, we estimate the CS measure by only considering investors' positions in stock categories defined according to one of these three characteristics.

The annualized CS estimates are reported in Table VIII, Panel B. When the bias level is low, high cognitive ability investors have higher CS estimates when the information asymmetry is higher (non-S&P 500 stocks, high idiosyncratic volatility stocks, and low B/M or growth stocks). But, the magnitudes of the CS estimates are low (between 1-2%).

When both the bias level and information asymmetry are high, high cognitive ability investors have significantly higher and economically significant CS estimates (between 4-5%). The superior performance among high idiosyncratic volatility stocks is particularly impressive because those stocks are relatively more difficult to value and are also known to earn low average returns (Ang, Hodrick, Xing, and Zhang (2006)). Because high cognitive ability investors generate superior returns from those stocks in spite of their worse average performance, evidence of investment skill appears strong.

H. Cognitive Abilities and Portfolio Performance: Other Biases

Our previous evidence (see Section II.D) that investors with high cognitive abilities are more likely to frame their investment decisions narrowly and exhibit stronger disposition effect appears puzzling because both behaviors are associated with lower average performance. In this section, we show that, in spite of their higher bias levels, high cognitive ability investors experience lower underperformance in these two instances where the biases do not have obvious alternative information-based explanations.

First, we consider the narrow framing bias. Kumar and Lim (2007) show that investors who are more likely to frame their decisions narrowly earn 1.63% lower returns on a risk-adjusted basis. When we examine the performance differential for the sub sample of high cognitive ability investors, it is not significantly different from zero. This evidence indicates that high cognitive ability investors do not experience greater underperformance from their framing decisions.

Second, we examine the effect of the disposition bias on performance, conditional upon the level of cognitive ability. Examining the influence of disposition effect on performance, Odean (1998b) shows that the winners investors sell outperform the losers that they hold by about 1.03% over the four month period and by 3.41% over the next one year. When we examine the *ex post* returns for cognitive ability sorted quintile portfolios, we find that there is little variation. The four month *ex post* returns for cognitive ability sorted quintile portfolios are 1.06%, 1.01%, 1.11%, 1.09%, and 0.99%, respectively. And the one year *ex post* returns for cognitive ability sorted quintile portfolios are 2.90%, 3.32%, 3.01%, 3.32%, and 3.20%, respectively.

We also find that high cognitive ability investors sell better "winners" (i.e., winners that have performed exceptionally well in the past) and hold on to better "losers" (i.e., losers that have under-performed considerably less in the past). Thus, the *realized* portfolio performance of high cognitive investors is moderately *higher,* even though they exhibit stronger disposition effect. For instance, examining only the winners that are held for about one year, the winners that are sold by high cognitive ability investors outperform the winners sold by low cognitive ability investors by about 6.31%. Similarly, examining only the losers that are held for one year, the losers that are held by high cognitive ability investors outperform the losers held by low cognitive ability investors by about 2.02%. The results are qualitatively very similar when we examine winners and losers with different holding periods.

Collectively, the disposition effect results further demonstrate that high ability investors exhibit superior stock picking abilities. In particular, they exhibit an ability to identify better winners. Of course, they could have earned even higher returns by appropriately timing the sale of their winners and losers. Their inability to optimally time the sale of winners and lowers is consistent with the results from DGTW decomposition presented in Section III.F.

I. How Do High Ability Investors Generate Superior Returns?

While our data do not allow us to precisely identify the channels through which investors generate superior returns from their portfolio deviations, we interpret the evidence presented so far and also conduct additional tests to identify channels that investors *might* use. Broadly speaking, high cognitive ability investors could generate superior returns because they have access to superior private and public information sources and/or they are better able to interpret their private and public information signals. Moreover, their ability to interpret information could be innate or acquired through some form of learning, i.e., they could either have greater cognitive *ability* or greater cognitive *skill.*[17]

Informational advantage could emerge from insider information, which could in turn

[17]I thank David Hirshleifer for helping me understand this important distinction.

induce superior bias-conditional returns. High cognitive ability investors are younger, urban, and more educated, have high income levels, and are likely to be part of large social networks. Due to their potentially superior information and social networks, those investors could have access to insider information, especially about local firms (e.g., as an employee). However, we find that the bias-conditional performance differential is weaker for investors who live in regions with stronger social networks. We also find that the bias-conditional performance differential is somewhat stronger for non-local stocks. Furthermore, in unreported results, we do not find any evidence of front-running by high cognitive ability investors prior to earnings announcements. Thus, our empirical evidence indicates that the superior performance of high cognitive ability investors is less likely to emerge from their insider information.

Alternatively, high cognitive ability investors might not have access to superior information sources, but they could just have quicker and easier access to information. Recent studies indicate that information is disseminated from urban centers to rural areas (e.g., Loughran (2007)). Thus, investors who live in urban regions or near financial centers are more likely to stumble across value-relevant information. Our empirical findings are consistent with this interpretation. We find that urban investors are able to generate higher bias-conditional performance than rural investors. However, high cognitive ability investors in rural and informationally-poor regions are also able to generate superior returns when they distort their portfolios. This evidence indicates that the positive bias-conditional performance do not solely reflect investors' ability to easily gather information in superior information environments. Cognitive ability has incremental positive effect on bias-conditional performance.

If better information sources or richer information environments do not offer an informational advantage to high cognitive ability investors, they are likely to generate superior returns through their superior information interpretation skills. We have already shown that high cognitive ability investors have superior stock picking abilities. In untabulated results, we also find that high cognitive ability investors are less likely to use inferior seasonal random walk model of earnings to interpret earnings news (Battalio and Mendenhall (2005)). These findings indicate that high cognitive ability investors exhibit greater financial sophistication.

To examine whether the ability to interpret information signals more effectively is innate or acquired through experience, we obtain residual cognitive ability measures by regressing investors' predicted cognitive ability measure on a proxy for investment experience (number of days since account opening date). We find that the bias-conditional estimates are very similar with the residual cognitive ability measures (see Table VI, Panel B, Row 6). We also find that our state-level cognitive ability estimates and state-level SAT scores are positively correlated. These results indicate that our cognitive ability proxy is more likely to reflect "raw" ability or acquired skill from other sources (e.g., education), but not through the positive effects of experience.

Overall, the empirical evidence indicates that the superior bias-conditional performance of high cognitive ability investors is unlikely to emerge from their ability to obtain insider information. The findings are also less likely to be induced by the superior quality of their informational environments. In light of our empirical findings, the most plausible explanation for the superior bias-conditional performance appears to be investors' ability to better interpret their private and public information signals, perhaps due to their superior cognitive abilities.

From our perspective though, the important finding is that, irrespective of the channels through which high cognitive ability investors generate superior returns, the evidence demonstrates that "all biases are not alike". We show that investment decisions that are observationally equivalent could be induced by entirely different set of mechanisms. This key insight helps us resolve the three puzzling findings reported in the recent retail investor literature.

IV. Portfolio-Based Tests

To better characterize and quantify the information contained in the investment decisions of high cognitive ability investors, we rotate the point of view from the cross-section of investors to the cross-section of stocks. We aggregate the cognitive abilities of investors at the stock-level and examine the performance of cognitive ability sorted portfolios. This portfolio-based approach allows us to provide evidence of superior information for an extended sample period. Evidence from a longer time period ensures that our results are not strongly influenced by the exceptional performance of certain industries or specific stock categories during the relatively short six year sample period.

A. Do Stocks with "Smarter" Clientele Earn Higher Returns?

For the portfolio-based tests, for each stock and every month, we first compute the equal-weighted average cognitive ability of investors who hold the stock at the end of that month. We use the empirical model of cognitive abilities estimated in Table I to obtain the imputed cognitive abilities of sample investors. Next, using the stock-level cognitive ability measures, we sort stocks at the end of each month, and construct low and high cognitive ability portfolios. Last, we use the value-weighted returns of cognitive ability sorted portfolios to investigate whether high cognitive ability investors exhibit superior stock pricking abilities.

Because the brokerage data spans only the 1991 to 1996 period, we can obtain the stock-level cognitive ability measures only for the 1991 to 1996 period. Fortunately, this measure is strongly persistent. About 92% of stocks that are in the lowest and the highest quintiles in a certain month remain in those respective categories in the following month, and less than 1% of stocks move across the extreme cognitive ability quintiles. After one year, the probability of remaining in the same quintile drops to 74% and after five years, the probability is 48%. The strong persistence in the stock-level cognitive ability measure allows us to extend the sample period in both backward and forward directions. Specifically, we use the stock-level cognitive ability measures from November 1996 for the 1997 to 2005 period and the stock-level cognitive ability measures from January 1991 for the 1980 to 1990 period.

Table IX reports the characteristics and performance of cognitive ability sorted portfolios, where the characteristic-adjusted returns are computed using the Daniel, Grinblatt, Titman, and Wermers (1997) methodology. Only stocks with CRSP share code 10 and 11 are included in the analysis. Panel A reports the main performance estimates, and Panel B reports the performance estimates for different sub periods and sub samples. For easier visualization, the two main performance measures of cognitive ability sorted portfolios are also plotted in Figure 3.

We find that the results from the portfolio-based tests echo our previous results obtained using investor-level analysis. The portfolio performance increases almost monotonically across the cognitive ability quintile portfolios (see Figure 3). The high cognitive ability portfolio outperforms the low cognitive ability portfolio by 3.90%-4.87% annually, depending upon the performance measure employed. These economically significant estimates obtained using a 26-year period indicates that the performance differential between the high and low cognitive ability investors are unlikely to reflect the superior performance of certain stocks or industries during the relatively short six-year sample period.

Examining the factor exposures of the cognitive ability sorted portfolios, we find that high (quintile 5) cognitive ability portfolio is tilted toward mid-cap and growth stocks. The SMB and HML factor exposures of the portfolio are -0.013 (t-stat $= -0.54$) and -0.316 (t-stat $= -8.12$), respectively. The low (quintile 1) cognitive ability portfolio, in contrast, is tilted toward relatively smaller and value stocks. The SMB and HML factor exposures for this portfolio are 0.165 (t-stat $= 7.06$) and 0.402 (t-stat $= 11.64$), respectively. These factor exposures are consistent with the evidence on the stock preferences of low and high cognitive ability investors reported in Table III.

Extending the sample backwards introduces survivorship bias in our sample. To ensure that our results are not influenced by survivorship, we obtain the performance estimates of cognitive ability sorted portfolios for the 1991-2005 period, where the sample period is not extended backwards (see Table IX, Panel B). We find that the raw performance differential between the high and low cognitive ability quintile portfolios is marginally lower (0.350 instead of 0.355). However, both the characteristic-adjusted and the risk-adjusted performance differentials are higher for the 1991-2005 period. The characteristic-adjusted performance differential estimate increases from 0.325 to 0.375, and the four-factor alpha estimate increases from 0.406 to 0.451.

We also ensure that microstructure effects are not contaminating our findings. For this test, we form cognitive ability sorted portfolios after excluding stocks priced below \$5. When we consider the "stock price $\geq$ \$5" sub sample, the performance differential estimates decrease. However, all three performance estimates are still significant, both statistically and economically.

B. Does the Spread Reflect Mispricing or Superior Information?

We examine the time series pattern in the performance differential between the high and the low cognitive ability portfolios to determine whether that spread reflects superior information of high cognitive ability investors or mispricing that eventually gets corrected. Each month, we obtain the performance differential estimate for a k-month period following the portfolio formation date. Figure 4 shows the post-formation period average cognitive ability performance differential for $k = 36$ months.

The plot indicates that the performance differential does not decreases over time. The spread estimates are positive and significant for both the 1991-2005 and 1980-2005 periods, where the 1991-2005 period estimates are stronger. This evidence is consistent with the results from the portfolio-based tests reported the previous section, where the average performance differential is stronger for the 1991-2005 time period. The non-decreasing pattern in the performance differential is consistent with our conjecture that high cognitive ability investors possess superior information.

V. Implications of Our Research

Our empirical findings make several important contributions to the growing literature on household finance. First, we present an empirical model of cognitive abilities that can identify skilled investors on an *ex ante* basis using their demographic characteristics. We do not use investors' portfolio holdings, trading decisions, or portfolio performance to identify ability. Thus, our model could be used to identify skilled investors in other related settings. For instance, the subset of skilled individual investors identified in Coval, Hirshleifer, and Shumway (2005) could consist of investors with higher cognitive abilities. The model can also be used to obtain more accurate overconfidence estimates in Graham, Harvey, and Huang (2006), which reflects the difference between perceived competence and true ability.

At a more fundamental level, our evidence points to the cognitive foundations of psychological biases and provides a unified way to think about different types of biases. Our results indicate that cognitive ability would be a common determinant of many psychological biases. Previous studies have examined the link between investor sophistication and behavioral biases (e.g., Dhar and Zhu (2006)). Our paper extends that insight and shows that the bias-sophistication relation generalizes to other settings. More importantly, we provide an empirical framework for formally defining investor sophistication.

If some "biases" are intentional and motivated by superior information rather than being psychologically motivated, learning might not eliminate them. Thus, studies that examine whether learning eliminates behavioral biases could design sharper tests by conditioning on the level of cognitive abilities. In particular, the evidence of learning might be *weaker* or even non-existent among smarter, high cognitive ability investors because their distortions are information-driven. Similarly, studies that examine the asset pricing implications of behavioral biases could develop sharper asset pricing tests by conditioning on the level of cognitive abilities of stockholders. The "mispricing and correction" pattern induced by behavioral biases would be weaker or non-existent when stockholders have higher levels of cognitive abilities.

Beyond the literature on household finance and asset pricing, our paper contributes to the broader literature in behavioral economics that examines how cognitive abilities shape economic preferences (risk and time preferences) and attempts to quantify the overall returns to cognitive ability. The extant evidence from this literature indicates that people with low cognitive abilities exhibit greater impatience and greater risk aversion (Frederick (2005), Benjamin, Brown, and Shapiro (2006), Dohmen, Falk, Huffman, and Sunde (2007)), which in turn influences their stock market participation decisions.

Our results provide insights into the relation between cognitive abilities and preferences when people choose to participate in the stock market. We also provide estimates of portfolio performance, conditional upon the degree of behavioral biases and cognitive abilities. Our evidence indicates that low cognitive ability investors do not hold less risky stocks. Thus, while low cognitive ability investors might exhibit greater risk aversion, because of their inability to appropriately assess the risk-return trade-offs, unknowingly they might undertake greater risks. Furthermore, we find that they take more of the wrong type of risk, i.e., idiosyncratic risk for which they do not earn higher average returns.

Furthermore, our conditional performance estimates could serve as an important ingredient for estimating the overall returns to cognitive ability. Cawley, Heckman, and Vytlacil (2001) show that high cognitive ability investors earn about 15% more than low cognitive ability investors. We provide estimates of returns to cognitive ability from a different setting (investment decisions) and using market-level data. Our evidence indicates that low cognitive ability investors who deviate from the normative prescriptions of portfolio theory earn about 5% lower risk-adjusted annual returns than high cognitive ability investors.

Finally, our evidence provides an alternative perspective on the costs of not participating in the stock market. Previous studies find that the stock market participation rates are lower among people with lower cognitive abilities (Christelis, Jappelli, and Padula (2007), Benjamin, Brown, and Shapiro (2006)). This evidence raises the concern that lack of participation might impose significant economic costs on low cognitive ability investors. But to obtain accurate estimates of economic costs associated with lower participation rates, it is important to obtain estimates of investment performance when low cognitive ability investors actually participate in the stock market.

In light of our evidence, low cognitive ability investors might be better off if they did not invest directly in the stock market. Indirect investments using mutual funds and other forms of delegated investment management might be more appropriate for those investors. Similarly, while there have been attempts to privatize the social security system, Kotlikoff (1996) and Mitchell and Zeldes (1996) note that, under a fully privatized system, the welfare of households that do not make "wise" investment decisions could be adversely affected. Echoing their concerns, our results show that households with low cognitive abilities are more likely to make inferior investment decisions if they are allowed to directly invest their retirement wealth in the stock market. This new evidence should be taken into consideration when evaluating the merits of a fully private social security system.

VI. Summary and Conclusion

This paper focuses on three recent puzzles identified in the retail investor literature: portfolio concentration, excess trading, and local bias. In all three instances, portfolio distortions could be induced by superior information or a psychological bias. Because of multiple competing explanations, there has been considerable debate about the underlying mechanisms that induce investors to deviate from the normative prescriptions of portfolio theory. In this study, we show that a portfolio choice framework with cognitive abilities is able to resolve the three puzzles.

Our main conjecture is that the investment decisions of investors with higher cognitive abilities would be driven by superior information, while the decisions of investors with lower cognitive abilities are more likely to reflect behavioral biases. Using imputed cognitive ability measures, we find that when high cognitive ability investors distort their portfolios significantly and hold concentrated portfolios, trade actively, or prefer to hold local stocks, they earn higher risk-adjusted returns. Thus, their deviations appear to be induced by an informational advantage. In contrast, when low cognitive ability investors distort their portfolios significantly, their decisions reflect psychological biases (overconfidence and familiarity) because they are associated with lower risk-adjusted returns. When portfolio distortions are small, the performance differential between low and high cognitive ability investors is positive, but economically small.

Overall, these results are strongly consistent with our main conjecture. As predicted, the investment decisions of low cognitive ability investors reflect behavioral biases, while the investment decisions of high cognitive ability investors are induced by superior information. Thus, we find empirical support for both behavioral and information-based explanations for the three puzzles, but the two explanations are applicable to different groups of investors. More importantly, these two investor groups can be identified *ex ante* based on investors' demographic characteristics such as education, age, and social network.

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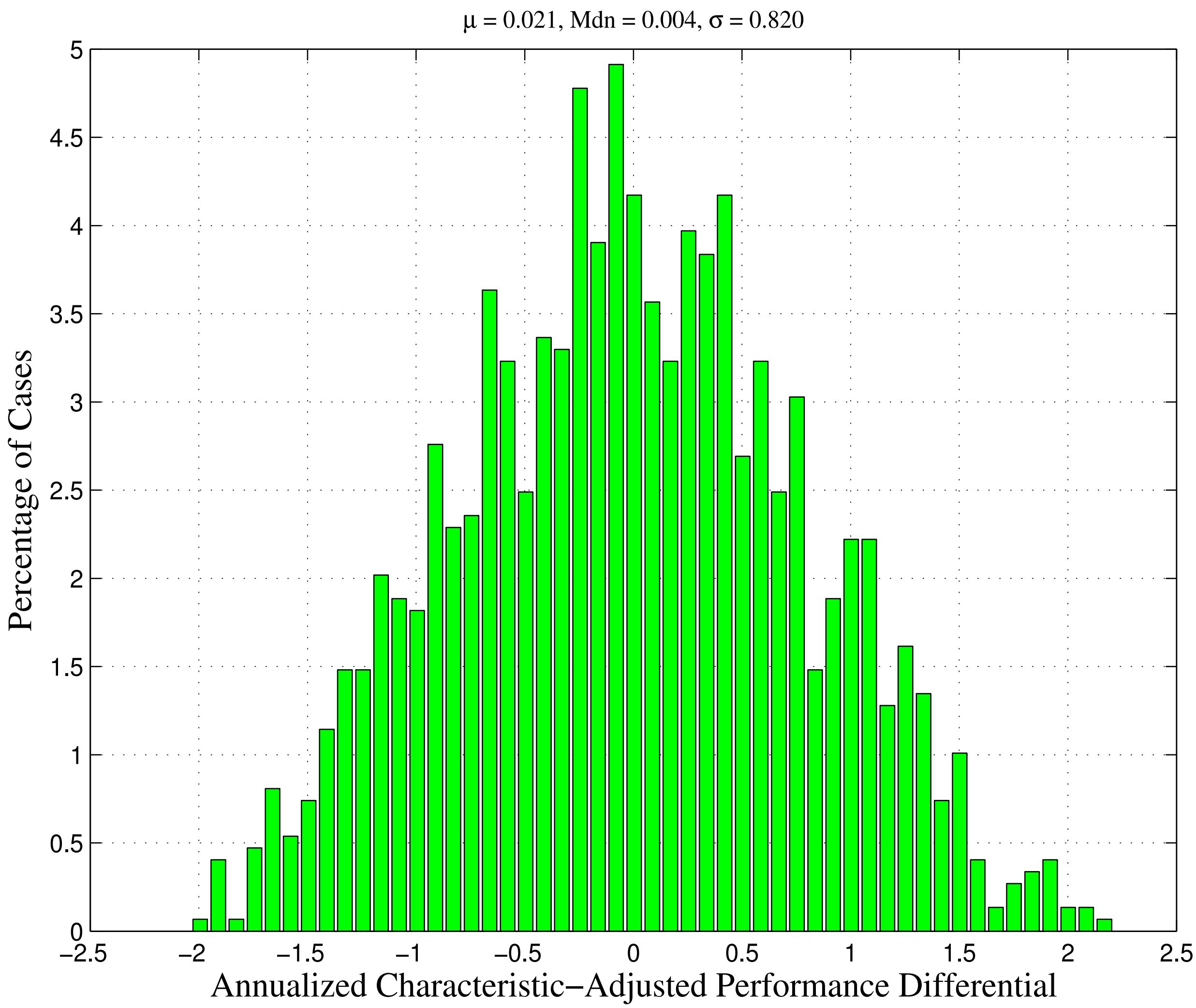

Figure 1. Performance differential distribution with randomized cognitive abilities. This figure shows the distribution of the characteristic-adjusted performance differential between high (quintile 5) and low (quintile 1) cognitive ability investors, where the predicted cognitive abilities are randomized. Specifically, the model predicted cognitive abilities are randomly assigned to investors. The empirical model of cognitive abilities estimated in Table I is used to obtain the predicted cognitive ability measures. The distribution is based on 1,500 iterations, where the characteristic-adjusted returns are computed using the Daniel, Grinblatt, Titman, and Wermers (1997) methodology. The individual investor data are from a large U.S. discount brokerage house for the period 1991 to 1996.

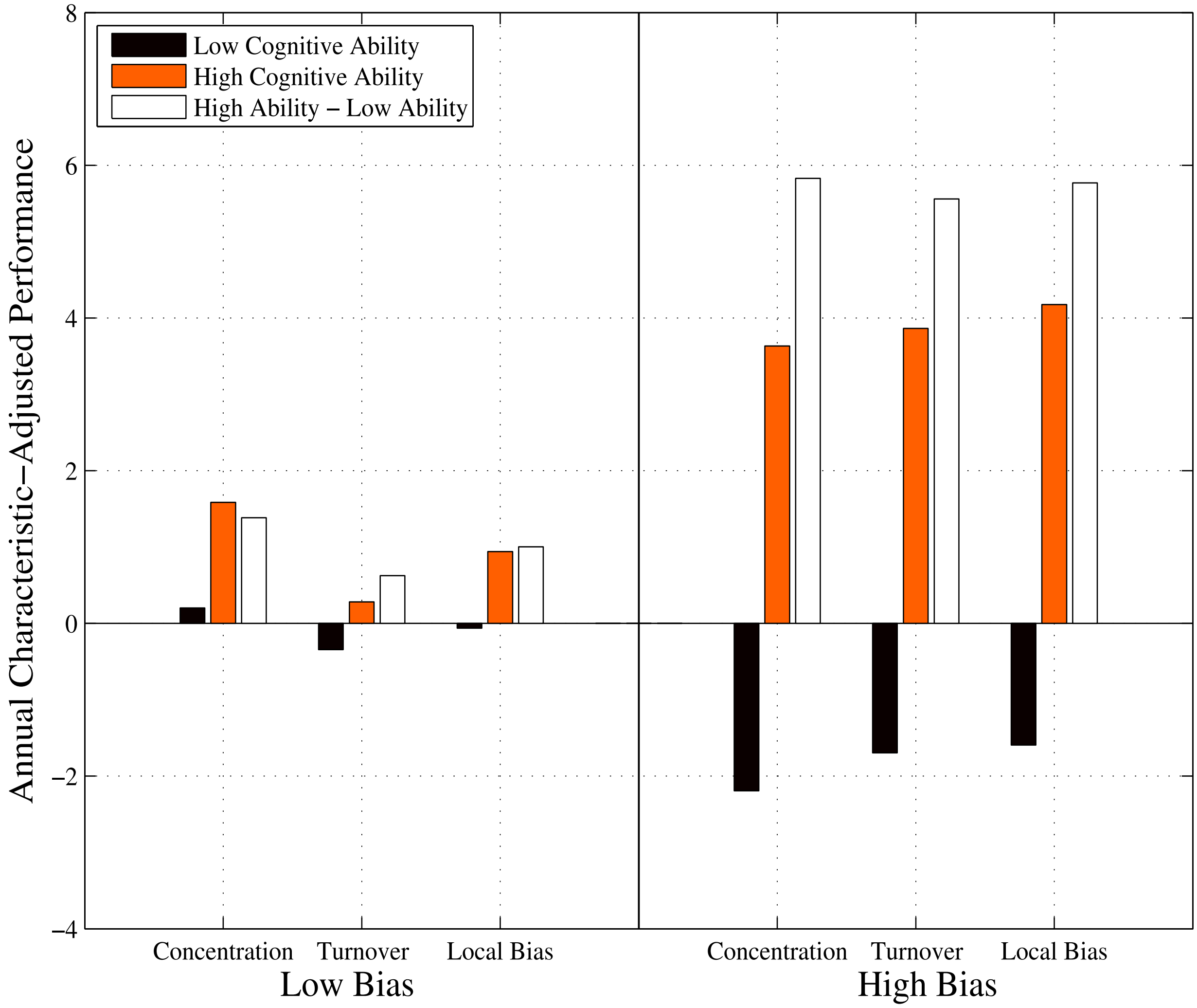

Figure 2. Cognitive abilities, behavioral biases, and portfolio performance. This figure shows the risk-adjusted performance (annualized characteristic-adjusted percentage returns), conditional upon the level of behavioral bias and predicted cognitive abilities. The characteristic-adjusted returns are computed using the Daniel, Grinblatt, Titman, and Wermers (1997) methodology. The empirical model of cognitive abilities estimated in Table I is used to obtain the predicted cognitive ability measures. Investors in quintile 5 (quintile 1) are identified as having high (low) cognitive abilities. The low and the high behavioral bias categories are defined in an analogous manner. Three biases are considered: portfolio concentration, portfolio turnover, and local bias. Portfolio concentration is defined using the average number of stocks in the investor portfolio. Portfolio turnover is the average of the buy and sell turnover rates. The local bias (LB) measure is defined as, $LB = 1 - D_{act}/D_{portf}$, where D_{act} is the distance between an investor's location and her stock portfolio and D_{portf} is the average distance between an investor's location and characteristic-matched portfolios. The individual investor data are from a large U.S. discount brokerage house for the period 1991 to 1996.

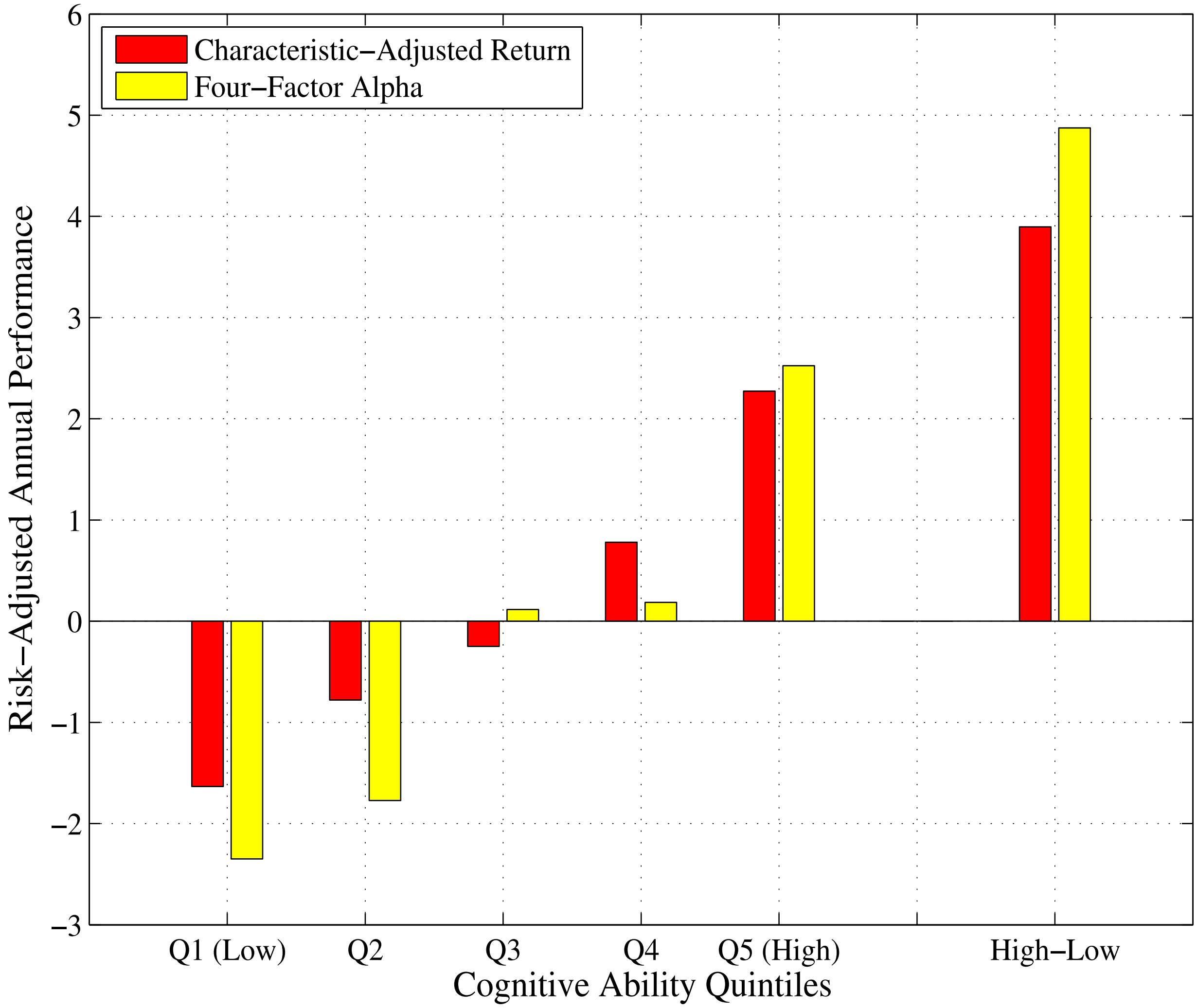

Figure 3. Performance of cognitive ability sorted portfolios. This figure shows the annual risk-adjusted and characteristic-adjusted performance of cognitive ability sorted portfolios for the 1980-2005 time period. The empirical model of cognitive abilities estimated in Table I is used to obtain investors' predicted cognitive ability measures. These investor level measures are aggregated to obtain stock-level cognitive ability measures. The cognitive ability of the individual investor clientele of a stock in a certain month is the equal-weighted average of the cognitive ability of the investors that hold the stock during the month. The cognitive ability portfolios formed in January 1991 and November 1996 are used during the 1980-1990 and 1997-2005 periods, respectively. The characteristic-adjusted returns are computed using the Daniel, Grinblatt, Titman, and Wermers (1997) methodology and the risk-adjusted performance measure is the four-factor alpha. The individual investor data are from a large U.S. discount brokerage house for the period 1991 to 1996.

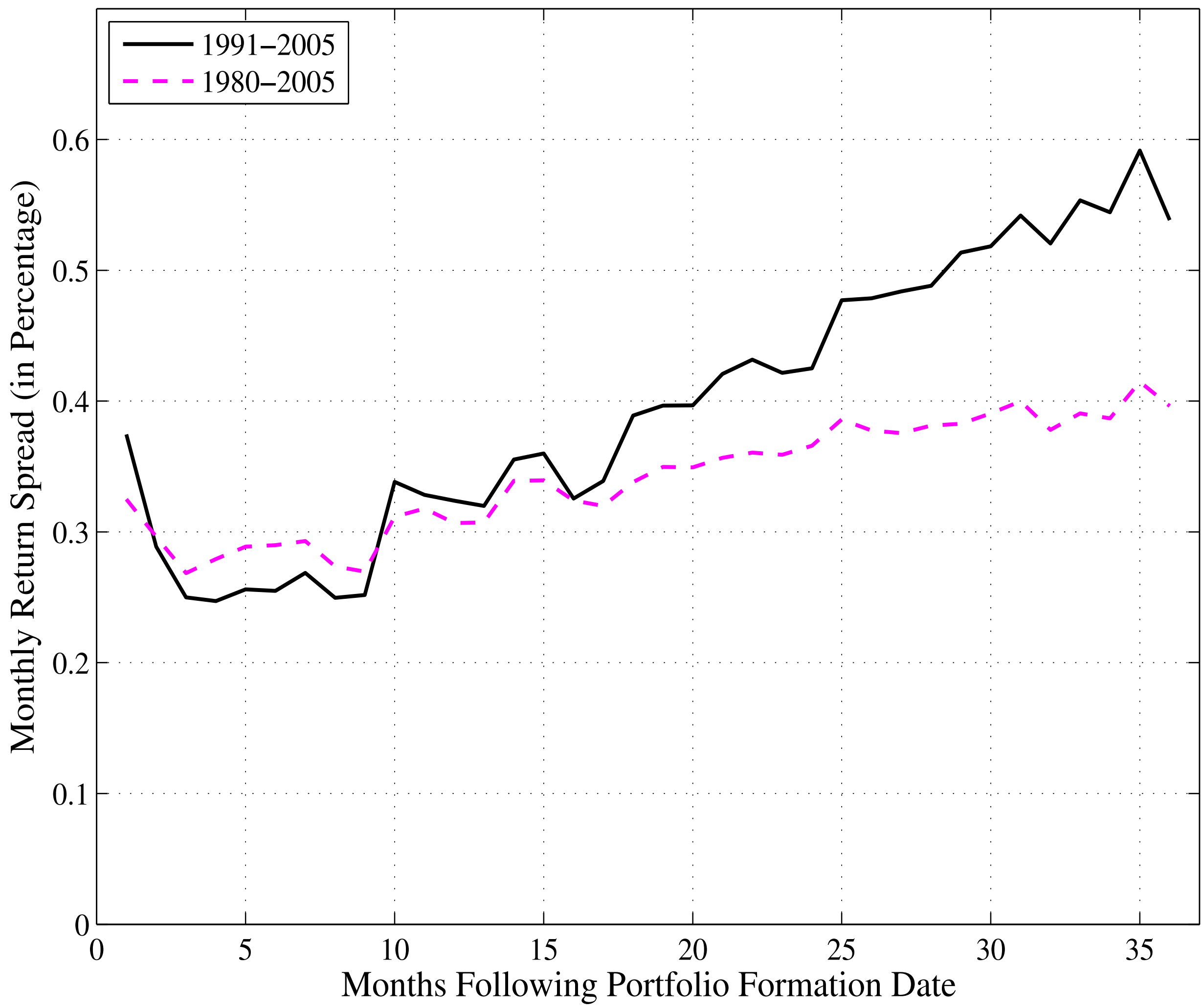

Figure 4. Cognitive ability spread following portfolio formation date. This figure shows the average performance differential between the high (quintile 5) and the low (quintile 1) cognitive ability stock portfolios. The empirical model of cognitive abilities estimated in Table I is used to obtain investors' predicted cognitive ability measures. These investor level measures are aggregated. The cognitive ability of the individual investor clientele of a stock in a certain month is the equal-weighted average of the cognitive ability of the investors that hold the stock during the month. The cognitive ability portfolios formed in January 1991 and November 1996 are used to estimate the return spreads during the 1980-90 and 1997-2005 periods, respectively. The individual investor data are from a large U.S. discount brokerage house for the period 1991 to 1996.

Table I

Correlates of Cognitive Abilities

This table reports the cross-sectional regression estimates, where the dependent variable is a measure of cognitive ability. The independent variables are the main determinants of cognitive ability identified in the psychological literature. Among the independent variables, *Wealth* is the total net-worth of the household including real-estate, *Income* is the total household income, *Age* is the age of the individual, *Education* is a categorical variable that denotes the level of education from pre-primary to post-tertiary. *Low (High) Income* dummy is set to one for investors who are in the lowest (highest) income quintile. *Low (High) Education* dummy is set to one for investors who are in the lowest (two highest) education level category. *Over 70 Dummy* is set to one for individuals with age over 70. The *Social Network Proxy* is the average level of social activities undertaken by a household, which includes sports, political and community activities, and religious activities. The "Avg" column uses an equal-weighted measure of the three cognitive ability measures (Verbal, Quantitative, and Memory). "First PC" uses the first principal component of the cognitive ability measures. To ensure that extreme values are not affecting our results, we winsorize all variables at their 0.5 and 99.5 percentile levels. The independent variables have been standardized so that each variable has a mean of zero and a standard deviation of one. The t-statistics for the coefficient estimates are shown in smaller font below the estimates. The salient numbers in the table are highlighted using the bold font. The household data are from the 2005 wave of the Survey of Health, Aging, and Retirement in Europe (SHARE). The estimates in the last column ("Avg2") are obtained using the 2004 wave of the Health and Retirement Study (HRS) data.

Table I (Continued)

Correlates of Cognitive Abilities

	Cognitive ability measure is:					
Variable	Verbal	Quantitative	Memory	Avg	First PC	Avg2
Wealth	0.049	0.020	0.012	**0.055**	0.047	**0.064**
	8.03	3.27	1.96	5.62	9.11	4.01
Income	0.047	0.053	0.002	**0.031**	0.018	**0.068**
	7.81	8.48	0.37	7.23	3.13	3.77
Education	0.365	0.313	0.312	**0.297**	0.304	**0.341**
	25.99	16.25	17.30	25.21	28.98	20.04
Age	−0.129	−0.160	−0.239	**−0.231**	−0.230	**−0.185**
	−13.17	−15.71	−24.08	−23.03	−19.83	−9.41
Retired Dummy	−0.081	−0.065	−0.011	−0.046	−0.019	−0.046
	−11.39	−10.39	−1.18	−9.95	−3.54	−3.10
Over 70 Dummy	−0.010	−0.036	−0.021	**−0.050**	−0.055	**0.004**
	−1.93	−3.18	−2.90	−3.19	−5.76	0.02
Social Network Proxy	0.088	0.092	0.096	**0.092**	0.130	**0.026**
	14.59	15.65	16.22	17.37	11.60	1.85
Over 70 × Low Income	−0.086	−0.055	−0.066	−0.058	−0.031	−0.038
	−12.14	−7.46	−9.19	−12.79	−4.98	−2.38
Over 70 × Low Education	0.001	−0.014	−0.030	−0.017	−0.013	−0.002
	0.11	−2.50	−4.14	−3.06	−2.47	−0.01
High Education × High Income	0.042	0.025	0.014	**0.038**	0.042	**−0.018**
	5.20	3.03	2.75	5.38	5.90	−1.31
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	No
Number of Households	22,153	21,777	21,904	22,215	22,215	4,230
Adjusted R^2	0.320	0.296	0.295	**0.441**	0.437	**0.211**

Table II

Cognitive Abilities, Portfolio Characteristics, and Investor Characteristics

This table reports the portfolio and demographic characteristics of cognitive ability sorted investor groups. The empirical model of cognitive abilities estimated in Table I is used to obtain the predicted cognitive ability measures. Most estimates in the table are time series averages computed over the entire sample period. The table also includes proportion measures that capture the proportion of investors within the cognitive ability quintile that have the reported characteristic. For instance, *Proportion Hold Foreign Equities* is the proportion of investors who hold foreign equities at least once during the sample period. Most other measures have self-explanatory labels. Investment experience is the number of years since the brokerage account opening date. Short seller dummy is set to one for investors who holds a short position at least once during the sample period. Similarly, option trader dummy is set to one for investors who trade options at least once during the sample period. Investors who live within 100 miles of the twenty largest metropolitan regions are identified as urban. Professional investors are those who hold either a technical or a managerial position. The salient numbers in the table are highlighted using the bold font. The individual investor data are from a large U.S. discount brokerage house for the period 1991 to 1996.

	Cognitive Ability Quintile				
Characteristic	Low	Q2	Q3	Q4	High
Equity Portfolio Size	\$34,925	\$26,014	\$23,943	\$25,631	\$27,987
Trade Size	\$8,042	\$7,413	\$7,793	\$8,244	\$8,591
Proportion Hold Foreign Equities	26.99%	26.75%	27.54%	28.07%	30.97%
Weight in Foreign Equities	1.74%	1.89%	1.72%	2.20%	2.24%
Proportion Hold Mutual Funds	21.08%	22.25%	20.93%	22.14%	21.21%
Weight in Equity Mutual Funds	42.29%	42.84%	43.93%	43.60%	42.28%
Annual Portfolio Dividend Yield	2.32%	2.06%	1.86%	1.76%	**1.71%**
Investment Experience in Years	10.30	10.17	9.94	9.88	9.79
Proportion Short Seller	9.16%	8.13%	9.51%	9.37%	11.24%
Proportion Option Trader	**6.96%**	7.31%	8.78%	9.28%	**10.50%**
Proportion Urban	**16.56%**	26.66%	32.53%	37.96%	**45.64%**
Annual Income	**\$58,684**	\$78,952	\$92,411	\$105,964	**\$126,342**
Wealth	\$282,089	\$248,927	\$228,514	\$243,099	\$264,075
Age	**65**	55	49	46	**43**
Proportion Male	90.99%	90.52%	92.13%	91.81%	**88.35%**
Proportion Professional	**18.62%**	**20.62%**	20.92%	20.61%	**18.57%**

Table III

Cognitive Abilities and Stock Preferences: Fama-MacBeth Cross-Sectional Regression Estimates

This table reports the Fama-MacBeth cross-sectional regression estimates for low and high cognitive ability investor groups, where the excess weight assigned to a stock in the aggregate group portfolio is the dependent variable. The excess portfolio weight allocated to stock i in month t is given by: $EW_{ipt} = \frac{w_{ipt} - w_{imt}}{w_{imt}} \times 100$, where, w_{ipt} is the actual weight assigned to stock i in group portfolio p in month t and w_{imt} is the weight of stock i in the aggregate market portfolio in month t. The set of independent variables include: (i) market beta, which is estimated using the previous six months of daily returns data, (ii) firm size, (iii) book-to-market ratio, (iv) short-term momentum (past one-month stock return), (v) longer-term momentum (past twelve-month stock return), (vi) stock price, (vii) idiosyncratic volatility, which is the variance of the residual obtained by fitting a four-factor model to the daily stock returns in the previous six months, (viii) firm age, (ix) an S&P500 dummy which is set to one if the stock belongs to the S&P500 index, and (x) a dividend paying stock dummy, which is set to one if the stock is a dividend paying stock during the previous year. We follow the Pontiff (1996) methodology to correct the Fama-MacBeth standard errors for serial correlation. To ensure that extreme values are not affecting our results, we winsorize all variables at their 0.5 and 99.5 percentile levels. The dependent and independent variables have been standardized so that each variable has a mean of zero and a standard deviation of one. The t-statistics for the coefficient estimates are shown in smaller font below the estimates. The salient numbers in the table are highlighted using the bold font. The individual investor data are from a large U.S. discount brokerage house for the period from 1991 to 1996.

Table III (Continued)

Cognitive Abilities and Stock Preferences: Fama-MacBeth Cross-Sectional Regression Estimates

	Cognitive Ability		
Variable	(1): Low	(2): High	(3): Low−High
Intercept	0.021	0.028	−0.006
	6.18	7.98	−2.44
Market Beta	0.025	**0.060**	**−0.036**
	7.68	7.69	−5.93
Firm Size	−0.046	−0.036	−0.011
	−9.91	−10.01	−1.90
Book-To-Market Ratio	−0.035	−0.010	−0.018
	−9.17	−3.68	−6.53
Past 1-Month Stock Return	0.001	−0.001	0.001
	0.51	−0.21	0.40
Past 12-Month Stock Return	−0.021	−0.033	0.013
	−3.95	−5.80	3.72
Stock Price	−0.042	−0.007	−0.029
	−7.72	−6.77	−8.31
Idiosyncratic Volatility	**0.113**	0.007	**0.105**
	10.84	3.39	6.15
Firm Age	−0.026	−0.022	−0.002
	−4.38	−5.57	−0.47
S&P500 Dummy	−0.003	0.008	−0.011
	−4.61	5.15	−5.71
Dividend Paying Stock Dummy	−0.035	**−0.084**	**0.045**
	−8.67	−7.67	6.30
Average Number of Observations	1,987	1,987	1,987
Average Adjusted R^2	0.026	0.028	0.011

Table IV

Cognitive Abilities and Behavioral Biases

This table reports the mean bias measures for cognitive ability (CAB) sorted investor categories. The empirical model of cognitive abilities estimated in Table I is used to obtain the predicted cognitive ability measures. Three measures of portfolio concentration are reported: Number of stocks is the average number of stocks in the investor portfolio during the sample period, average correlation is the average correlation among the stocks in the portfolio, and normalized variance is the ratio of portfolio variance and the average correlation of stocks in the portfolio. Two turnover measures are reported: Monthly turnover, which the average of the buy and sell turnover rates (in percentage), and the average stock holding period. Three local bias measures are reported: the main local bias (LB) measure is defined as, $LB = 1 - D_{act}/D_{portf}$, where D_{act} is the distance between an investor's location and her stock portfolio and D_{portf} is the average distance between an investor's location and characteristic-matched portfolios. The other two local bias measures capture the proportion of total equity portfolio that is invested in stocks that are located within 250 miles of investor's location. For the "Positive Only" measure, we only consider the local portfolio weight of investors who hold local stocks. Other bias measures are: (i) Odean's (1998b) disposition effect measure, which is the difference in the proportion of winners realized and the proportion of losers realized, (ii) Narrow framing, which is an adjusted measure of trade clustering, (iii) Overconfidence dummy, which is set to one for investors who are in the highest portfolio turnover quintile but lowest performance quintile, and (iv) Lottery Weights, which is the proportion of investor portfolio that is invested in "lottery-type" stocks that have high idiosyncratic volatility, high idiosyncratic skewness, and low prices. We use the Kolmogorov-Smirnov test to examine the statistical significance of the differences in the bias measures. *, **, and *** denotes significance at 10%, 5%, and 1% levels, respectively. To ensure that extreme values are not affecting our results, we winsorize all variables at their 0.5 and 99.5 percentile levels. The individual investor data are from a large U.S. discount brokerage house for the period from 1991 to 1996.

Table IV (Continued)

Cognitive Abilities and Behavioral Biases

	Cognitive Ability Quintile					
Measure	Low	Q2	Q3	Q4	High	High−Low
Portfolio Concentration						
Number of Stocks	5.18	4.59	4.45	4.06	4.37	-0.81^{*}
Average Correlation	0.241	0.239	0.238	0.234	0.235	−0.006
Normalized Variance	0.410	0.426	0.433	0.444	0.434	0.024^{*}
Portfolio Turnover						
Monthly Turnover	5.49%	5.89%	6.02%	6.22%	5.96%	0.47%
Average Holding Period (Days)	354	348	339	327	334	-20^{*}
Local Bias						
Local Bias	16.41%	17.83%	18.65%	18.14%	17.11%	0.70%
Proportion Total Portf Local	9.73%	11.18%	11.75%	12.87%	13.28%	$3.55\%^{**}$
Proportion Portf Local (Pos Only)	16.32%	17.80%	18.19%	19.19%	19.53%	$3.21\%^{**}$
Other Biases						
Disposition Effect	5.10%	6.27%	4.71%	9.15%	7.73%	$2.63\%^{**}$
Narrow Framing	0.197	0.078	−0.180	−0.103	−0.477	-0.674^{**}
Proportion Overconfident	6.37%	6.25%	6.80%	6.47%	5.80%	−0.57%
Lottery Weights	16.21%	17.78%	17.41%	17.64%	16.81%	0.60%

Table V

Cognitive Abilities and Portfolio Performance: Cross Sectional Regression Estimates

This table reports the cross-sectional regression estimates, where the dependent variable is the characteristic-adjusted portfolio performance measured over the sample period. The characteristic-adjusted returns are computed using the Daniel, Grinblatt, Titman, and Wermers (1997) methodology. The independent variables includes a measure of cognitive ability, measures of three behavioral biases, and interactions among these variables. The empirical model of cognitive abilities estimated in Table I is used to obtain the predicted cognitive ability measures. Portfolio concentration is defined using the average number of stocks in the investor portfolio. The local bias (LB) measure is defined as, $LB = 1 - D_{act}/D_{portf}$, where D_{act} is the distance between an investor's location and her stock portfolio and D_{portf} is the average distance between an investor's location and characteristic-matched portfolios. Portfolio turnover is the average of the buy and sell turnover rates. High (low) ability dummy is set to one for investors in the highest (lowest) cognitive ability quintile. The high and low bias dummy variables are defined in an analogous manner. The set of control variables includes the following known determinants of portfolio performance: portfolio size (size of the investor portfolio when she enters the sample), portfolio dividend yield, investment experience (the number of days between the account opening date and December 31, 1996), and gender. The high and low dummy measures used in the interaction terms are also included in the specification. In column (4), we report the estimates from errors-in-variables regression (Kmenta (1997)), where we assume that the reliability ratio of variables that include a cognitive ability measure is the adjusted R^2 ($= 0.441$) of the cognitive abilities model in Table I. To ensure that extreme values are not affecting our results, we winsorize all variables at their 0.5 and 99.5 percentile levels. The independent variables have been standardized so that each variable has a mean of zero and a standard deviation of one. Robust, clustered standard errors are used (except in specification (4)) to account for potential cross-sectional dependence within zip codes. The t-statistics for the coefficient estimates are shown in smaller font below the estimates. The salient numbers in the table are highlighted using the bold font. The individual investor data are from a large U.S. discount brokerage house for the period from 1991 to 1996.

Table V (Continued)

Cognitive Abilities and Portfolio Performance: Cross Sectional Regression Estimates

Variable	(1)	(2)	(3)	(4)
Intercept	0.225	0.243	0.218	0.237
	14.37	14.47	10.90	8.83
Cognitive Ability	0.069	0.079	0.055	**0.106**
	3.96	4.15	3.14	2.95
Portfolio Concentration		0.008	0.016	0.015
		0.62	0.70	0.86
Portfolio Turnover		0.115	0.091	0.119
		8.84	3.75	6.99
Local Bias		0.032	0.036	0.051
		3.83	2.76	2.98
High Ability × *High Concentration*			**0.030**	0.031
			3.22	2.52
High Ability × *High Turnover*			**0.058**	0.039
			4.88	2.56
High Ability × *High Local Bias*			**0.033**	0.028
			2.22	2.01
Low Ability × *High Concentration*			**−0.024**	−0.031
			−2.03	−1.92
Low Ability × *High Turnover*			**−0.031**	−0.026
			−2.52	−2.21
Low Ability × *High Local Bias*			**−0.043**	−0.071
			−2.20	−2.61
(Estimates of control variables have been suppressed.)				
Number of Investors	36,251	32,129	32,129	32,129
Adjusted R^2	0.009	0.033	0.054	0.062

Table VI

Performance Differential Conditional Upon Behavioral Biases: Robustness Check Results

This table reports bias-conditional performance (annualized characteristic-adjusted percentage returns) estimates for different definitions of cognitive ability (Panel A) and for different sub-samples (Panel B). The characteristic-adjusted returns are computed using the Daniel, Grinblatt, Titman, and Wermers (1997) methodology. Investors in quintile 5 (quintile 1) are identified as having high (low) cognitive abilities. The low and the high behavioral bias categories are defined in an analogous manner. Three biases (defined earlier) are considered: portfolio concentration, portfolio turnover, and local bias. In the *Simple Linear Combination* row, we combine income, education, age, and social network, with a negative sign on age. The equal-weighted sum is computed after standardizing the four variables. Investment experience is defined as the number of days between the account opening date and December 31, 1996. Urban investors are those who live within 50 miles of the 20 most populated U.S. cities. Rural investors are those who live at least 250 miles away from the 20 largest cities. * and ** denotes significance at 10% and 5% levels, respectively. The individual investor data are from a large U.S. discount brokerage house for the period from 1991 to 1996.

Panel A: Separating the Effects of Determinants of Cognitive Abilities

Cognitive Ability	Low Bias			High Bias		
Definition	Conc	Turnover	LB	Conc	Turnover	LB
Income	−0.21	1.33	1.15	1.12	1.93*	1.83*
Education	−0.29	1.63	0.68	2.49**	2.66*	3.24**
Age	0.78	0.46	1.11	3.05**	2.53*	2.49*
Social Network	1.29	0.43	−0.21	1.74*	1.13	1.59*
Simple Linear Combination	1.76*	0.97	1.13	3.38**	2.76*	3.55**
Cognitive Ability Model	1.38	0.62	1.00	5.83**	5.56**	5.77**
Investment Experience	1.63*	1.56*	1.26	−0.33	0.14	0.37

Panel B: Sub Sample Estimates

Sub Sample	Low Bias			High Bias		
Criteria	Conc	Turnover	LB	Conc	Turnover	LB
Exclude Investors Over Age 60	0.15	1.52	1.11	5.12**	5.38**	5.97**
Portfolio Size > $25,000	1.28	1.02	1.68*	6.28**	4.65**	6.25**
Rural Investors Only	1.06	1.45	1.21*	4.92**	5.13**	4.71**
Urban Investors Only	0.67	0.40	2.20*	6.04**	6.52**	6.90**
Exclude One-Stock Portfolios	1.31	1.32	1.47*	5.64**	6.09**	5.99**
Exclude Experience Effects	1.20	1.33	1.67*	5.47**	6.42**	6.01**

Table VII

Cognitive Abilties and Performance of Local Investments

This table reports position and trade based performance measures of investors' local investments, conditional upon the level of cognitive ability (CAB). Stocks that are within a 250 mile radius of the investor's location are considered local. The empirical model of cognitive abilities estimated in Table I is used to obtain the predicted cognitive ability measures. In Panel A, we report the actual and expected performance and characteristics of local portfolios, where the equal-weighted average of all investors within the CAB quintile are used to compute the performance measures for the category. The expected local performance for an investor is the average monthly return of characteristic (size, B/M, and past 12-month returns) matched local portfolios not held by the investor. The following measures of the local portfolio are reported: Average monthly return (LocalActual), monthly standard deviation (StandardDeviation), expected average monthly return (LocalExpected), the four-factor alpha, and the four factor exposures. Panel B reports the average k-day buy-sell return differential (PTBSD) measures. PTBSD for a given investor is defined as the difference in the k-day returns following local buy and local sell trades executed by the investor. In this panel, we use the Kolmogorov-Smirnov test to examine the statistical significance of the differences in the PTBSD measures. *, **, and *** denotes significance at 10%, 5%, and 1% levels, respectively. The salient numbers in the table are highlighted using the bold font. The individual investor data are from a large U.S. discount brokerage house.

Panel A: Characteristics and Performance of Local Portfolios

CAB	LocAct	StdDev	LocExp	Act−Exp	Alpha	RMRF	SMB	HML	UMD
Low	1.479	3.540	1.497	−0.018	−0.007	1.127	0.602	0.259	−0.238
Q2	1.537	3.840	1.482	0.055	0.060	1.172	0.704	0.186	−0.284
Q3	1.638	4.066	1.485	0.152	0.167	1.188	0.766	0.103	−0.284
Q4	1.669	4.139	1.460	0.209	0.184*	1.225	0.735	0.075	−0.288
High	1.776	4.147	1.481	0.295	0.273**	1.229	0.677	0.024	−0.304
High−Low	**0.297****	0.607	0.016	**0.281****	**0.279****	0.102**	0.076**	−0.235***	−0.066*

Panel B: k-day Post-Trade Buy-Sell Return Differential Estimates

	k						
CAB	5	10	21	42	63	84	126
Low	−0.115	−0.128	−0.157	−0.255	−0.290	−0.213	−0.647
Q2	−0.008	−0.036	−0.091	−0.187	−0.073	−0.151	−0.184
Q3	−0.094	−0.227	−0.236	−0.222	−0.163	0.144	0.117
Q4	0.173	0.117	0.376	0.097	0.202	0.180	0.341
High	0.146	0.163	0.322	0.524	0.817	1.282	1.449
High−Low	**0.261****	**0.291****	**0.479****	**0.779****	**1.136****	**1.302****	**2.096****

Table VIII

Cognitive Abilities, Investment Skill, and Stock Characteristics: DGTW Performance Decomposition

This table reports the DGTW performance measures for high and low cognitive ability (CAB) investors, conditional upon the degree of concentration, turnover, and local bias. The empirical model of cognitive abilities estimated in Table I is used to obtain the predicted cognitive ability measures. Portfolio concentration is defined using the average number of stocks in the investor portfolio. The local bias (LB) measure is defined as, $LB = 1 - D_{act}/D_{portf}$, where D_{act} is the distance between an investor's location and her stock portfolio and D_{portf} is the average distance between an investor's location and characteristic-matched portfolios. Portfolio turnover is the average of the buy and sell turnover rates. Following the Daniel, Grinblatt, Titman, and Wermers (1997) methodology, four performance measures are computed: characteristic selectivity (CS), characteristic timing (CT), average style (AS), and the total return (TOTAL). In Panel B, we report only the CS performance measure, conditional upon the degree of bias and stock characteristics. Three stock characteristics are considered: (i) membership in the S&P 500 index, (ii) idiosyncratic volatility (IVOL), which is the variance of the residual obtained by fitting a four-factor model to the daily stock returns in the previous six months, and (iii) book-to-market (B/M) ratio. The salient numbers in the table are highlighted using the bold font. The individual investor data are from a large U.S. discount brokerage house.

Panel A: Performance Measures Conditional Upon Cognitive Ability and Behavioral Bias

Cognitive	Low Bias				High Bias			
Ability	CS	CT	AS	TOTAL	CS	CT	AS	TOTAL
Portfolio Concentration								
Low CAB	−0.56	−1.62	13.43	11.25	−0.30	−2.38	13.40	10.72
High CAB	−0.29	−1.30	13.49	11.91	**2.78**	−0.33	13.26	15.71
High − Low	0.28	0.32	0.06	**0.66**	**3.08**	**2.05**	−0.14	**4.99**
Portfolio Turnover								
Low CAB	−1.57	−2.12	13.26	9.57	−0.89	−1.80	13.48	10.79
High CAB	−0.55	−2.10	12.66	10.01	**3.72**	−0.86	13.44	16.29
High − Low	1.02	0.02	−0.60	**0.44**	**4.61**	**0.94**	−0.04	**5.50**
Local Bias								
Low CAB	−0.81	−1.18	13.77	11.78	−0.57	−1.56	13.07	10.94
High CAB	−0.05	−1.04	13.12	12.03	**2.57**	−0.35	13.50	15.72
High − Low	0.76	0.14	−0.65	**0.25**	**3.14**	**1.21**	0.43	**4.78**

Table VIII (Continued)

Cognitive Abilities, Investment Skill, and Stock Characteristics: DGTW Performance Decomposition

Panel B: Stock Selection Ability (CS Measure) and Stock Characteristics

	Low Bias						High Bias					
	S&P 500		IVOL		B/M		S&P 500		IVOL		B/M	
CAB	Yes	No	Low	High	Low	High	Yes	No	Low	High	Low	High
Portfolio Concentration												
Low	−0.30	−0.94	−0.98	−0.31	0.25	−0.98	0.55	−1.25	−1.08	−1.38	−0.41	0.35
High	−0.16	0.29	0.22	0.86	1.22	0.85	1.87	3.32	1.34	3.04	4.96	−0.50
Diff	0.14	**1.23**	1.20	**1.17**	**0.97**	1.83	1.32	**4.57**	2.42	**4.42**	**5.37**	−0.85
Portfolio Turnover												
Low	0.12	−1.28	0.66	0.31	−0.18	−1.71	−0.15	−1.09	−0.26	0.39	−0.85	−1.57
High	0.53	0.60	0.61	1.98	0.75	−0.74	1.05	2.83	1.69	3.69	2.96	0.81
Diff	0.41	**1.88**	−0.05	**1.67**	**0.93**	0.97	1.20	**3.92**	1.95	**3.08**	**3.81**	2.38
Local Bias												
Low	−1.09	−1.17	0.13	0.38	0.22	−0.40	−0.44	−1.80	−0.22	0.82	0.45	0.22
High	−0.41	0.96	0.89	1.81	0.61	−0.47	−0.45	3.19	0.54	5.04	4.23	−0.53
Diff	0.68	**2.13**	0.76	**1.43**	**0.39**	−0.07	−0.01	**4.99**	0.76	**4.22**	**3.78**	−0.75

Table IX

Characteristics and Performance of Cognitive Ability Sorted Portfolios

This table reports the characteristics and performance of cognitive ability sorted portfolios. The quintile portfolios are formed at the end of each month using the predicted cognitive ability breakpoints. The cognitive ability of the individual investor clientele of a stock in a certain month is the equal-weighted average of the cognitive ability of the investors that hold the stock during the month. The empirical model of cognitive abilities estimated in Table I is used to obtain investors' predicted cognitive ability measures. The characteristic-adjusted returns are computed using the Daniel, Grinblatt, Titman, and Wermers (1997) methodology. The cognitive ability portfolios formed in January 1991 and November 1996 are used during the 1980-1990 and 1997-2005 periods, respectively. Panel A reports the main performance estimates. Panel B reports the performance estimates for different sub periods and sub samples. In the first case, we report results for the 1991-2005 period, where the portfolio composition is not extended backwards. In the second test, we exclude stocks priced below $5. The t-statistics for the coefficient estimates are shown in smaller font below the estimates. The salient numbers in the table are highlighted using the bold font. Only stocks with CRSP share code 10 and 11 are included in the analysis. The sample period is from January 1980 to December 2005.

Panel A: Main Performance Estimates

CAB Quintile	MeanRet	StdDev	CharAdjRet	Alpha	RMRF	SMB	HML	UMD
Low	**0.927**	3.912	**−0.136**	**−0.196**	0.914	0.165	**0.402**	−0.019
			−2.56	−3.52	20.41	7.06	11.64	−1.26
Q2	1.036	4.017	−0.065	−0.148	0.946	−0.102	0.297	−0.019
			−1.16	−2.14	16.54	−4.84	8.69	−1.39
Q3	1.108	4.030	−0.021	−0.004	0.923	−0.205	0.126	−0.004
			−0.61	−0.07	20.34	−12.25	4.39	−0.33
Q4	1.112	5.239	0.064	0.015	1.041	0.269	−0.080	0.009
			1.02	0.16	11.17	10.32	−2.79	0.44
High	**1.282**	5.282	**0.189**	**0.210**	0.991	−0.013	**−0.316**	−0.049
			3.14	2.09	12.28	−0.54	−8.12	−1.96
High−Low	**0.355**	3.144	**0.325**	**0.406**	0.077	−0.177	**−0.718**	−0.030
	2.63		3.00	3.35	2.50	−4.48	−12.43	−1.08

Table IX (Continued)

Characteristics and Performance of Cognitive Ability Sorted Portfolios

Panel B: Robustness of Cognitive Ability Spread Estimates

Robustness Test	MeanRet	StdDev	CharAdjRet	Alpha	RMRF	SMB	HML	UMD
1991-2005 Period	0.350	3.151	0.375	0.451	0.148	−0.216	−0.862	0.013
	2.74		2.61	3.57	3.17	−4.42	−10.32	0.38
Stock Price $\geq$ *\$5*	0.322	2.705	0.314	0.408	0.078	−0.166	−0.719	−0.029
	3.16		2.93	3.24	2.52	−4.17	−11.43	−1.09