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

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ABSTRACT

This paper provides a unified explanation for three puzzles identified in the recent retail investor literature: portfolio concentration, excess trading, and preference for local stocks. In each of these three instances, the portfolio distortion could be induced by an informational advantage or psychological biases. Using an *ex ante* measure of investors' cognitive abilities, we show that the portfolio distortions of investors with high cognitive abilities reflect an informational advantage and generate higher risk-adjusted returns. In contrast, the distortions of investors with low cognitive abilities arise from psychological biases and result in low risk-adjusted performance. High ability investors outperform low ability investors by about 3 percent annually on a risk-adjusted basis, and when portfolio distortions are large, the performance differential is over 5 percent. Similarly, a portfolio of stocks with "smart" investor clientele outperforms the "dumb" clientele portfolio by more than 3.50 percent. Collectively, our results indicate that behavioral and rational explanations for the three puzzles are applicable to investors with low and high cognitive abilities, respectively.

THE RECENT LITERATURE ON RETAIL INVESTORS has identified three puzzles. The first puzzling finding is that, contrary to the normative prescriptions of traditional portfolio theory, 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 (2008)), they exhibit a preference for skewness (Mitton and Vorkink (2007)), or they are resourceful and able to gather better information about those stocks (Ivković, Sialm, and Weisbenner (2008)).

Second, retail investors trade actively even though standard portfolio theory prescribes a buy-and-hold strategy. Active trading could be induced by behavioral biases. For instance, overconfident investors who over-estimate either 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 (2008)), or a pure entertainment motive (Dorn and Sengmueller (2006)).

In addition to these behavioral determinants of trading, aggressive trading by investors could also reflect their attempts to exploit superior, time-sensitive private information (e.g., Kyle (1985), Admati and Pfleiderer (1988), Holden and Subrahmanyam (1992), Wang (1994)). In this setting, active trading by individual investors could be optimal and need not be excessive.

Third, retail investors exhibit a preference for local stocks, i.e., a disproportionately large proportion of their equity portfolios is invested in geographically proximate stocks. The preference for local stocks could be induced by familiarity, where investors over-weight 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 local stock preference could also be driven by investors' superior information about firms located in their neighborhood (e.g., Ivković and Weisbenner (2005), Massa and Simonov (2006), Bodnaruk (2008)).

Because of two competing explanations, there has been considerable debate about the underlying mechanisms that induce investors to hold concentrated portfolios, trade actively, and hold a disproportionate share of local stocks. In this study, we introduce cognitive abilities in the portfolio choice framework and examine whether this extended framework can provide a unified explanation for the three puzzling findings.

Our main idea is simple and fairly intuitive. We conjecture that the investment decisions of investors with high cognitive abilities will reflect superior information, while the decisions of investors with low cognitive abilities are more likely to be induced by behavioral (or psychological) 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 and stronger behavioral biases (e.g., greater level of impatience, stronger short-stakes risk aversion, etc.).

One of the key implications of our conjecture is that the level of cognitive abilities will determine the impact of portfolio distortions on portfolio performance. In particular, when investors with high cognitive abilities deviate from the normative prescriptions of portfolio theory and choose to 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. The availability of better information would subsequently generate high risk-adjusted returns.

There are several reasons why investors with high cognitive abilities could possess an informational advantage. These investors are likely to be more attentive, have access to better information networks (e.g., due to their superior social networks), exhibit greater skill in gathering information, and might even be better at interpreting the acquired information. High cognitive ability investors can also possess superior learning abilities because of their stronger memory and superior analytical and numerical abilities (Kezdi and Willis (2006)). As a result, they are 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, the portfolio distortions of investors with low cognitive abilities are more likely to result from behavioral biases, which would generate low realized returns. When investors with low cognitive abilities hold concentrated portfolios, it is more likely due to their lack of sophistication and improper understanding of the benefits of diversification. Similarly, active trading by investors with low cognitive abilities is likely to reflect overconfidence or impatience. And they are likely to overweight local stocks not because of an informational advantage, but merely because they are more familiar with them, which can generate a perception of information.

To empirically test whether the level of cognitive abilities is a critical determinant of the relation between portfolio distortion and portfolio performance, ideally we need both 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 about people's investment decisions and estimates of their cognitive abilities simultaneously. To side-step this data hurdle, we adopt the imputation method that is commonly used to link multiple data sets (e.g., Skinner (1987), Ziliak (1998), Browning and Leth-Petersen (2003)).[1]

Specifically, using a data set that contains multiple and direct 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 strongly correlated with cognitive abilities. Using a U.S. data set, we also demonstrate that the relation between cognitive abilities and demographic characteristics is strong and robust.[2]

The model estimates indicate that a handful of demographic characteristics is able to explain a significant proportion of cross-sectional variation in cognitive abilities. In particular, age, education, social network, and wealth are strong correlates of cognitive abilities. The in-sample correlation between the actual and the model-predicted cognitive abilities measures is 0.664. Even out-of-sample, our model performs well. When we apply the model estimated using the European data to a sample of U.S. individuals, we find that the correlation between the actual and model-implied cognitive abilities estimates is 0.516.

Because the cognitive abilities model works effectively out-of-sample, we use it to estimate the cognitive abilities of a sample of individual investors at a large U.S. brokerage house. To set the stage for our main empirical analysis, we use these imputed cognitive abilities of brokerage investors and examine their personal and portfolio characteristics across cognitive abilities quintiles. We find that many characteristics such as wealth, gender, investment experience, and mutual fund holdings do not vary significantly with cognitive abilities. However, investors with high abilities are younger, have significantly higher incomes, and tend to live in urban regions.[3]

Examining the unconditional relation between cognitive abilities and portfolio distortion, we find that investors with high cognitive abilities trade actively, hold more concentrated portfolios, and exhibit strong preference for local stocks. In spite of these deviations from the normative prescriptions of the traditional portfolio theory, high cognitive abilities investors earn marginally positive gross returns. They outperform the group of investors with low cognitive abilities by about 3 percent annually on a risk-adjusted basis. When we account for transaction costs and use net returns to evaluate performance, as expected, the average performance levels decline. The average performance of investors with high cognitive abilities is no longer significantly different from zero, but the average performance differential between the high and the low cognitive abilities categories remains virtually unchanged.

To test the key elements of our main conjecture, we evaluate the performance of high and low cognitive abilities investors, conditional upon the degree of their portfolio distortions. We find that the performance differentials between investors with high and low cognitive abilities are indistinguishable from zero when both groups follow the normative advice and hold relatively diversified portfolios, trade infrequently, and do not tilt their portfolios toward local stocks. However, when investors distort their portfolios and hold concentrated portfolios, trade aggressively, or over-weight local stocks, the performance differentials are economically significant. During the six-year sample period, investors with high predicted cognitive abilities outperform investors with low cognitive abilities by about 6 percent annually on a risk-adjusted basis.

When we account for transaction costs and use net returns to measure distortion-conditional performance, the average performance levels of high (low) cognitive abilities investors decline in magnitude but remain significantly positive (negative). In addition, the annualized performance differentials between the high and the low cognitive abilities categories drop to about 5 percent but remain economically significant.

Using the Daniel, Grinblatt, Titman, and Wermers (1997) performance decomposition method, we find that a significant part of this performance differential is due to the superior stock selection skill of investors with high cognitive abilities. Interestingly, the stock selection skill is concentrated among stocks that have greater information asymmetry, are harder-to-value, and have low average performance (e.g., non-S&P 500 stocks, stocks with greater forecast dispersion).

For robustness, we conduct portfolio-based tests. We estimate the average cognitive abilities of the stockholders of each stock and sort stocks based on the cognitive abilities of their investor clienteles. We find that stocks with a "smart" investor clientele earn higher returns than stocks that attract a "dumb" investor clientele. The annualized, risk-adjusted cognitive abilities spread estimates are about 3.50 percent. From our perspective, more importantly, the spread estimate is larger when the high cognitive abilities clientele holds concentrated portfolios, trades more actively, and exhibits a preference for local stocks.

Collectively, these empirical results are consistent with our main conjecture. As predicted, the portfolio distortions of investors with high cognitive abilities reflect an informational advantage and generate high risk-adjusted returns. In contrast, the distortions of investors with low cognitive abilities are induced by psychological biases and result in low risk-adjusted performance. Thus, our results provide empirical support for both behavioral and rational explanations for the three puzzles. We show that the behavioral and rational explanations are applicable to investors with low and high cognitive abilities, respectively.

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 how investment style and portfolio performance varies with cognitive abilities. In Sections III and IV, we test our main hypothesis. In Section V, we perform stock-level analysis to gather additional support for our main hypothesis. We conclude in Section VI. An online appendix summarizes results from additional tests.

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 key correlates of cognitive abilities identified in the cognitive psychology literature (e.g., Arbuckle, Gold, and Andres (1986), Fair (1994), Baltes and Lang (1997), Cagney and Lauderdale (2002)). This set includes wealth, income, age, education, social network, and a retired dummy variable. To align our model more closely to the predictions from the cognitive psychology literature, we also define an *Over 70* dummy and several interaction terms. In particular, to capture the prediction that cognitive abilities are likely to be lower among older investors who are less educated and less resourceful, we define *Over 70* $\times$ *Low Education* and *Over 70* $\times$ *Low Income* interaction terms.

A. SHARE and HRS Data

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.[4] The SHARE data contain three direct and standardized measures of cognitive abilities (verbal ability, quantitative ability, and memory) for more than 21,000 households. These measures are constructed based on responses from a paper-based survey. They are positively correlated, but the maximum correlation among them is below 0.50. Using the three cognitive measures, we obtain a composite (equal-weighted average) measure of the cognitive abilities of each household.

The SHARE data also contain demographic variables such as 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 will have larger social networks.

We use the SHARE data set to estimate the model because it contains accurate measures of cognitive abilities and social networks. Nevertheless, for robustness, we use the 2004 wave of the Health and Retirement Study (HRS) data from the U.S. Like the SHARE data, the HRS data contain information about the health and financial status for a sample of about 4,000 U.S. households over the age of 50.[5] In contrast to the earlier versions of HRS, the 2004 wave contains direct measures of verbal ability, quantitative ability, and memory. We use the standardized values of the three measures to obtain a composite (equal-weighted average) cognitive abilities measure for 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. Further, to facilitate comparisons of coefficient estimates within and across regression specifications, we standardize both the dependent and the independent variables, such 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 ability, quantitative ability, and memory measures. In the fourth column, the dependent variable is the composite cognitive abilities measure.[6]

The coefficient estimates are qualitatively similar across the four regression specifications (see columns (1)-(4)). Consistent with the psychological evidence, cognitive abilities decline with age and increase with education level and size of social network. The coefficient estimates for wealth and income are also significantly positive, although their magnitudes are weak. In addition, we find that cognitive abilities are lower for older individuals (age > 70). The strong positive relation between cognitive abilities and education is intuitive and consistent with the evidence from previous studies that find a strong (above 0.60) correlation between education level and cognitive abilities (e.g., Brown and Reynolds (1975), Barber (2005), Zagorsky (2007)). The relatively weak relation between cognitive abilities and income/wealth is also consistent with the previous evidence.

We obtain qualitatively similar results when the dependent variable is the composite cognitive abilities measure obtained using the HRS data (see the "AvgHRS" column). One exception is the coefficient estimate of the social network proxy, which is considerably weaker. This evidence is not very surprising because the HRS social network proxy (church attendance) is likely to be inferior to the social network proxy available in the SHARE data.

Overall, the cognitive abilities model estimates indicate that a handful of demographic characteristics is able to explain a significant proportion of the cross-sectional variance in people's cognitive abilities. In particular, age, education, social network, and wealth are strong correlates of cognitive abilities. When we use the coefficient estimates of the "Avg" model, the in-sample correlation between the actual and the model predicted cognitive abilities measures is 0.664, which translates into an adjusted R^2 of about 44 percent.

C. An Out-of-Sample Test

To better assess the predictive power of our empirical model of cognitive abilities, we perform an out-of-sample test. Although we observe the actual cognitive abilities of individuals in the HRS sample, we use the model estimated using the SHARE data ("Avg" column in Table I) to obtain imputed cognitive abilities for individuals in the HRS sample. We find that the correlation between the actual cognitive abilities of individuals in the HRS sample and their imputed cognitive abilities estimates obtained using the SHARE model is 0.516.

The high correlation estimate indicates that the imputation method works effectively and, therefore, our empirical model performs well even out-of-sample. Our evidence also indicates that the cognitive abilities model estimated using a European data set works reasonably well in the U.S. In the online appendix (see Sections A.1 to A.3), we present evidence from additional tests to demonstrate that the empirical model of cognitive abilities contains useful information for separating informed and behaviorally biased investors on an *ex ante* basis.

II. Cognitive Abilities and Investment Decisions

In this section, we use our empirical model of cognitive abilities to obtain the imputed cognitive abilities of a group of U.S. individual investors. Using these estimates, we examine whether investors' cognitive abilities influence their portfolio characteristics, trading behavior, and portfolio performance. This unconditional analysis sets the stage for the main conditional empirical tests discussed in Sections III to V.

A. *Individual Investor Database and Other Data Sources*

We consider a sample of individual investors at a large U.S. discount brokerage house. The brokerage data contain the monthly positions and all trades of those 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 characteristics including age, income, location (zip code), total net worth, occupation, marital status, family size, gender, etc. are available. The demographic measures were compiled by Infobase Inc. in June 1997. Additional details about the individual investor database are available in Barber and Odean (2000, 2001).[7]

We enrich the individual investor data using 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 brokerage investors.[8] We assume that investors who live in more educated zip codes are better educated. With this assumption, we use the proportion of the population in a zip code that holds a bachelor's degree or higher to assign an educational status to all investors located in 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 dividends, monthly prices, returns, and market capitalization data from the Center for Research on Security Prices (CRSP), and, we obtain 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 Kenneth French's data library. Last, we obtain characteristic-based performance benchmarks from Russell Wermers' web site.[10]

B. *Imputed Cognitive Abilities Estimates of Individual Investors*

Because we do not have direct measures of the cognitive abilities of brokerage investors, we use the empirical model of cognitive abilities presented in Table I to impute their cognitive abilities. A key advantage of the imputation method, 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' skill estimates *ex ante* using only their demographic characteristics.

Specifically, we use the coefficient estimates from the SHARE model reported 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, but our results are very similar when we use the HRS model ("AvgHRS" column).[11] Using the imputed cognitive abilities of brokerage investors and their actual portfolio holdings and trades, we evaluate various dimensions of their stock investment decisions.

C. Cognitive Abilities and Investor Characteristics

First, using the imputed cognitive abilities measures, we sort brokerage investors and define five investor categories (quintiles). Table II presents the sample-period average portfolio and investor characteristics for these cognitive abilities-sorted investor categories. We find that several characteristics such as gender, investment experience, and mutual fund holdings do not vary significantly with cognitive abilities. However, there are considerable differences between low and high cognitive abilities investors along other important dimensions.

For instance, a very large proportion (about 46 percent) of high cognitive abilities investors live in urban regions (within 100 miles of the top 20 metropolitan regions in the U.S.). In contrast, only about 17 percent of low cognitive abilities investors are located in urban areas. Moreover, we find that high cognitive abilities investors are not wealthier than low cognitive abilities investors, although they earn significantly higher income than investors with low cognitive abilities ($126,342 vs. $58,684).[12] We also find that high cognitive abilities 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. Collectively, these summary statistics indicate that high cognitive abilities investors are likely to possess greater financial sophistication.

D. Cognitive Abilities and Portfolio Distortions

Next, we examine whether investors' cognitive abilities are correlated with their propensities to deviate from the normative prescriptions of the traditional portfolio theory. We focus on portfolio distortion measures that capture investors' diversification preferences (i.e., portfolio concentration), extent of trading, and propensity to invest in local stocks. We measure portfolio concentration using the sample period average number of stocks in the portfolio and the normalized portfolio variance (the ratio of portfolio variance and the average variance of stocks in the portfolio).[13] We measure investors' propensity to trade using the monthly portfolio turnover (the average of buy and sell turnover rates) and the average stock holding period measures.[14]

To capture investors' propensity to invest in local stocks, we construct a measure of local stock preference (LP), which is defined as $LP = 1 - D_{act}/D_{portf}$. In this definition, D_{act} is the average distance between an investor's location and stocks in her portfolio, while D_{portf} is the average distance between an investor's location and other characteristic-matched portfolios not held by the investor.[15] We also consider an alternative measure of local stock preference, which is defined as the proportion of the total equity portfolio invested in the stocks of companies that are headquartered within 250 miles of the investor's location.[16]

Table III, Panel A reports the average distortion measures for cognitive abilities sorted investor categories (quintiles). We find that high cognitive abilities investors hold more concentrated portfolios, trade somewhat more actively, and exhibit stronger preference for local stocks. For instance, low cognitive abilities investors hold an average of 5.18 stocks, while high cognitive abilities investors hold an average of 4.37 stocks. Similarly, the average proportion of local stocks in the portfolios of high cognitive abilities investors is 13.28 percent, while the portfolios of low cognitive abilities investors contain an average of 9.73 percent local stocks. The monthly portfolio turnover rates do not vary significantly across the cognitive abilities quintiles, but high cognitive abilities investors on average hold a stock for 20 fewer days (334 vs. 354 days). Overall, investors with high cognitive abilities distort their portfolios more than investors with low cognitive abilities.

E. Cognitive Abilities and Portfolio Performance

In the last part of this section, we examine the unconditional relation between cognitive abilities and portfolio performance. We obtain estimates for both gross and net portfolio performance, which accounts for trading costs. We use the Barber and Odean (2000) method to compute the net monthly returns of investor portfolios.[17]

The month-t portfolio return of investor i is given by

$$R_{it} = \sum_{j=1}^{N_{it}} w_{ijt} R_{jt}, \tag{1}$$

where N_{it} is the number of stocks held by investor i in month t and w_{ijt} is the portfolio weight allocated by investor i to stock j at the beginning of month t. R_{jt} is the month-t raw or characteristic-adjusted gross or net return of stock j.[18] The return of a certain cognitive abilities-sorted investor category s in month t is the equal-weighted average of the month-t return of investors who belong to the group:

$$R_{st} = \frac{1}{N_{st}} \sum_{i \in CAB_s} R_{it}; \qquad s = 1, \ldots, 5. \tag{2}$$

In this definition, CAB_s is the set of investors in cognitive abilities-sorted category s, R_{it} is either the gross or the net month-t raw or characteristic-adjusted return of investor i, and N_{st} is the number of investors in category s in month t.

The sample period average performance of category s is denoted by R_s, which is the equal-weighted average of the monthly performance measures of category s, i.e., R_{st}. We use the standard deviation (σ_s) of the monthly performance time series $\{R_{st}\}_{t=1,\ldots,71}$ to measure the statistical significance of the mean monthly performance of category s.[19] The statistical significance of the mean performance differential between two categories is computed in an analogous manner using the standard deviation of the monthly performance differential time-series.

We obtain gross and net characteristic-adjusted performance measures of cognitive abilities-sorted portfolios using characteristic-adjusted monthly stock returns instead of "raw" monthly returns. The risk-adjusted performance measure of each investor portfolio is the intercept from a four-factor asset pricing model that contains the three Fama-French factors (Fama and French (1992, 1993)) and the momentum factor (Jegadeesh and Titman (1993), Carhart (1997)). We use both gross and net stock returns to measure the risk-adjusted portfolio performance. The characteristic- and risk-adjusted performance measures are reported in Table III, Panel B.

We find that in spite of exhibiting marginally stronger portfolio distortions, investors with high cognitive abilities have better average performance than those with low cognitive abilities. When we compute the average performance estimates of cognitive abilities-sorted investor quintiles using gross returns, the lowest cognitive abilities category significantly under-performs various benchmarks. In contrast, the average performance of investors in the high cognitive abilities category is positive, although the statistical significance is weak. The annualized raw, characteristic-adjusted, and risk-adjusted (i.e., the four-factor alpha) performance differentials between the highest and the lowest cognitive abilities investor categories are $0.321 \times 12 = 3.85$ percent, $0.286 \times 12 = 3.43$ percent, and $0.303 \times 12 = 3.64$ percent, respectively.

When we use net returns to measure performance, the characteristic- and risk-adjusted performance levels of low cognitive abilities investors are even more negative, while the corresponding performance measures of high cognitive abilities investors are negative but statistically insignificant. The average performance differential between the extreme cognitive abilities categories, however, remains significantly positive. The annualized raw, characteristic-adjusted, and risk-adjusted performance differentials between the highest and the lowest cognitive abilities investor categories are $0.331 \times 12 = 3.97$ percent, $0.292 \times 12 = 3.50$ percent, and $0.315 \times 12 = 3.78$

percent, respectively. These performance estimates are consistent with our main hypothesis and indicate that high cognitive abilities investors make better investment decisions.[20]

Our results from one-dimensional cognitive abilities sorts are also consistent with the evidence from previous studies, which demonstrates that a subset of individual investors might be skillful (e.g., Barber and Odean (2000), Coval, Hirshleifer, and Shumway (2005), Ivković and Weisbenner (2005), Ivković, Sialm, and Weisbenner (2008)).[21] For instance, Barber and Odean (2000) show that 43.4 percent of brokerage investors outperform the market index after accounting for trading costs, and about 25 percent of investors beat the index by about 6 percent on an annual basis. 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.

III. Cognitive Abilities and the Three Puzzles

In this section, we test the key elements of our main hypothesis. The identification strategy focuses on the relation between portfolio distortions and portfolio performance, conditional upon the level of cognitive abilities of investors. We focus on three types of portfolio distortions that could be induced by behavioral biases or could reflect superior information: (i) the decision to hold a concentrated portfolio, i.e., a portfolio with only a handful of stocks, (ii) the decision to trade actively, and (iii) the decision to tilt the stock portfolio toward local stocks.

We conjecture that when investors follow the normative prescriptions of the traditional portfolio theory (i.e., hold well-diversified portfolios and trade infrequently), having high cognitive abilities is unlikely to yield significant advantages. But, differences in cognitive abilities would significantly alter portfolio performance when investors depart from these normative prescriptions and intentionally distort their portfolios. Specifically, when investors' portfolio distortions are induced by psychological biases, the realized performance of their portfolios will underperform typical performance benchmarks. In contrast, when portfolio distortions reflect superior information, those portfolios will generate abnormal risk-adjusted returns.

A. Evidence From Ability-Distortion Double Sorts

In the first set of tests, we sort investors independently using their imputed cognitive abilities estimates and the three portfolio distortion measures. For each of the three portfolio distortion measures, we compute the average portfolio performance of high (top quintile) and low (bottom quintile) cognitive abilities investor categories when the distortion level is low (bottom quintile) and high (top quintile). Specifically, we compute the month-t return of each ability-distortion category as:

$$R_{s_1,s_2,t} = \frac{1}{N_{s_1,s_2}} \sum_{i \in \{CAB_{s_1} \cap Distortion_{s_2}\}} R_{it}; \qquad s_1 = 1, \ldots, 5; \quad s_2 = 1, \ldots, 5. \tag{3}$$

Here, CAB_{s_1} is the set of investors who belong to cognitive abilities quintile s_1, $Distortion_{s_2}$ is the set of investors in portfolio distortion quintile s_2, and N_{s_1,s_2} is the number of investors in the ability-distortion category that contains investors from cognitive abilities quintile s_1 and bias quintile s_2. R_{it} is the month-t portfolio return of investor i and $R_{s_1,s_2,t}$ is the average month-t return of investors who belong to cognitive abilities quintile s_1 and distortion quintile s_2. We estimate the performance of ability-distortion categories separately for portfolio concentration, portfolio turnover, and local stock preference measures.

We obtain the performance estimates of ability-distortion categories using characteristic-adjusted stock returns. We measure the monthly characteristic-adjusted performance for each ability-distortion category and compute its time-series average to obtain the sample-period performance of the investor category. To measure the performance differential between two ability-distortion categories, we compute the performance differential each month and use the standard deviation of the performance differential time-series to assess its statistical significance.

Figure 1 presents one of the key results of the paper. In Panel A, we show the distortion-conditional average portfolio performance for low and high cognitive abilities investor groups computed using gross characteristic-adjusted returns. The low distortion investors hold an average of 7.56 stocks, trade infrequently (average monthly turnover = 0.63 percent), and tilt their portfolios away from local stocks (average local preference = −15.55 percent). In contrast, the high bias investors hold an average of 1.62 stocks, trade actively (monthly portfolio turnover = 8.15 percent), and exhibit a strong preference for local stocks (average local preference = 66.64 percent).

We find that when portfolio distortions are low, on average, high cognitive abilities investors earn only one percent higher annualized, characteristic-adjusted returns than low cognitive abilities investors. But when portfolio distortions are significant, high cognitive abilities investors out-perform low cognitive abilities investors by about six percent.[22] This evidence indicates that the level of portfolio distortions and cognitive abilities *jointly* determine the performance of investor portfolios.

When we account for trading costs and measure the distortion-conditional performance differentials using net returns, the performance levels of both high and low cognitive abilities investors decline (see Figure 1, Panel B). The positive performance of high cognitive abilities investors is significant at the 0.05 level in two cases (portfolio concentration and local preference) and it is significant at the 0.10 level when we measure distortion using portfolio turnover. The negative performance of low cognitive abilities investors is significant at the 0.05 level in all three instances. Further, the distortion-conditional performance differentials between the high and the low cognitive abilities investor groups remain positive and significant in all three instances ($\approx$ 5 percent).

To quantify the combined effects of the three distortions on portfolio performance, we define a composite distortion measure that is the equal-weighted average of the portfolio concentration, portfolio turnover, and local preference measures. The average is computed after the three distortion measures have been standardized (mean is set to zero and the standard deviation is set to one). As before, we perform two independent sorts using the cognitive abilities and the composite distortion measures and define ability-distortion categories. The performance estimates of ability-distortion categories are obtained using equation (3).

Figure 2 shows the average performance differential between the high and the low cognitive abilities investors for the five composite distortion quintiles. We report the annualized gross as well as net raw and characteristic-adjusted performance differential estimates. The plot shows that all four performance differentials increase as the level of portfolio distortion increases. The mean performance differential is only 0.28 percent when the composite portfolio distortion measure is in the lowest quintile and it increases uniformly to 5.49 percent when composite distortion is in the highest quintile.

Taken together, these results from ability-distortion double sorts are consistent with our main hypothesis, which posits that large distortions in the portfolios of investors with high cognitive abilities reflect superior information rather than psychological biases. Because investors with low cognitive abilities earn negative characteristic-adjusted returns, the evidence also indicates that the large distortions in the portfolios of those investors are more likely to be due to psychological biases.

B. Performance Regression Estimates: Baseline Results

To examine the interactions among portfolio distortions, cognitive abilities, and portfolio performance in a multivariate setting, we estimate investor-level cross-sectional regressions. The dependent variable in these regressions is an investor's sample-period average characteristic-adjusted gross or net portfolio return. The set of independent variables includes the imputed value of cognitive abilities, the three portfolio distortion measures, and interactions among these variables. Our main focus is on the cognitive abilities variable and the cognitive abilities-distortion interaction terms, which capture the incremental effects of portfolio distortions by low and high cognitive abilities investors. To define the interaction terms, we define a high (low) cognitive abilities dummy, which is set to one for investors in the highest (lowest) cognitive abilities quintile. The high and low distortion dummy variables are defined in an analogous manner.

The regression specification also includes the following 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 of the head of the household. The high and low dummy variables used to define the interaction terms are also included as additional control variables. We use robust, clustered standard errors to account for potential cross-sectional dependence in performance within zip codes.[23]

The regression estimates are reported in Table IV. Consistent with our evidence from cognitive abilities single sorts reported in Section II.E, we find that investors with higher cognitive abilities earn higher characteristic-adjusted returns (see column (1)).[24] Further, the portfolio turnover and the local preference variables have positive coefficient estimates, which indicate that these distortions might have an information-based explanation (see column (2)). In particular, the positive estimate of the local preference variable is consistent with the evidence in Ivković and Weisbenner (2005). More importantly, consistent with our main hypothesis and similar to the results from ability-distortion double sorts reported in Figure 1, we find that the high abilities $\times$ high distortion interactions have significantly positive estimate, while the low abilities $\times$ high distortion interactions have significantly negative estimates (see columns (3) and (4)).

Most coefficient estimates retain their signs and significance levels when we use net returns to obtain the characteristic-adjusted performance (see columns (5) and (6)). An exception is the estimate for portfolio turnover, which has a significantly positive estimate in gross return regressions but a significantly negative estimate in net return regressions. This evidence in consistent with the results in Barber and Odean (2000), who show that active traders have worse negative average performance when trading costs are taken into account. However, all ability-distortion interaction terms maintain their significant estimates and continue to support our main hypothesis. In particular, although portfolio turnover has a negative coefficient estimate, the high abilities $\times$ high turnover interaction has a positive coefficient estimate. Thus, although portfolio turnover and net performance measures are negatively correlated, when high cognitive abilities investors trade actively, they are able to improve their net performance.

The coefficient estimates of interaction terms are easy to interpret economically. For example, the portfolio concentration interaction terms in column (6) indicate that, all else equal, a high cognitive abilities investor would earn a $0.043 \times 12 = 0.52$ percent higher characteristic-adjusted annual net return, a low cognitive abilities investor would earn a $0.037 \times 12 = 0.44$ percent lower characteristic-adjusted annual net return, and the performance differential between the two categories would be 0.96 percent. Similarly, if a high cognitive abilities investor distorts the portfolio on all three dimensions, she would earn a 1.60 percent higher net return. In contrast, a low cognitive abilities investor would earn a 1.49 percent lower net return, and the annual characteristic-adjusted performance differential between the two groups would be 3.09 percent, which is economically significant.

Collectively, the performance regression estimates support our main hypothesis and indicate that high cognitive abilities investors are able to generate high returns from their portfolio distortions, perhaps due to their superior information. In contrast, the portfolios of low cognitive abilities investors under-perform because their distortions are more likely to reflect behavioral biases.[25]

C. Performance Regression Estimates using Other Estimation Methods

In the performance regressions, we implicitly assume that the average sample period performance of each investor is independent. This is likely to be a reasonable assumption because brokerage investors hold an average of only four stocks, and about 28 percent of them hold only one stock (Goetzmann and Kumar (2008)). Thus, the overlap in investors' portfolios would be small and the extent of cross-sectional dependence in performance is unlikely to be strong. Nonetheless, all investor portfolios are exposed to a common set of systematic factors and, thus, the sample-period performance estimates could be correlated.[26]

To ensure that potential cross-sectional dependence in performance is not overstating the statistical significance of our coefficient estimates, we re-estimate the performance regressions using the Fama-MacBeth cross-sectional regression method. Specifically, we estimate the cross-sectional performance regression each month, where the month-t characteristic-adjusted performance of an investor is the dependent variable and all independent variables are measured at the end of the previous month. To further ensure that the standard error estimates are not downward biased, we estimate a panel regression specification with month fixed effects and compute month- and firm-clustered standard errors (Petersen (2008)).[27]

In the Fama-MacBeth approach, we estimate 70 monthly regressions and use the time series of the coefficient estimates to assess their statistical significance. The cross-sectional dependence in performance could inflate the statistical significance of the coefficient estimates in each of the 70 monthly performance regressions, but it does not introduce a bias in the coefficient estimates themselves. Since we use the time series of the monthly coefficient estimates to measure their statistical significance, our results are not affected by the potential cross-sectional dependence in performance within a certain month. In addition, we use the Pontiff (1996) method to correct the Fama-MacBeth standard errors for potential higher order serial correlation.[28]

The regression estimates obtained using net returns are reported in the last two columns of Table IV.[29] We find that all our results remain qualitatively similar even when we explicitly account for cross-sectional dependence in the monthly performance measures. Both Fama-MacBeth and panel estimation methods yield similar results. This evidence indicates that the statistical significance of the coefficient estimates in the cross-sectional performance regressions is not inflated by potential cross-sectional dependence in portfolio performance across investors.

D. Which Cognitive Abilities Correlates are More Important?

The imputed cognitive abilities measure for an investor is a linear combination of investor characteristics such as education, age, social network, and income. Therefore, the distortion-conditional performance differential between low and high cognitive abilities investors would also be some combination of these investor characteristics. To identify the component of the performance differential that can be attributed to each of these investor characteristics, we estimate the distortion-conditional performance differentials when only subsets of investor attributes are used as proxies for cognitive abilities. The results are summarized in Table V, Panel A. Similar to the results shown in Figure 1, we report the annualized, characteristic-adjusted performance differential between high (quintile 5) and low (quintile 1) cognitive abilities investor categories, conditional upon the level of portfolio distortion.

When we use only income to define the cognitive abilities proxy, the performance differentials are positive ($\approx$ 2 percent) when portfolio distortions are high (see row (1)). The evidence is qualitatively similar, although somewhat weaker, when we use the social network proxy (see row (2)). In both instances, the estimates are either insignificant or statistically significant at the 0.10 level. When we use the education proxy or age as the cognitive abilities proxy, the performance differential estimates are stronger (about 2.75 percent), and the statistical significance improves (see rows (3) and (4)).

Next, we consider an equal-weighted linear combination of standardized income, education proxy, age, and social network, with a negative sign on age (see row (5)). In this case, we find that the performance differentials are higher ($\approx$ 3.25 percent).[30] This evidence indicates that a simple linear combination of the demographic characteristics is a better proxy for cognitive abilities than the demographic characteristics individually.

As expected, the imputed cognitive abilities measures obtained from our empirical model deliver the strongest result. The annualized characteristic-adjusted performance differentials corresponding to the portfolio concentration, turnover, and local preference measures are 5.83 percent, 5.56 percent, and 5.77 percent, respectively (see Panel A, row (6)). All three performance differential estimates are significant at the 0.05 level. This evidence indicates that, while the individual cognitive abilities determinants or their simple linear combination have the power to discriminate between informed and biased investors, the imputed values of cognitive abilities have considerably higher discriminatory power.

To further demonstrate that the imputed values of cognitive abilities can effectively discriminate between informed and biased investors, we examine the distortion-conditional performance differential for a factor that is an important determinant of portfolio performance, namely, investment experience (see Table IV). We find that investors with greater experience outperform those with low experience by about 1.5 percent when the degree of portfolio distortions are *low*. However, when distortions are high, the performance differentials are not statistically different from zero (see row (7)). This evidence indicates that an arbitrarily chosen proxy for investor sophistication that is known to influence portfolio performance is unlikely to generate positive distortion-conditional performance differentials. The strong discriminatory power of imputed cognitive abilities appears to be unique.

For robustness, we use the composite distortion measure and both gross and net return measures to investigate how the interactions between cognitive abilities and portfolio distortions determine the overall portfolio performance. The results are reported in Table V, Panels B and C. We find that high cognitive abilities investors earn economically significant returns when they distort their portfolios. Both the gross and the net return estimates are significant. For instance, high abilities-high distortion investors earn 5.95 percent (6.39 percent) higher gross (net) characteristic-adjusted annual returns than low abilities-high distortion investors (see row (6)). When we use the individual correlates of cognitive abilities or their simple linear combination as proxies for abilities, we get similar but weaker performance differential estimates (see rows (1) to (5)). This evidence indicates that our empirical model of cognitive abilities is able to generate significant performance differential over and above a "naive" model of cognitive abilities that uses a simple linear combination of the demographic characteristics.

E. Are We Truly Capturing Investors' Cognitive Abilities?

We do not observe the cognitive abilities of investors directly, but use a linear combination of their demographic characteristics to impute their cognitive abilities. Thus, we are essentially capturing the joint effects of investors' demographic characteristics that are correlated with cognitive abilities. For example, investors with higher imputed cognitive abilities are younger, better-educated, urban, and high income individuals with strong social networks. Similarly, lower cognitive abilities investors are typically older, less educated, low-income investors who live in rural areas and have smaller social networks.

Thus, another potential interpretation of our results is that a particular combination of demographic characteristics that is strongly correlated with investors' cognitive abilities allows us to separate informed and behaviorally biased investors. Although this interpretation does not exclusively rely on the notion of cognitive abilities, it does not dilute the significance of our results. Our main point is that a specific linear combination of demographic characteristics allows us to separate skilled and unskilled investors on an *ex ante* basis. Using this classification, we show that "all distortions are not alike," because the investment decisions that are observationally equivalent could be induced by two fundamentally different mechanisms. This insight allows us to provide a unified explanation for the three puzzles.

We use the label "cognitive abilities" to characterize the combined effects of the demographic characteristics because the concept permeates all key dimensions of our study. In particular, our main hypothesis is motivated by the recent research in behavioral economics, which demonstrates that behavioral biases are weaker among individuals with higher cognitive abilities. Further, to separate informed and biased investors, we use an empirical model that uses direct measures of cognitive abilities.

Of course, *ex post* the combination of demographic characteristics that we use appears intuitive, and one could have conjectured that some combination of age, education, income, and other investor characteristics would produce similar results. But, the precise combination of demographic variables we use would have been difficult to identify. In particular, the interaction terms in our cognitive abilities model do not have a meaningful interpretation outside the framework of cognitive abilities. Even if this combination could have been identified, it would have lacked theoretical validity. In contrast, our cognitive abilities model provides a firm theoretical foundation for our empirical exercise and ensures that our results are immune to potential concerns about data-mining.

IV. Channels of Superior Performance

Our evidence thus far indicates that the performance differentials between high and low cognitive abilities investors are economically significant when portfolio distortions are high. In this section, we attempt to identify the channels that high cognitive abilities investors are likely to use to generate superior returns. Although our data do not allow us to precisely identify the channels through which high cognitive abilities investors generate superior returns from their portfolio deviations, we interpret the current evidence and conduct additional tests to identify the channels that investors *might* use. The results from these additional tests are summarized in Table V, Panel D.

A. *Superior Information Sources or Better Interpretation of Information?*

Broadly speaking, high cognitive abilities investors can 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 *abilities* or greater cognitive *skill*.[31]

One potential channel through which investors can possess an informational advantage is insider information. High cognitive abilities investors are better educated, have high income levels, and have large social networks. Due to their superior social networks, these investors could have access to insider information, especially about local firms (e.g., as an employee).

However, we find that the distortion-conditional performance differential is only weakly positive for investors who live in regions with strong social networks (see Table V, Panels A, B, and C, row (2)). In unreported results, we also find that the distortion-conditional performance differential is somewhat stronger for non-local stocks. Further, we do not find any evidence of front-running by high cognitive abilities investors prior to earnings announcements.

To formally exclude potential insiders, we adopt an approach similar to that of Ivković, Sialm, and Weisbenner (2008) and exclude portfolios with only one stock. We re-estimate the distortion-conditional performance differentials and find that the results are essentially unchanged (see Table V, Panel D, row (1)). In untabulated results, we find that these 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.

We also examine whether the superior performance of employer stocks or easier access to information from employer-based networks is driving our results. We consider a sub-sample of investors who are unemployed and a sub-sample of female investors, because all else equal, female investors are less likely to be employed. For both sub-samples (see Panel D, rows (2) and (3)), the distortion-conditional performance differentials are qualitatively similar to the baseline results, although the evidence is somewhat weaker. These results suggest that the superior performance of high cognitive abilities investors is unlikely to emerge from easier access to insider information.

If high cognitive abilities investors do not have access to superior information sources, they could have quicker and easier access to public information. Recent studies indicate that information is disseminated from urban centers to rural areas (e.g., Loughran (2007)) and, therefore, 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 distortion-conditional performance than rural investors, perhaps due to the superior information environment in urban regions (see Panel D, rows (4) and (5)). However, high cognitive abilities investors in rural and informationally-poor regions are also able to generate superior returns when they distort their portfolios (see Panel D, row (5)). Additionally, in untabulated results, we find that the performance of low cognitive abilities investors is similar in both rural and urban settings. This evidence indicates that the positive distortion-conditional performance does not solely reflect investors' ability to gather information in richer information environments. A higher level of cognitive abilities has an incremental positive effect on distortion-conditional performance estimates.

High cognitive abilities investors might also generate abnormal returns through their skill in interpreting information. In untabulated results, consistent with this conjecture, we find that high cognitive abilities investors are less likely to use the inferior seasonal random walk model of earnings to interpret earnings news (Battalio and Mendenhall (2005)). This evidence suggests that high cognitive abilities investors exhibit greater financial sophistication, which allows them to better interpret public information signals.

To examine whether the ability to interpret information signals more effectively is innate or acquired through experience, we obtain a residual cognitive abilities proxy by regressing the investors' predicted cognitive abilities measure on a proxy for investment experience (number of days since the brokerage account opening date). We find that the distortion-conditional estimates obtained using the residual cognitive abilities measures (see Panel D, row (6)) are very similar to our baseline estimates reported earlier in Table IV. In untabulated results, we also find that our state-level cognitive abilities estimates and state-level SAT scores are positively correlated (correlation = 0.285). These results suggest that our cognitive abilities proxy is more likely to reflect "raw" ability or acquired skill from other sources (e.g., education), rather than the positive effects of learning through trading.[32]

Overall, the sub-sample estimates indicate that the positive distortion-conditional performance of high cognitive abilities investors is unlikely to emerge from their ability to obtain insider information. A component of this abnormal performance could be induced by the superior quality of high cognitive abilities investors' informational environments. However, in light of our empirical findings, the most plausible explanation for the superior distortion-conditional performance appears to be investors' ability to better interpret their private and public information signals, perhaps due to their superior cognitive abilities.[33]

B. Superior Stock Selection and Market Timing Abilities?

If high cognitive abilities investors are better at interpreting information signals, this skill should translate into better stock selection and market timing abilities. To examine this possibility, we use the Daniel, Grinblatt, Titman, and Wermers (1997) 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 abilities (CAB) and one of the portfolio distortion measures. As before, we consider three distortion measures (portfolio concentration, portfolio turnover, and local preference) individually and also a composite distortion measure that combines the three individual distortion measures. We compute the CS, CT, and AS performance measures for each of the 25 ability-distortion categories. Those annualized performance measures are presented in Table VI, Panel A, where for brevity, we only report the estimates for the following four extreme ability-distortion categories: low CAB and low distortion, low CAB and high distortion, high CAB and low distortion, and high CAB and high distortion.

The DGTW performance estimates indicate that, when the portfolio distortion levels are low, both the low and the high cognitive abilities investors have negative CS and CT estimates, and the differences are economically small. The AS differences are also small and economically insignificant. However, when the portfolio distortions are large, high cognitive abilities investors exhibit superior stock-picking abilities. The CS estimates for low cognitive abilities investors are negative, while the CS estimates for high cognitive abilities investors are positive and economically significant. Specifically, the CS estimates corresponding to portfolio concentration, portfolio turnover, local preference, and the composite distortion measures are 2.78 percent, 3.72 percent, 2.57 percent, and 4.87 percent, respectively. The differences between the CS estimates for the high and the low cognitive abilities groups are significantly positive.

Examining the CT estimates for the low and the high cognitive abilities investor categories, we find that CT estimates are negative for both categories. The annual CT estimates for the low cognitive abilities category are -2.38 percent, -1.80 percent, -1.56 percent, and -1.94 percent, respectively. In contrast, corresponding to the four distortion measures, the CT estimates for the high cognitive abilities investors are -0.33 percent, -0.86 percent, -0.35 percent, and -0.28 percent, respectively. These estimates indicate that when the level of portfolio distortion is high, investors lack characteristic timing abilities irrespective of their levels of cognitive abilities. However, the low cognitive abilities investors have more negative CT estimates and exhibit worse timing abilities.

Last, examining the AS estimates, we find that, irrespective of the distortion levels, the AS estimates for high and low cognitive ability investor categories are very similar. Overall, the total annual performance differential estimates corresponding to portfolio concentration, portfolio turnover, local preference, and composite distortion measures are 4.99 percent, 5.50 percent, 4.78 percent, and 5.70 percent, respectively. These performance estimates indicate that high cognitive abilities investors are able to generate superior returns through their better stock selection abilities and relatively less inferior characteristic timing skills.

C. Better Stock Selection Ability When Information Asymmetry Is High?

If high cognitive abilities investors have superior stock selection skill, it is unlikely that those investors would have the ability to successfully pick widely followed stocks, such as the stocks that belong to the S&P500 index. They are more likely to exploit their skill among stocks with greater information asymmetry.

To investigate whether the stock selection abilities of high cognitive abilities investors vary with information asymmetry, we consider four 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), (iii) book-to-market (B/M) ratio, and (iv) dispersion in analysts' quarterly earnings forecasts (the standard deviation of the most recent earnings forecasts of all analysts who cover the stock). For each of the four extreme ability-distortion categories, we estimate the CS measure by only considering investors' positions within the stock categories that are defined according to one of the four information asymmetry proxies.

The annualized CS estimates are reported in Table VI, Panel B. We find that when the distortion levels are low, high cognitive abilities investors have higher CS estimates when the information asymmetry is high (non-S&P 500 stocks, high idiosyncratic volatility stocks, low B/M or growth stocks, or high dispersion stocks). But, the magnitudes of the CS estimates are small (less than 2 percent).

When both the distortion and the information asymmetry levels are high, high cognitive abilities investors have significantly higher and economically significant CS estimates (over 4 percent). The superior performance levels among high idiosyncratic volatility and high dispersion stocks are particularly impressive because those stocks are relatively more difficult to value (e.g., Zhang (2006)) and are also known to earn low average returns (Diether, Malloy, and Scherbina (2002), Ang, Hodrick, Xing, and Zhang (2006)). Because high cognitive abilities investors generate positive returns from those stocks in spite of their negative average performance, evidence of stock selection abilities appears to be strong.

V. Evidence From Portfolio-Based Tests

To further characterize and quantify the information contained in the investment decisions of high cognitive abilities 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, obtain stock-level estimates of cognitive abilities, and examine the performance of cognitive abilities-sorted portfolios. One of the key advantages of portfolio-based tests is that the results from these tests are insensitive to concerns about potential cross-sectional dependence in portfolio performance.

A. *Portfolio Construction Method*

For the portfolio-based tests, we use the imputed cognitive abilities of sample investors and obtain monthly estimates of the aggregate cognitive abilities of each stock's investor clientele.[34] The stock-level cognitive abilities measure in a certain month is defined as the equal-weighted average cognitive abilities of investors who hold the stock at the end of that month. Specifically, we use the following equation:

$$ACAB_{jt} = \sum_{i=1}^{N_{jt}} w_{ijt} CAB_i. \tag{4}$$

Here, $ACAB_{jt}$ is the average cognitive abilities of the individual investor clientele of stock j at the end of month t, N_{jt} is the number of investors who hold stock j at the end of month t, w_{ijt} is the weight given to investor i holding stock j at the end of month t, and CAB_i is the imputed cognitive abilities of investor i. Because all investors are assigned equal weights, $\forall i, w_{ijt} = 1/N_{jt}$.[35]

Using the monthly $ACAB$ estimates, we sort stocks at the end of each month, and define five $ACAB$ quintile portfolios. We obtain the monthly value-weighted returns of these portfolios and use the performance time-series to obtain the sample-period risk-adjusted and the characteristic-adjusted performance estimates. The characteristic-adjusted returns are computed using the Daniel, Grinblatt, Titman, and Wermers (1997) method and the risk-adjusted performance measures are obtained by estimating a four-factor model that includes the three Fama-French factors (Fama and French (1992, 1993)) and the momentum factor (Jegadeesh and Titman (1993), Carhart (1997)).

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

Table VII reports the characteristics and performance estimates of cognitive abilities-sorted portfolios. Only stocks with CRSP share codes 10 and 11 are included in the analysis. Panel A reports the main performance estimates. For easier visualization, the two main performance measures of $ACAB$-sorted portfolios reported in columns (3) and (4) are also shown in Figure 3, Panel A.

We find that the results from portfolio-based tests echo our previous results obtained using investor-level analysis. Portfolio performance increases almost monotonically across the $ACAB$ quintile portfolios (see Figure 3, Panel A). Irrespective of the performance measure employed, the high $ACAB$ portfolio outperforms the low $ACAB$ portfolio by more than 3.50 percent annually. This evidence is consistent with our main conjecture and indicates that investors with higher cognitive abilities are able to identify better performing stocks.

Examining the factor exposures of $ACAB$ quintile portfolios, we find that the high (quintile 5) $ACAB$ portfolio is tilted toward mid-cap and growth stocks. The low (quintile 1) $ACAB$ portfolio, in contrast, is tilted toward relatively smaller and value stocks. These factor exposures are consistent with the evidence on the stock preferences of low and high cognitive abilities investors reported in Table A.I of the online appendix.

C. Performance of Ability-Distortion Double Sorted Portfolios

To link the portfolio-based tests more closely to our main hypothesis, we refine our portfolio-based tests and construct ability-distortion double sorted portfolios. At the end of each month, we perform independent sorts along stock-level cognitive abilities ($ACAB$) and composite distortion measures. Using the quintile break-points of $ACAB$ and stock-level composite distortion measures, we define ability-distortion portfolios. Like the $ACAB$ measure, the monthly stock-level composite distortion is obtained by averaging the composite distortion estimates of all investors who hold the stock at the end of the month. In this definition, the composite distortion of an investor is the equal-weighted average of her standardized concentration, turnover, and local preference measures.

Figure 3, Panel B shows the annualized characteristic-adjusted performance estimates of ability-distortion double sorted portfolios. The low, medium, and high cognitive abilities portfolios correspond to cognitive abilities quintiles 1, 3, and 5, respectively. When stocks have low cognitive abilities (or "dumb") investor clientele, the average portfolio performance declines as the level of composite portfolio distortion increases. In contrast, for stocks with high cognitive abilities (or "smart") clientele, the average portfolio performance increases with portfolio distortion. There is no clear relation between portfolio distortion and portfolio performance when the investor clientele has moderate cognitive abilities.

For example, when the composite distortion is high (quintile 5), stocks with a high cognitive abilities investor clientele earn an average of about 3 percent annualized characteristic-adjusted returns, stocks with a low cognitive abilities investor clientele earn an average of about -2 percent annualized characteristic-adjusted returns, and the annualized performance differential between the two groups is about 5 percent. These results are consistent with the evidence from investor-level analysis (see Figures 1 and 2) and provide further empirical support to our main hypothesis.

D. *Robustness of Portfolio-Based Tests*

We conduct three additional tests to examine the robustness of the results from our portfolio-based tests. First, we ensure that micro-structure effects (e.g., large bid-ask spreads) are not contaminating our findings. When we form $ACAB$-sorted portfolios after excluding stocks priced below \$5 (see row (1)), the performance differential estimates decrease. However, all three performance estimates are still significant, both statistically and economically. This evidence indicates that our results are not driven mainly by the performance of very low priced stocks.

In the second test, we examine the potential adverse effects of trading costs on the cognitive abilities spread estimates. It is likely that although the performance differentials between the high and the low $ACAB$ quintile portfolios are economically significant, the net cognitive ability spread estimates that account for trading costs might not remain economically significant if the portfolio turnover rates are high.

We measure the turnover rates for $ACAB$ quintile portfolios, where the turnover represents the proportion of stocks that leaves an $ACAB$ quintile portfolio across two monthly periods. We find that the monthly turnover rates for the two extreme (quintiles 1 and 5) $ACAB$ portfolios are 7.35 percent and 7.83 percent, respectively. These moderate turnover estimates indicate that transaction costs are unlikely to eliminate the profitability of cognitive abilities-based portfolios.

Even with a generous one-way transaction cost of 1 percent, the cognitive abilities spread would remain economically significant.[36]

To further examine the sensitivity of the spread estimates to trading costs, we estimate the cognitive abilities spread estimates for an annual rebalancing frequency (see row (2)). We find that the spread estimates are still economically significant. Even when we never rebalance the portfolios and use the portfolios constructed in January 1991 for the entire 1991 to 1996 period, the cognitive abilities spread estimates are significant (see row (3)). These robustness test results indicate that the profitability of the cognitive abilities-based trading strategy is unlikely to disappear when trading costs are explicitly taken into account.

VI. Summary and Conclusion

Why do individual investors hold concentrated portfolios and tilt their portfolios toward local firms instead of holding a well-diversified portfolio? Why do they trade excessively instead of adopting passive, buy-and-hold type strategies? The evidence from the recent retail investor literature indicates that investors deviate from the normative prescriptions of traditional portfolio theory either because of an informational advantage or due to psychological biases such as familiarity, over-confidence, or narrow framing. In this study we attempt to reconcile the conflicting results and provide a unified explanation for the three puzzling findings. Our key innovation is to introduce a measure of cognitive abilities in the portfolio choice framework that can be defined *ex ante* using investors' demographic characteristics.

We show that when investors with high cognitive abilities significantly distort their portfolios and hold concentrated portfolios, trade actively, or over-weight local stocks, they earn high risk-adjusted returns. Thus, their portfolio distortions seem to reflect an informational advantage. In contrast, when low cognitive abilities investors significantly distort their portfolios, their decisions are more likely to be induced by psychological biases because these investors earn low risk-adjusted returns. When investors follow the normative advice and portfolio distortions are small, the performance differential between investors with high and low cognitive abilities is positive, but economically small.

Collectively, our results provide empirical support for both behavioral and information-based explanations for the three types of portfolio distortions. The behavioral explanation is more appropriate for investors with low cognitive abilities, while the information-based explanation is consistent with the investment behavior of investors with high cognitive abilities.

These empirical findings make several important contributions to the growing literature on household finance.[37] First, we present an empirical model of cognitive abilities that can identify skilled investors on an *ex ante* basis using only their demographic characteristics. This empirical model can be used to identify skilled investors in other related settings. 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 the level of cognitive abilities could be a common determinant of other psychological biases. Previous studies have examined the link between investor sophistication and behavioral biases. Our paper extends that insight. We provide an empirical framework for formally defining investor sophistication and show that the bias-sophistication relation generalizes to other settings.

If some "distortions" are intentional and motivated by superior information rather than being psychologically motivated, learning might not eliminate them. In particular, the evidence of learning might be *weaker* or even non-existent among smarter, high cognitive abilities investors because their deviations are more likely to be information-driven. Thus, studies that examine whether learning eliminates behavioral biases could design sharper tests by conditioning on the level of people's cognitive abilities. Similarly, studies that examine the asset pricing implications of behavioral biases could develop sharper asset pricing tests by conditioning on the level of stockholders' cognitive abilities. The "mispricing and correction" pattern induced by the dynamic interaction between behavioral biases and arbitrage forces would be weaker or even non-existent when stockholders with high levels of cognitive abilities significantly distort their portfolios.

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Notes

[1]This imputation method is also similar to Graham, Harvey, and Huang (2006), who use investor characteristics to estimate models of perceived competence and optimism. They estimate the models in one setting and use the predicted values of competence and optimism from their models in another setting in which competence and optimism measures are unavailable.

[2]We use the European instead of the U.S. data set in our main tests because it contains accurate measures of cognitive abilities and social network.

[3]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 (1998, 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 (2008), and Ivković, Sialm, and Weisbenner (2008).

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

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

[6]For additional robustness, we also examine whether some weighted combination of the three cognitive measures is a better proxy for people's cognitive abilities. Specifically, we obtain model estimates when the dependent variable is the first principle component of the three cognitive abilities measures. We find that the first principal component explains 63.10 percent of the total variance in the cognitive abilities measures and the coefficient estimates are very similar to the reported results.

[7]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. 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)). Thus, the low cognitive abilities investors in our sample are likely to have higher cognitive abilities than the typical low cognitive abilities 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 more representative group of low cognitive abilities individuals.

[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.

[10]Kenneth French's data library: `http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/`; Russell Wermer's web site: `http://www.smith.umd.edu/faculty/rwermers/ftpsite/Dgtw/coverpage.htm`.

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

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

[13]The normalized variance (NV) for portfolio p is defined as $NV_p = \frac{\sigma_p^2}{\bar{\sigma}^2}$, where σ_p^2 is the portfolio variance, and $\bar{\sigma}^2$ is the average variance of all stocks in the portfolio. See Goetzmann and Kumar (2008) for additional details.

[14]The buy turnover rate in month t is the ratio of the dollar value of purchases in month t (beginning of month stock prices are used to compute the value) and the dollar value of the portfolio at the end of month $t-1$. The sell turnover rate is defined in an analogous manner.

[15]The distance between an investor's location and a portfolio p is computed as $D(i,p) = \sum_{k=1}^{N_i} w_k d(i,k)$, where w_k is the weight of stock k in investor's portfolio, $d(i,k)$ is the distance between the zip code of the residence of investor i and the headquarter of stock k, and N_i is the number of stocks in the investor portfolio. The matching stock is in the same size, book-to-market, and momentum deciles of the original stock and, furthermore, it belongs to the same Fama and French (1997) industry as the original stock. In several instances, we are unable to find a stock that matches on all dimensions, but we match stocks on at least the size and the book-to-market dimensions.

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

[17]See Section II.B of the Barber and Odean (2000) study for details on the method used to compute net returns.

[18]The characteristic-adjusted return is measured using the Daniel, Grinblatt, Titman, and Wermers (1997) method. Specifically, the characteristic-adjusted return of stock j in month t is $R_{jt}^{cadj} = R_{jt} - R_t^{bench,j}$. Here, R_{jt} is the month-t return of stock j and $R_t^{bench,j}$ is the month-t return of size, book-to-market, and momentum matched portfolio of stock j.

[19]The t-statistic for the null that the mean monthly category return R_s is insignificantly different from zero is given by $t = \sqrt{71} \times \frac{R_s}{\sigma_s}$, where σ_s is the standard deviation of the monthly performance time series $\{R_{st}\}_{t=1,\ldots,71}$.

[20]We find a similar relation between cognitive abilities and portfolio performance when we examine only the local component of investors' stock portfolios. See Section A.5 of the online appendix.

[21]In related settings, Chevalier and Ellison (1999) and Li, Zhang, and Zhao (2008) show that younger and more educated mutual fund and hedge fund managers exhibit superior performance, perhaps due to their higher cognitive abilities.

[22]The results are similar when we compare medians. Moreover, other risk-adjusted performance measures yield similar results because the portfolio variance levels of low and high cognitive abilities investors do not vary significantly within the high distortion category.

[23]In the next section, we use alternative estimation methods to better address potential concerns about cross-sectional dependence in the dependent variable (i.e., sample-period portfolio performance).

[24]The low adjusted R^2 in these performance regressions are consistent with the evidence in Barber and Odean (2001), who estimate similar performance regressions. See Table III (second specification) of their paper.

[25]To examine whether potential measurement errors influence our estimates, we estimate an errors-in-variables regression (Kmenta (1997)), where we assume that the reliability ratio of variables that include the cognitive abilities proxy is the adjusted R^2 ($= 0.441$) of the cognitive abilities model in Table I. In untabulated results, we find that the coefficient estimates of all ability-distortion interactions are still statistically significant. The coefficient estimates of cognitive abilities related variables become significantly stronger while the estimates of other variables are similar to the baseline estimates.

[26]See Barber and Odean (2001), footnote 16 for an additional discussion on concerns about cross-sectional dependence in performance regressions.

[27]We obtain similar results when we use the non-parametric approach of Driscoll and Kraay (1998) to correct standard errors for potential serial and cross correlations.

[28]For each independent variable, we estimate an autoregressive model using the time-series of its coefficient estimates. The standard error of the intercept in this model is the autocorrelation corrected standard error of the coefficient estimate. The order of the autoregressive model is chosen such that its Durbin-Watson statistic is close to two. We find that three lags are usually sufficient to eliminate the serial correlation in errors ($DW \approx 2$).

[29]The results are very similar when we use gross monthly characteristic-adjusted return as the dependent variable in the Fama-MacBeth and panel regression estimation.

[30]We obtain the equal-weighted, linear combination after standardizing the variables.

[31]We thank David Hirshleifer for helping us understand this important distinction.

[32]The sub-sample results in Table V, Panel D are similar when we use the composite distortion measure or use net returns to compute the performance differentials. For brevity, we do not report those results.

[33]In Section A.6 of the online appendix, we show that our results are not induced by investors' "play money" accounts. We also investigate whether lower levels of financial literacy rather than lower levels of cognitive abilities induce investors to make worse investment decisions (e.g., Choi, Laibson, and Madrian (2006)). Among the group of investors who report their overall level of financial knowledge and experience, we find that both self-reported measures do not vary significantly with cognitive abilities. If investors are truthfully reporting their levels of financial knowledge and experience, this evidence indicates that heterogeneity in the level of financial literacy is unlikely to explain our findings.

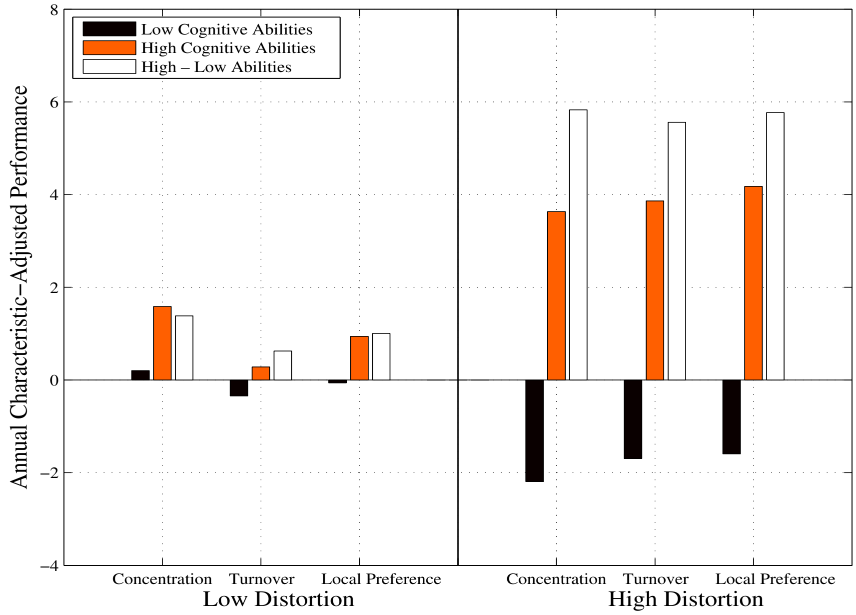
[34]We use the empirical model of cognitive abilities estimated in Table I to obtain the imputed cognitive abilities of each investor in the sample.

[35]The results are similar when we use value-weighted measure of cognitive abilities, where the dollar value of the positions in the stock are used to determine the weights.

[36]The choice of 100 basis points as the one way transaction cost is based on the evidence in Bessembinder (2003). He finds that the average *round-trip* transaction cost for all NASDAQ and NYSE stocks are 73 and 65 basis points, respectively. For the small-cap, mid-cap, and large-cap stocks, the average costs are 24.5, 53, and 140 (26, 49, and 120) basis points for NASDAQ (NYSE) stocks, respectively. Thus, a 100 bp *one-way* transaction cost seem quite generous.

[37]See Section A.7 of the online appendix for a summary of the broader implications of our results.

Panel A: Performance Measures Computed Using Gross Returns



Panel B: Performance Measures Computed Using Net Returns

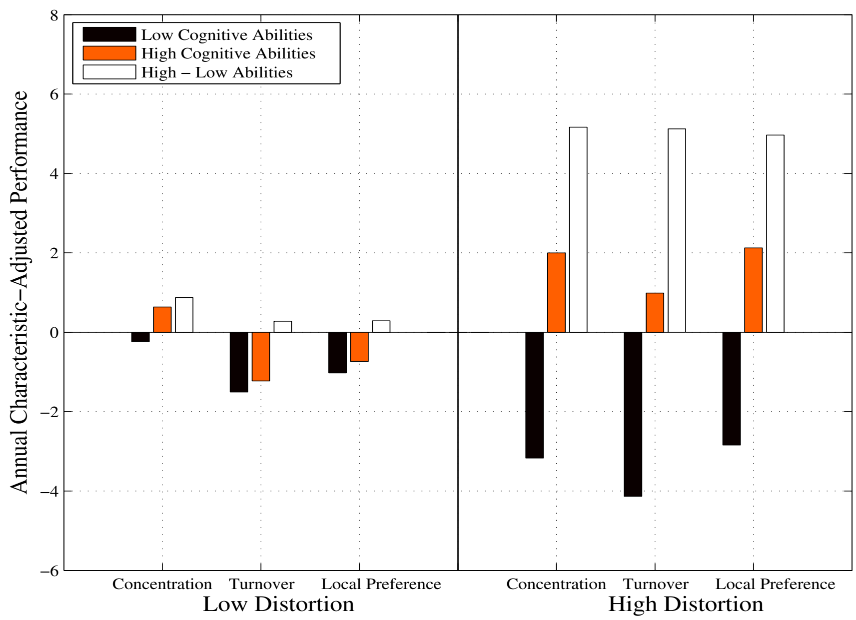


Figure 1. Cognitive abilities, portfolio distortions, and portfolio performance. This figure shows the sample-period average annualized characteristic-adjusted percentage returns of ability-distortion investor categories. Panel A (Panel B) reports performance estimates using gross (net) returns. The characteristic-adjusted returns are computed using the Daniel, Grinblatt, Titman, and Wermers (1997) method. Equation (3) is used to measure the performance of ability-distortion categories. The empirical model of cognitive abilities estimated in Table I ("Avg" column) is used to measure investors' cognitive abilities. Investors in quintile 5 (quintile 1) are identified as high (low) cognitive abilities investors. The low and the high portfolio distortion categories are defined in an analogous manner. Three distortion measures are considered: portfolio concentration, portfolio turnover, and local stock preference. These three distortion measures have been defined in Section II.D.

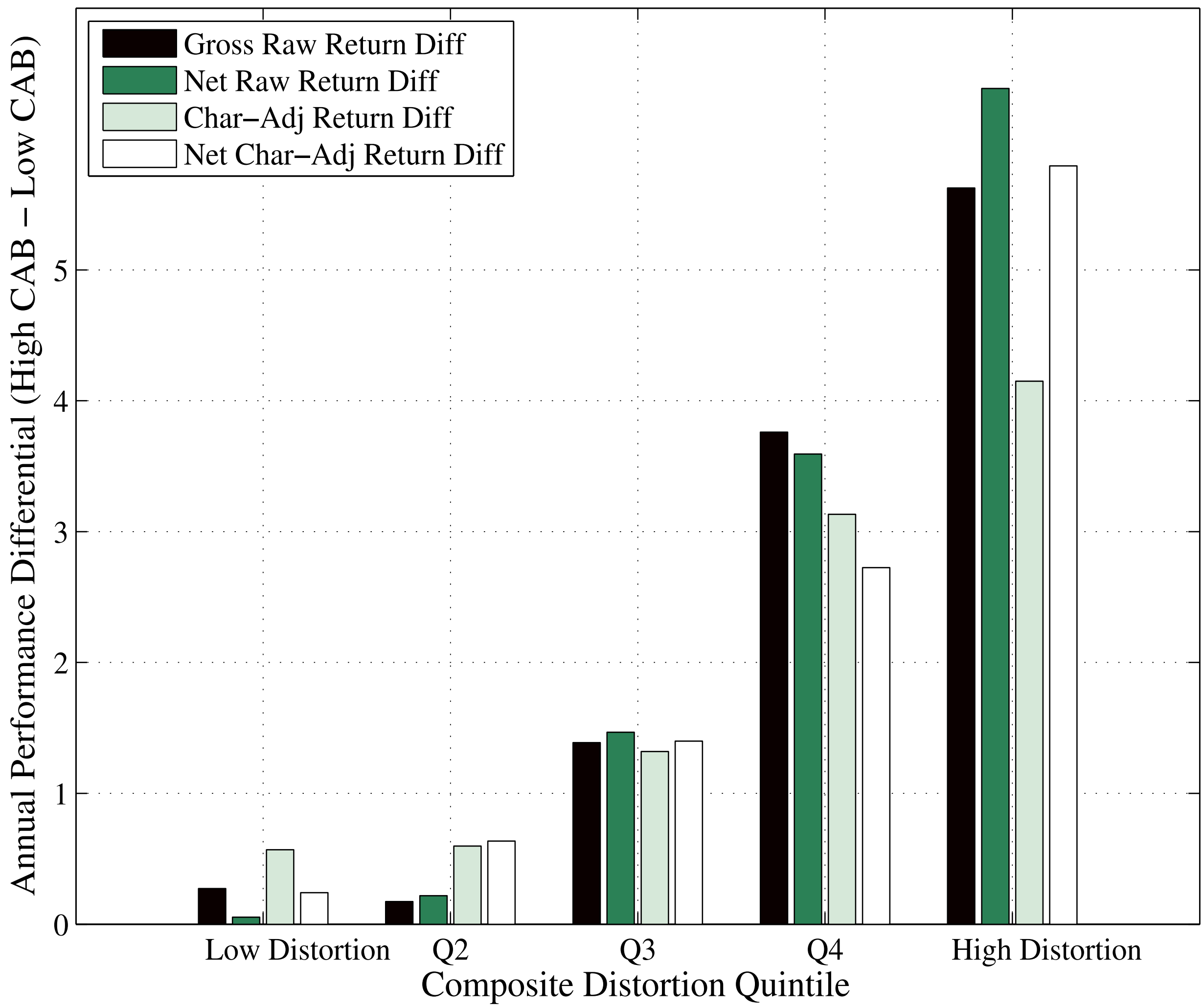
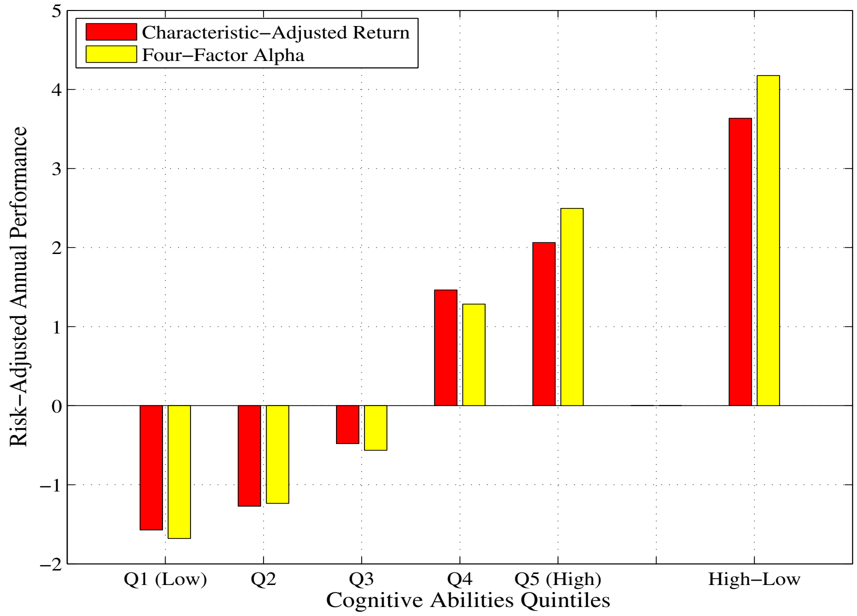


Figure 2. Performance differentials using a composite distortion measure. This figure shows the average annualized performance differentials between high and low cognitive abilities investor groups for five composite distortion-sorted investor categories. Four performance measures are reported: gross and net raw returns, gross and net characteristic-adjusted returns. The characteristic-adjusted returns are computed using the Daniel, Grinblatt, Titman, and Wermers (1997) method. Equation (3) is used to measure the performance of ability-distortion categories. The empirical model of cognitive abilities estimated in Table I ("Avg" column) is used to obtain investors' cognitive abilities. Investors in quintile 5 (quintile 1) are identified as high (low) cognitive abilities investors. The low and the high composite distortion categories are defined in an analogous manner. The composite distortion measure is the equal-weighted average of the standardized portfolio concentration, portfolio turnover, and local stock preference measures. These three distortion measures have been defined in Section II.D.

Panel A: Performance of Cognitive Abilities Sorted Portfolios



Panel B: Performance of Ability-Distortion Sorted Portfolios

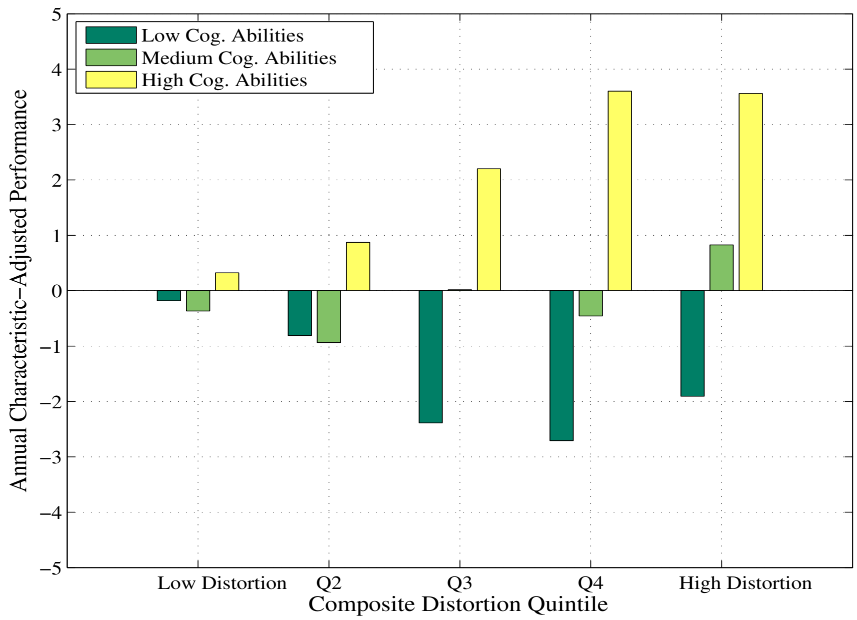


Figure 3. Performance of cognitive abilities and distortion-sorted portfolios. Panel A shows the annualized risk-adjusted and characteristic-adjusted performance of stock-level cognitive abilities ($ACAB$) sorted portfolios for the 1991-1996 time period. Equation (4) defines the $ACAB$ measure. Panel B shows the annualized characteristic-adjusted performance of portfolios formed by sorting independently along $ACAB$ and composite portfolio distortion dimensions. The low, medium, and high cognitive abilities categories correspond to $ACAB$ quintiles 1, 3, and 5, respectively. The quintile portfolios are formed at the end of each month using the stock-level cognitive abilities and composite distortion break-points. The composite distortion measure is the equal-weighted average of the standardized portfolio concentration, portfolio turnover, and local stock preference measures. The characteristic-adjusted returns are computed using the Daniel, Grinblatt, Titman, and Wermers (1997) method and the risk-adjusted performance measure in Panel A is the four-factor alpha.

Table I

Correlates of Cognitive Abilities: Cross-Sectional Regression Estimates

This table reports the cross-sectional regression estimates, where the dependent variable is a measure of cognitive abilities. The independent variables are the main determinants of cognitive abilities identified in the cognitive psychology 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). 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 such 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. Heteroskedasticity corrected standard errors are used to obtain these t-statistics (White (1980)). 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 ("AvgHRS") are obtained using the 2004 wave of the Health and Retirement Study (HRS) data. In this case, the *Social Network Proxy* is the frequency of church attendance.

Table I (Continued)

Correlates of Cognitive Abilities: Cross-Sectional Regression Estimates

	Cognitive ability measure is:				
	(1)	(2)	(3)	(4)	(5)
Variable	Verbal	Quantitative	Memory	Avg	AvgHRS
Wealth	0.049	0.020	0.012	0.055	0.064
	8.03	3.27	1.96	5.62	4.01
Income	0.047	0.053	0.002	0.031	0.068
	7.81	8.48	0.37	7.23	3.77
Education	0.365	0.313	0.312	0.297	0.341
	25.99	16.25	17.30	25.21	20.04
Age	−0.129	−0.160	−0.239	−0.231	−0.185
	−13.17	−15.71	−24.08	−23.03	−9.41
Retired Dummy	−0.081	−0.065	−0.011	−0.046	−0.046
	−11.39	−10.39	−1.18	−9.95	−3.10
Over 70 Dummy	−0.010	−0.036	−0.021	−0.050	0.004
	−1.93	−3.18	−2.90	−3.19	0.02
Social Network Proxy	0.088	0.092	0.096	0.092	0.026
	14.59	15.65	16.22	17.37	1.85
Over 70 × Low Income	−0.086	−0.055	−0.066	−0.058	−0.038
	−12.14	−7.46	−9.19	−12.79	−2.38
Over 70 × Low Education	0.001	−0.014	−0.030	−0.017	−0.002
	0.11	−2.50	−4.14	−3.06	−0.01
High Education × High Income	0.042	0.025	0.014	0.038	−0.018
	5.20	3.03	2.75	5.38	−1.31
Country Fixed Effects	Yes	Yes	Yes	Yes	No
Number of Households	22,153	21,777	21,904	22,215	4,230
Adjusted R^2	0.320	0.296	0.295	0.441	0.211

Table II

Portfolio and Investor Characteristics Across Cognitive Abilities Categories

This table reports the portfolio and demographic characteristics of cognitive abilities-sorted investor groups. The empirical model of cognitive abilities estimated in Table I ("Avg" column) is used to obtain investors' cognitive abilities. The portfolio characteristics are the time series averages computed over the 1991-96 sample period. The table also reports proportion measures that reflect the proportion of investors within a cognitive abilities quintile that have the reported characteristic. *Proportion Hold Foreign Equities* is the proportion of investors who hold foreign equities at least once during the sample period. *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 20 largest metropolitan regions are identified as *Urban*. *Professional* investors are those who hold either a technical or a managerial position. Other measures have self-explanatory labels. We use the Kolmogorov-Smirnov test to examine the statistical significance of the differences in the mean. *, **, and *** denotes significance at 0.10, 0.05, and 0.01 levels, respectively. We do not conduct any statistical test when we compare the proportions across the extreme investor groups (rows (4), (6), (10)-(12), (16), and (17)).

	Cognitive Abilities Quintile					
Characteristic	Low	Q2	Q3	Q4	High	High−Low
(1) Mean Cognitive Abilities	−0.779	−0.357	0.012	0.261	0.693	1.472**
(2) Equity Portfolio Size	\$34,925	\$26,014	\$23,943	\$25,631	\$27,987	−\$6,938**
(3) Trade Size	\$8,042	\$7,413	\$7,793	\$8,244	\$8,591	\$542
(4) Proportion Hold Foreign Equities	26.99%	26.75%	27.54%	28.07%	30.97%	3.98%
(5) Weight in Foreign Equities	1.74%	1.89%	1.72%	2.20%	2.24%	0.50%
(6) Proportion Hold Mutual Funds	21.08%	22.25%	20.93%	22.14%	21.21%	0.13%
(7) Weight in Mutual Funds	42.29%	42.84%	43.93%	43.60%	42.28%	−0.01%
(8) Portfolio Dividend Yield	2.32%	2.06%	1.86%	1.76%	1.71%	−0.61%*
(9) Investment Experience	10.30	10.17	9.94	9.88	9.79	−0.51
(10) Proportion Short Seller	9.16%	8.13%	9.51%	9.37%	11.24%	2.08%
(11) Proportion Option Trader	6.96%	7.31%	8.78%	9.28%	10.50%	3.54%
(12) Proportion Urban	16.56%	26.66%	32.53%	37.96%	45.64%	29.08%
(13) Annual Income	\$58,684	\$78,952	\$92,411	\$105,964	\$126,342	\$67,658***
(14) Wealth	\$282,089	\$248,927	\$228,514	\$243,099	\$264,075	−\$20,014
(15) Age	65	55	49	46	43	−22**
(16) Proportion Male	90.99%	90.52%	92.13%	91.81%	88.35%	2.64%
(17) Proportion Professional	18.62%	20.62%	20.92%	20.61%	18.57%	−0.05%

Table III

Cognitive Abilities, Portfolio Distortions, and Portfolio Performance: Sorting Results

This table reports the mean portfolio distortion (Panel A) and the mean portfolio performance (Panel B) estimates for cognitive abilities (CAB) sorted investor categories. The empirical model of cognitive abilities estimated in Table I ("Avg" column) is used to impute investors' cognitive abilities. We report two measures of portfolio concentration, two turnover measures, and two local stock preference measures. These three portfolio distortion measures have been defined in Section II.D. We also report three performance measures, using both gross and net returns: the mean monthly portfolio return, the mean characteristic-adjusted portfolio return computed using the Daniel, Grinblatt, Titman, and Wermers (1997) method, and the mean risk-adjusted return (four-factor alpha) estimated using a four-factor model that contains the three Fama-French factors and the momentum factor. All performance measures are reported in percentage terms. For the distortion measures in Panel A, we use the Kolmogorov-Smirnov test to examine the statistical significance of the difference in the mean estimates. For the performance measures in Panel B, we use the standard deviation of the time-series of the average performance levels and the performance differentials to measure statistical significance. * and ** denotes significance at 0.10 and 0.05 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.

Panel A: Average Portfolio Distortion Estimates

	Cognitive Abilities 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*
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 Stock Preference						
Local Preference	16.41%	17.83%	18.65%	18.14%	17.11%	0.70%
Proportion Total Portfolio Local	9.73%	11.18%	11.75%	12.87%	13.28%	3.55%**

Panel B: Average Portfolio Performance Estimates

Gross Returns						
Mean Monthly Return	1.432	1.533	1.573	1.631	1.753	0.321**
Mean Monthly Char-Adj Return	−0.163*	−0.107*	0.020	0.019	0.123*	0.286**
Mean Monthly Risk-Adj Return	−0.178*	−0.121*	−0.081	−0.031	0.125*	0.303**
Net Returns						
Mean Monthly Return	1.281	1.311	1.333	1.482	1.612	0.331**
Mean Monthly Char-Adj Return	−0.323**	−0.240**	−0.129*	−0.107	−0.031	0.292**
Mean Monthly Risk-Adj Return	−0.362**	−0.320**	−0.288**	−0.175*	−0.047	0.315**

Table IV

Cognitive Abilities and Portfolio Performance: Regression Estimates

This table reports the performance regression estimates from cross-sectional, Fama-MacBeth, and panel regression specifications. In the cross-sectional regressions (columns (1)-(6)), the dependent variable is the characteristic-adjusted portfolio performance measured over the 1991-96 sample period. The characteristic-adjusted returns are computed using the Daniel, Grinblatt, Titman, and Wermers (1997) method. In specifications (1) to (4), the performance is measured using gross returns, while in specifications (5) to (8), we use net returns to measure performance. The set of independent variables include the three portfolio distortion measures (portfolio concentration, portfolio turnover, and local stock preference), which have been defined in Section II.D. The empirical model of cognitive abilities (CAB) estimated in Table I ("Avg" column) is used to obtain investors' cognitive abilities. High (low) abilities dummy is set to one for investors in the highest (lowest) cognitive abilities quintile. The high and low distortion dummy variables are defined in an analogous manner. Other independent variables have been defined in Table II. In specifications (1)-(6), robust, clustered standard errors are used to account for potential cross-sectional dependence within zip codes. Specification (7) is estimated using Fama-MacBeth cross-sectional regression method. We estimate a cross-sectional regression each month and use the time-series of the coefficient estimates to measure their statistical significance. We also use the Pontiff (1996) method to correct the Fama-MacBeth standard errors for potential higher order serial correlation (see footnote 28). In the last column, we report estimates from a panel regression specification with month fixed effects. In Fama-MacBeth and panel regression specifications, the dependent variable is the monthly characteristic-adjusted portfolio performance and the independent variables are defined using investor and portfolio characteristics in the previous month. The t-statistics of the coefficient estimates are shown in smaller font below the estimates. 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 (mean is set to zero and the standard deviation is one).

	Gross Returns				Net Returns			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variable							F-M	Panel
Intercept	0.225	0.233	0.228	0.218	−0.154	−0.145	−0.135	−0.137
	14.37	14.47	11.13	10.90	−13.07	−10.07	−6.13	−9.67
Cognitive Abilities (CAB)	0.069	0.079	0.049	0.055	0.057	0.054	0.061	0.054
	3.96	4.15	3.18	3.14	3.22	2.78	3.35	5.46
Portfolio Concentration		0.008	−0.007	0.016	0.029	0.017	0.016	0.018
		0.62	−0.44	0.70	2.36	1.97	2.02	2.04
Portfolio Turnover		0.115	0.105	0.091	−0.084	−0.080	−0.085	−0.101
		8.84	5.54	3.75	−9.25	−8.07	−3.76	−5.71
Local Preference		0.032	0.049	0.045	0.046	0.037	0.039	0.047
		3.83	3.41	3.16	4.20	3.45	3.16	4.77

Continued. . .

Table IV (Continued)

Cognitive Abilities and Portfolio Performance: Regression Estimates

	Gross Returns				Net Returns			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variable							F-M	Panel
High CAB × High Conc			0.032	0.030		0.043	0.041	0.044
			2.81	3.22		4.70	4.01	5.52
High CAB × High Turnover			0.053	0.058		0.055	0.045	0.050
			3.76	4.88		2.09	3.43	3.99
High CAB × High Local Pref			0.041	0.038		0.035	0.041	0.046
			2.88	2.22		2.86	2.52	2.61
Low CAB × High Conc			−0.032	−0.030		−0.037	−0.035	−0.030
			−2.79	−2.03		−2.11	−2.38	−2.17
Low CAB × High Turnover			−0.029	−0.031		−0.033	−0.029	−0.032
			−2.04	−2.52		−2.73	−2.08	−2.99
Low CAB × High Local Pref			−0.050	−0.048		−0.054	−0.057	−0.050
			−2.39	−2.20		−4.10	−2.85	−3.01
High CAB			0.024	0.022		0.019	0.027	0.025
			2.13	1.73		1.33	1.78	2.54
Low CAB			−0.019	−0.013		−0.022	−0.019	−0.028
			−1.71	−1.62		−2.06	−1.86	−1.83
High Concentration			0.021	0.016		0.012	0.014	0.008
			2.02	1.81		1.05	1.28	0.89
High Turnover			0.132	0.124		−0.108	−0.089	−0.070
			11.14	8.14		−9.57	−4.43	−6.07
High Local Preference			0.062	0.060		0.065	0.054	0.055
			4.33	4.29		5.59	3.34	4.39
Portfolio Size				−0.018		−0.019	0.006	0.014
				−1.54		−1.04	1.13	1.01
Portfolio Dividend Yield				−0.057		−0.050	−0.048	−0.062
				−4.54		−3.79	−3.84	−4.68
Investment Experience				0.051		0.036	0.044	0.064
				3.78		2.74	3.62	6.56
Male Dummy				−0.020		−0.025	−0.015	−0.020
				−1.12		−1.37	−1.13	−1.69
(Avg) Number of Obs	36,251	32,129	32,129	32,129	36,251	32,129	21,303	1,512,513
(Avg) Adjusted R^2	0.009	0.015	0.043	0.054	0.017	0.051	0.033	0.094

Table V

Performance Differential Estimates using Different Cognitive Abilities Proxies

This table reports the average difference in the performance (annualized characteristic-adjusted percentage returns) of high and low cognitive abilities investors. In Panels A, B, and C, we consider different proxies for cognitive abilities. Investors in quintile 5 (quintile 1) are identified as having high (low) cognitive abilities. The low and the high portfolio distortion categories are defined in an analogous manner. Three distortion measures are considered: portfolio concentration, portfolio turnover, and local stock preference. These three distortion measures have been defined in Section II.D. In Panels A and D, we consider the three distortion measures individually, while in Panels B and C, we consider a composite distortion measure. It is defined as the equal-weighted average of the standardized concentration, turnover, and local preference measures. We use gross (net) characteristic-adjusted return based measures in Panels A, B, and D (Panel C). The characteristic-adjusted returns are computed using the Daniel, Grinblatt, Titman, and Wermers (1997) method. Equation (3) is used to measure the performance of ability-distortion categories. All cognitive abilities proxies have been defined in Table I. In the *Simple Linear Combination* row, we combine income, education proxy, age, and social network, with a negative sign on age. The equal-weighted sum is computed after standardizing the four variables. In the *Imputed Cognitive Abilities* row, we use the empirical model of cognitive abilities estimated in Table I ("Avg" column) to obtain investors' cognitive abilities. *Investment Experience* is defined as the number of days between the account opening date and December 31, 1996. In Panel D, the methodology used to obtain the performance differential estimates is identical to the method used in Panel A. In rows (1)-(5), we consider different sub-samples. In the first sub-sample, we exclude investors who hold only one stock. In the next four sub-samples, we consider only unemployed, female, urban, and rural investors, respectively. Urban investors are those who live within 100 miles of the 20 largest metropolitan regions. Rural investors are those who live at least 250 miles away from the 20 largest metropolitan regions. In the last row, we do not use a sub-sample, but use a residual cognitive abilities measure. It is defined as the residual from a cross-sectional regression, in which the imputed cognitive abilities measure is the dependent variable and the investment experience is the independent variable. *, **, and *** denotes significance at 0.10, 0.05, and 0.01 levels, respectively.

Panel A: Gross Performance Differential Estimates using Individual Distortion Measures

	Low Distortion			High Distortion		
CAB Proxy	Conc	Turnover	LocPref	Conc	Turnover	LocPref
(1) Income	−0.21	1.33	1.15	1.12	1.93*	1.83*
(2) Social Network Proxy	1.29	0.43	−0.21	1.74*	1.13	1.59*
(3) Education Proxy	−0.29	1.63	0.68	2.49**	2.66*	3.24**
(4) Age	0.78	0.46	1.11	3.05**	2.53*	2.49*
(5) Simple Linear Combination	1.76*	0.97	1.13	3.38**	2.76*	3.55**
(6) Imputed Cognitive Abilities	1.38	0.62	1.00	5.83**	5.56**	5.77**
(7) Investment Experience	1.63*	1.56*	1.26	−0.33	0.14	0.37

Table V (Continued)

Performance Differential Estimates using Different Cognitive Abilities Proxies

Panel B: Gross Performance Differential Estimates for Composite Distortion-Sorted Categories

	Composite Distortion Quintile				
CAB Proxy	Low Distortion	Q2	Q3	Q4	High Distortion
(1) Income	−0.52	−0.15	−0.67	−0.28	1.81*
(2) Social Network Proxy	0.59	−0.37	0.71	0.88	1.78*
(3) Education Proxy	−0.24	−0.45	1.10	2.01*	2.45*
(4) Age	0.63	1.07	1.14	2.02*	2.78*
(5) Simple Linear Combination	0.80	0.46	0.62	2.15*	2.77*
(6) Imputed Cognitive Abilities	0.53	0.81	1.78*	2.87**	5.95**

Panel C: Net Performance Differential Estimates for Composite Distortion-Sorted Categories

	Composite Distortion Quintile				
CAB Proxy	Low Distortion	Q2	Q3	Q4	High Distortion
(1) Income	−0.03	−0.12	−0.34	−0.27	1.10
(2) Social Network Proxy	0.19	−0.62	−0.18	−0.29	0.96
(3) Education Proxy	−0.19	−0.15	1.03	1.80*	2.37**
(4) Age	0.22	0.43	0.52	1.88*	2.47*
(5) Simple Linear Combination	0.85	0.41	0.43	1.85*	3.27**
(6) Imputed Cognitive Abilities	0.05	0.22	1.47*	3.59**	6.39***

Panel D: Gross Performance Differential Estimates From Robustness Tests

	Low Distortion			High Distortion		
Robustness Test	Conc	Turnover	LocPref	Conc	Turnover	LocPref
(1) Exclude One-Stock Portfolios	1.31	1.32	1.47*	5.64**	6.09**	5.99**
(2) Unemployed Investors Only	0.92	1.19	1.52*	5.26**	4.53**	4.89**
(3) Female Investors Only	0.70	1.25	1.16	5.11**	5.09**	4.95**
(4) Urban Investors Only	0.67	0.40	2.20*	6.04**	6.52**	6.90**
(5) Rural Investors Only	1.06	1.45	1.21*	4.92**	5.13**	4.71**
(6) Exclude Experience Effects	1.20	1.33	1.67*	5.47**	6.42**	6.01**

Table VI

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

This table reports the average DGTW performance estimates for the high and the low cognitive abilities (CAB) investors, conditional upon their level of portfolio distortion. The empirical model of cognitive abilities estimated in Table I ("Avg" column) is used to obtain investors' predicted cognitive abilities. Three distortion measures are considered: portfolio concentration, portfolio turnover, and local stock preference. These three distortion measures have been defined in Section II.D. The composite distortion measure is defined as the equal-weighted average of the standardized concentration, turnover, and local preference measures. High (low) cognitive abilities categories represent the highest (lowest) cognitive ability quintile. The high and low distortion categories are defined in an analogous manner. Following the Daniel, Grinblatt, Titman, and Wermers (1997) method, 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 portfolio distortion and stock characteristics. Four 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, (iii) book-to-market (B/M) ratio, and (iv) dispersion in analysts' quarterly earnings forecasts (DISP), which is defined as the standard deviation of the most recent earnings estimates of all analysts who cover a stock.

Panel A: Performance Measures Conditional Upon Cognitive Abilities and Portfolio Distortion

Cognitive	Low Distortion				High Distortion			
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	16.30
High − Low	1.02	0.02	−0.60	0.44	4.61	0.94	−0.04	5.51
Local Preference								
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
Composite Distortion								
Low CAB	0.03	−1.21	13.53	12.35	−0.14	−1.94	13.38	11.30
High CAB	0.56	−1.02	13.86	13.40	4.87	−0.28	13.41	18.00
High − Low	0.53	0.19	0.33	1.05	5.01	1.66	0.03	5.70

Table VI (Continued)

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

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

	Low Distortion								High Distortion							
	S&P 500		IVOL		B/M		DISP		S&P 500		IVOL		B/M		DISP	
CAB	Yes	No	Low	High	Low	High	Low	High	Yes	No	Low	High	Low	High	Low	High
Portfolio Concentration																
Low	−0.30	−0.94	−0.98	−0.31	0.25	−0.98	0.89	−3.13	0.55	−1.25	−1.08	−1.38	−0.41	0.35	1.62	−2.85
High	−0.16	0.29	0.22	0.86	1.22	0.85	0.73	−2.15	1.87	3.32	1.34	3.04	4.96	−0.50	1.52	2.03
Diff	0.14	1.23	1.20	1.17	0.97	1.83	−0.16	0.98	1.32	4.57	2.42	4.42	5.37	−0.85	−0.10	4.88
Portfolio Turnover																
Low	0.12	−1.28	0.66	0.31	−0.18	−1.71	0.17	−3.57	−0.15	−1.09	−0.26	0.39	−0.85	−1.57	1.41	−3.22
High	0.53	0.60	0.61	1.98	0.75	−0.74	1.19	−2.28	1.05	2.83	1.69	3.69	2.96	0.81	1.96	0.87
Diff	0.41	1.88	−0.05	1.67	0.93	0.97	1.02	1.29	1.20	3.92	1.95	3.08	3.81	2.38	0.55	4.09
Local Preference																
Low	−1.09	−1.17	0.13	0.38	0.22	−0.40	1.00	−2.09	−0.44	−1.80	−0.22	0.82	0.45	0.22	2.83	−2.04
High	−0.41	0.96	0.89	1.81	0.61	−0.47	1.43	−0.87	−0.45	3.19	0.54	5.04	4.23	−0.53	3.13	2.46
Diff	0.68	2.13	0.76	1.43	0.39	−0.07	0.43	1.22	−0.01	4.99	0.76	4.22	3.78	−0.75	0.30	4.50
Composite Distortion																
Low	−0.55	−1.36	0.14	0.32	0.33	−1.18	0.82	−2.95	−0.37	0.72	−1.01	0.19	0.41	−1.08	1.11	−3.17
High	0.25	1.00	0.62	2.52	0.54	0.52	0.47	1.02	1.54	4.06	0.54	4.50	5.58	0.78	1.89	3.10
Diff	0.80	2.36	0.48	1.80	0.21	1.70	−0.35	1.93	1.91	3.34	1.55	4.31	5.17	1.86	0.78	6.17

Table VII

Characteristics and Performance of Cognitive Abilities-Sorted Portfolios

This table reports the characteristics and performance of stock-level cognitive abilities (*ACAB*) sorted value-weighted portfolios. The quintile portfolios are formed at the end of each month using the stock-level cognitive abilities break-points. The *ACAB* measure and the portfolio construction method are described in Section V.A. Panel A reports the main performance estimates and Panel B reports the results from several robustness tests. In the first test, we exclude stocks priced below \$5. In the second test, we rebalance the portfolio only once during the year (in January). In the last test, the portfolios constructed at the end of January 1991 are used during the entire sample period (1991 to 1996). The following measures are reported: *MeanRet* is the average monthly portfolio return (in percent); *StdDev* is the standard deviation of the monthly portfolio return series; *CadjRet* is the characteristic-adjusted returns computed using the Daniel, Grinblatt, Titman, and Wermers (1997) method; *Alpha* is the intercept from a four-factor model that contains the three Fama-French factors (RMRF, SMB, and HML) and the momentum factor (UMD); RMRF, SMB, HML, and UMD are the factor exposures of the portfolio. The t-statistics for the coefficient estimates are shown in smaller font below the estimates. Only stocks with CRSP share codes 10 and 11 are included in the analysis.

Panel A: Main Performance Estimates

CAB Quintile	(1) MeanRet	(2) StdDev	(3) CadjRet	(4) Alpha	(5) RMRF	(6) SMB	(7) HML	(8) UMD
Low	0.983	3.530	−0.131	−0.140	0.881	0.207	0.199	0.084
			−2.48	−2.40	21.29	4.99	4.38	2.09
Q2	0.993	3.639	−0.106	−0.103	0.908	0.005	0.115	0.076
			−1.76	−0.92	20.13	0.14	3.09	2.33
Q3	1.096	3.605	−0.040	−0.047	0.976	−0.140	−0.0212	−0.029
			−0.93	−0.71	14.32	−5.61	−0.78	−1.19
Q4	1.174	4.569	0.122	0.107	1.043	0.108	−0.075	0.096
			1.61	1.57	11.34	2.16	−1.30	2.15
High	1.280	5.384	0.172	0.208	1.016	0.009	−0.205	0.103
			2.19	2.12	13.53	0.20	−3.89	1.85
High−Low	0.297	1.943	0.303	0.348	0.125	−0.198	−0.402	0.019
	2.64		2.13	2.23	3.38	−2.62	−4.89	0.34

Panel B: Performance Estimates From Robustness Tests

Robustness Test	(1) MeanRet	(2) StdDev	(3) CadjRet	(4) Alpha	(5) RMRF	(6) SMB	(7) HML	(8) UMD
(1) Stock Price $\geq$ \$5	0.292	1.705	0.284	0.298	0.078	−0.166	−0.719	−0.029
	3.16		2.93	3.24	2.52	−4.17	−6.43	−1.09
(2) Annual Rebalancing	0.288	1.811	0.298	0.308	0.136	−0.225	−0.380	0.006
	2.99		2.93	3.13	2.77	−3.40	−4.91	0.17
(3) Jan 1991 Portfolio	0.276	1.826	0.285	0.295	0.067	−0.324	−0.391	0.017
	2.49		2.59	2.84	1.30	−6.06	−4.42	0.86

A Online Appendix

In this online appendix, we present background material and results from additional robustness tests to further support the main results reported in the paper.

A.1. Randomization Tests

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 in our brokerage sample. 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 $(-1, +1)$. 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. Using the model with randomized coefficients, we obtain imputed cognitive ability measures for all investors in the brokerage sample. We sort investors into five quintiles using the imputed cognitive abilities measures and compute the performance differential between the high (quintile 5) and low (quintile 5) cognitive abilities categories. The quintile performance is the sample-period, equal-weighted average performance of all investors in the group.

We repeat the procedure 1500 times and generate a distribution of the annualized characteristic-adjusted performance differential between the high and the low cognitive abilities categories (see Figure A.1). We find that the actual performance differential of 3.43% (see Section II.E) 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.

A.2. How Valuable is the Empirical Model of Cognitive Abilities?

It is remarkable that only 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 about 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 0.664, 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 abilities of our sample of individual investors 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 = 2.15).

A.3. Cognitive Abilities or Perceived Competence?

The coefficient estimate of education proxy 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 abilities investors exhibit a greater propensity to invest in foreign securities (see Section II.C). Thus, one might be concerned that our imputed cognitive abilities measure is a proxy for investor competence. There are several reasons why this is unlikely to be the case.

First, the evidence in Graham, Harvey, and Huang (2006) indicates that investors with greater competence trade more often and hold larger portfolios. But we find that high cognitive abilities investors unconditionally do not trade more frequently and hold somewhat smaller portfolios (see Table II). Second, age is one of the main determinants of cognitive abilities, 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 abilities investors (see Section II.E). These comparisons indicate that while certain aspects of competence and cognitive abilities might be related, these appear to be two distinct investor attributes.

A.4. 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 abilities. Investors in quintile one (five) are identified as low (high) cognitive abilities investors. Next, by combining the portfolios of all investors within a group, we construct an aggregate group portfolio for both low and high cognitive abilities 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 Fama-MacBeth regression estimates are presented in Table A.I. Specification (1) reports the estimates for low cognitive abilities investors, specification (2) reports the estimates for high cognitive abilities investors, and specification (3) shows the estimates for the difference between the two investor groups. The most salient result in the table is that high cognitive abilities investors hold stocks with higher systematic risk that yield higher average returns. In contrast, low cognitive abilities 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 abilities 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 abilities investors have distinct stock preferences.

A.5. Cognitive Abilities and Performance of Local Investments

If the choice of local stocks by high cognitive abilities investors is influenced by superior information, they should perform better than low cognitive abilities investors from their local investments. To test this conjecture, 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.[38]

The performance estimates (equal-weighted average) of local portfolios of cognitive abilities sorted investor groups are reported in Table A.II. We report the actual and expected performance and characteristics of local portfolios. The expected local performance for an investor is the average monthly return of characteristics (size, B/M, and past 12-month returns) matched local stocks that are not in the investor's portfolio, i.e., the set of similar local stocks that the investor could have held but chooses not to hold.

The local performance estimates indicate that high cognitive abilities investors outperform low cognitive abilities investors by $0.279 \times 12 = 3.35\%$ annually on a risk-adjusted basis. High cognitive abilities investors also outperform the expected or the investor-specific local performance benchmarks. For high cognitive abilities investors, the annual average performance differential relative to the local benchmarks is $0.295 \times 12 = 3.54\%$. In contrast, the low cognitive abilities investors mildly under-perform the investor-specific local performance benchmarks. Overall, the local performance estimates provide further support to the conjecture that investors with high cognitive abilities are able to generate higher risk-adjusted returns from their local investments due to superior local information.

A.6. "Play Money" of Older Investors?

We conduct additional tests to examine the possibility that the performance differential estimates reported in Figure 1 and Table V primarily reflect the "old and retired" effect. It is possible that older investors with the bulk of their retirement money invested elsewhere are more likely to use the brokerage accounts as their "play money" accounts. When we compute the distortion-conditional performance estimates for low and high cognitive abilities investors after excluding investors with age above 60, the estimates (Row 1) are very similar to the full sample results shown in Table V, Panel A (row (6)).[39] When the distortion level is high, the performance differentials corresponding to the concentration, turnover, and local preference measures are 5.12 percent, 5.38 percent, and 5.97 percent, respectively. This evidence indicates that it is unlikely that the large performance differentials between the high and the low cognitive abilities investors primarily reflect the unique behavior of old and retired investors.

To formally examine the "play money" hypothesis, we obtain the distortion-conditional performance estimates only for investors who hold larger portfolios (portfolio size > \$25,000).[40] The untabulated results indicate that the performance differentials between the high and the low cognitive abilities investors are still positive and economically significant. The estimates are larger for portfolio concentration and local preference (= 6.28 percent and 6.25 percent, respectively) measures, and the differential is significantly positive (= 4.65 percent) even for the portfolio turnover measure. We obtain similar estimates when we use high (top quintile) portfolio size to annual income ratio to identify portfolios that are unlikely to represent play money accounts. These sub-sample estimates indicate that our main results are unlikely to be driven by investors' play money accounts.

A.7. Broader Implications of Our Results

In addition to its contributions to 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 abilities. The existing 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 portfolio distortion and cognitive abilities. These conditional performance estimates could serve as an important ingredient for estimating the overall returns to cognitive abilities.

Last, our evidence provides an alternative perspective on the costs of non-participation. 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 abilities investors. But to accurately estimate the economic costs of lower market participation, it is useful to obtain estimates of investment performance when low cognitive abilities investors actually participate in the stock market.

In light of our evidence, it appears that direct stock market participation might be a sub-optimal strategy for low cognitive abilities investors. 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.

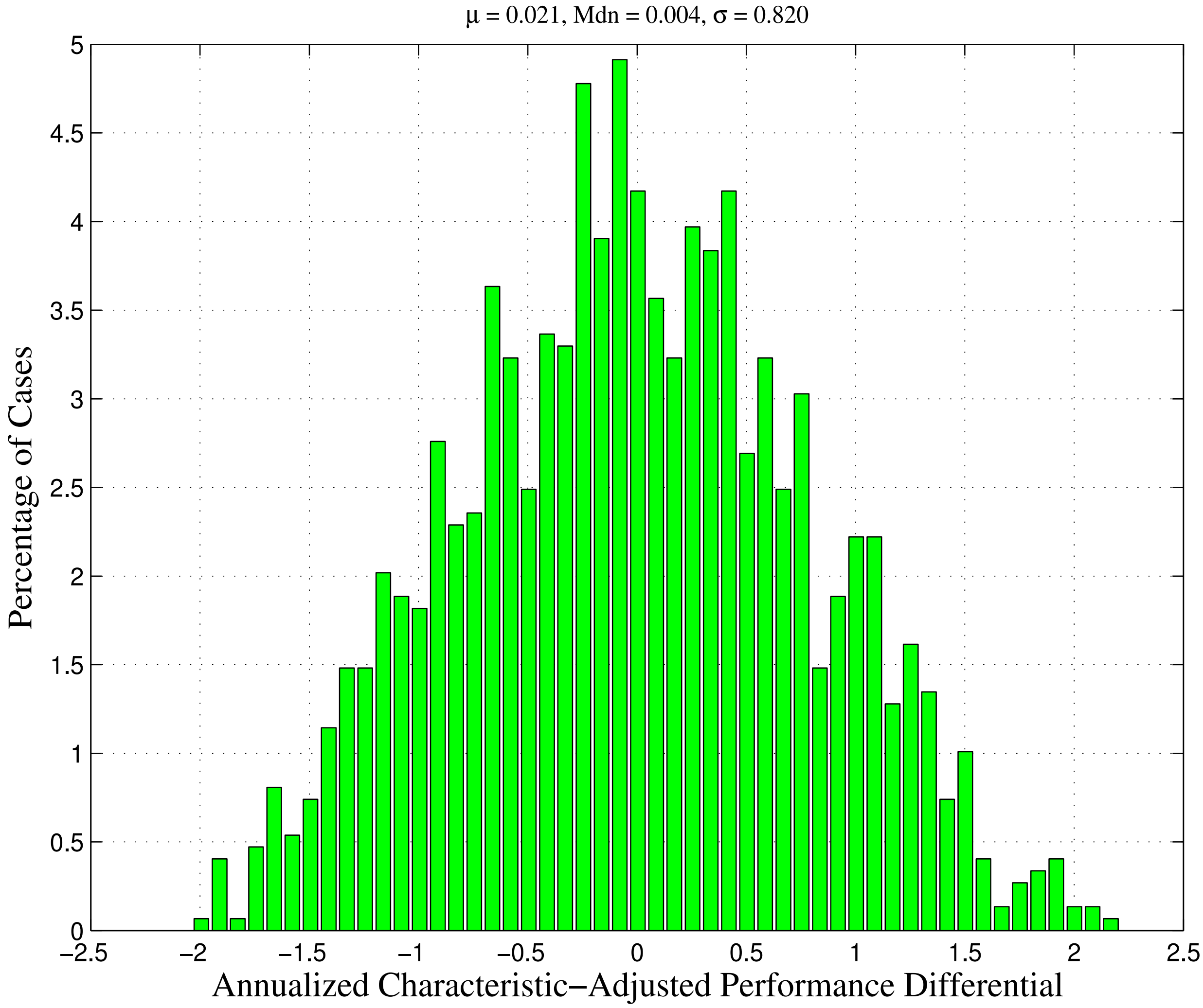


Figure A.1. Performance differential distribution with randomized cognitive abilities estimates. This figure shows the distribution of the characteristic-adjusted performance differential between high (quintile 5) and low (quintile 1) cognitive abilities investors, where the predicted cognitive abilities are randomized. Specifically, the model predicted cognitive abilities are randomly assigned to investors. The empirical model of cognitive abilities estimated in Table I ("Avg" column) is used to obtain the predicted cognitive abilities measures. The distribution is based on 1,500 iterations, where the characteristic-adjusted returns are computed using the Daniel, Grinblatt, Titman, and Wermers (1997) method.

Table A.I

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 abilities 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. All independent variables are measured at the end of month $t-1$. We estimate a cross-sectional regression each month and use the time-series of the coefficient estimates to measure their statistical significance. We also follow the Pontiff (1996) method to correct the Fama-MacBeth standard errors for serial correlation (see footnote 28). 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.

Table A.I (Continued)

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

	Cognitive Abilities		
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 A.II

Cognitive Abilities and Performance of Local Investments

This table reports several performance measures of investors' local investments, conditional upon the level of their cognitive abilities (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 ("Avg" column) is used to obtain investors' cognitive abilities. We report the actual and expected performance and characteristics of local portfolios, where the equal-weighted average of monthly performance of investors within a CAB quintile is used to compute the monthly performance of an investor 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 that are not held by the investor. The following measures of the local portfolio are reported: Average monthly return (LocalAct), monthly standard deviation (StdDev), expected average monthly return (LocalExp), the four-factor alpha, and the four factor exposures (RMRF, SMB, HML, and UMD). We use the time-series of performance differentials to estimate their statistical significance. The time *, **, and *** denotes significance at 0.10, 0.05, and 0.01 levels, respectively.

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*