Does Investment Skill Decline due to Cognitive Aging or Improve with Experience?*

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Does Investment Skill Decline due to Cognitive Aging or Improve with Experience?

Abstract

This study examines whether cognitive aging adversely affects the stock investment decisions of older individual investors. Motivated by the evidence from psychological and learning research, we conjecture that older investors' portfolio decisions reflect greater knowledge about investing but investment skill deteriorates with age due to the adverse effects of cognitive aging. Consistent with our hypothesis, we find that older and experienced investors follow "rules of thumb" that reflect greater investment knowledge. But older investors also exhibit worse investment skill, especially if they are less educated, earn lower income, and belong to minority racial/ethnic groups. Overall, the adverse effects of cognitive aging dominate: Investors with greater cognitive decline earn 3% lower risk-adjusted annual returns, and the performance differential is 5% among investors who hold larger portfolios.

1. Introduction

The older population in the United States is growing at a dramatic pace and it is also becoming more diverse in terms of its racial and ethnic composition.[1] Because of this growth in the proportion of older people, there has been heightened interest in understanding their post-retirement quality of life. The popular media has raised some concerns that older people would not be able to generate the annual income necessary to sustain the pre-retirement quality of life.[2] Thus, as the U.S. population ages, it becomes important to understand the investment decisions of older individual investors because investment income is likely to be a significant proportion of their post-retirement income, and therefore, one of the main determinants of their post-retirement quality of life.

In this study, we focus on an important but previously unexplored determinant of the stock investment decisions of older investors, namely, cognitive aging. We examine whether older people make better investment choices as they gain more investment experience, or

[1] According to the 2004 Federal Interagency Forum on Aging-Related Statistics, older people (people aged 65 and above) represented about 12% of the population in 2000, but by 2030, their proportion is expected to increase to about 20%. During the same period, the proportional share of African Americans and Hispanics in the older population is expected to increase from 14% to 31%.

[2] In a recent article, available at `http://www.nd.edu/~ndbizmag/spring2005/Feature_Old_web.shtml`, Reynolds (2005) raises several thought-provoking questions about the ability of older people to retire successfully.

whether their investment skill deteriorates with age due to the adverse effects of cognitive aging. This is an important issue that has implications for how individual investors should structure their portfolios over time, the type of investment advice they should seek over their lifetime, and the potential effects of changes in government policy on investment generated retirement income. To our knowledge, this is the first study that highlights the potential role and the importance of cognitive aging in people's investment decisions.

The extant evidence from cognitive aging and learning research indicates that aging and learning processes operate jointly. The psychological evidence on cognitive aging indicates that both physical and cognitive abilities, especially memory, decline with age (e.g., Horn (1968), Fair (1994, 2004), Salthouse (2000), Schroeder and Salthouse (2004)). Furthermore, research in learning suggests that with experience, older investors might accumulate greater investment knowledge and exhibit greater awareness of the fundamental principles of investing. Their accumulated investing wisdom could help them make better investment decisions. Investors might also be less prone to behavioral biases as they grow older and become more experienced (e.g., List (2003), Goetzmann and Kumar (2005), Feng and Seasholes (2005), Dhar and Zhu (2006)).

Motivated by these earlier findings, we conjecture that, on the one hand, older investors would accumulate greater knowledge about the fundamental principles of investing. But on the other hand, their declining cognitive abilities could hinder the effective application of those principles. As a result, older investors' portfolios might under-perform the common performance benchmarks.[3] Using the end-of-month portfolio holdings and trades of a sample of individual investors at a large U.S. brokerage house, we empirically test this dual pronged conjecture.[4]

The empirical analysis focuses on the relative influences of age and investment experience on investors' portfolio decisions and performance. We estimate "rules of thumb" and "skill" regressions, where the dependent variable is either a measure that reflects the outcome of following an investing "rule of thumb" or a measure of investment skill. The key explanatory

[3]In a related study, Agarwal, Driscoll, Gabaix, and Laibson (2007) examine whether the interaction between cognitive abilities and experience generates a hump-shaped pattern in financial sophistication, which influences the prices people pay for financial services.

[4]The individual investor database has 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 (2007), and Ivković, Sialm, and Weisbenner (2007).

variables are age and investment experience. We use age to capture the adverse effects of cognitive aging and use experience (the number of days between the account opening date and December 31, 1996) to capture the positive effects of experience.[5] Without the experience measure, age would capture two confounding effects, one related to experience and the other related to cognitive aging. By including age and experience variables simultaneously, we can separate the positive effects of experience from the negative effects of cognitive aging.

Our empirical evidence strongly supports our main conjecture. Consistent with the theoretical predictions of life-cycle and learning models, we find that older and more experienced investors hold less risky portfolios, exhibit stronger preference for diversification, trade less frequently, and exhibit greater propensity for year-end tax-loss selling. And consistent with the psychological evidence, we find that older investors exhibit worse stock selection ability and poor diversification skill. The age-skill relation has an inverted U-shape and, furthermore, the skill deteriorates sharply around the age of 70. Thus, older investors exhibit a greater propensity to use common investing "rules of thumb" but they appear less skillful in successfully implementing those rules.

To gather additional support for our main hypothesis, we seek guidance from the psychology literature that examines the conditional effects of cognitive aging. The psychological evidence indicates that people who are more educated, more resourceful, and undertake intellectually stimulating jobs are able to better compensate for their declining cognitive abilities (Arbuckle, Gold, and Andres (1986), Baltes and Lang (1997), Cagney and Lauderdale (2002)). The evidence also suggests that the age-related decline in cognitive abilities is steeper for African Americans and Hispanic minority groups (e.g., Avolio and Waldman (1986), Black (2004)).

Motivated by this psychological evidence, we use age-income, age-education, and age-race/ethnicity interaction terms as additional proxies for cognitive aging and examine the conditional deterioration in cognitive abilities with age. Consistent with our hypothesis, we find that the adverse effects of aging are stronger among older investors who are also relatively less educated, earn lower income, and belong to the Hispanic ethnic group.

Because we cannot measure the cognitive abilities of investors directly, our results are open to alternative interpretations. To further ensure that the variables we use to capture

[5]The brokerage account opening date can be prior to the sample start date of January 1991. The earliest accounts were opened in 1972 and all investors in the sample have an account opening date prior to 1992. About 88% of investors in the sample opened their accounts prior to the beginning of the sample period.

cognitive aging are appropriate, we estimate a model of cognitive aging using a representative European household-level data set, which includes direct measures of cognitive abilities. The model estimates indicate that cognitive abilities increase with education, wealth, and income but decline with age. Furthermore, the cognitive decline is steeper among individuals who are also less educated and have lower income. This evidence indicates that demographic variables such as age, income, wealth, education, and their interactions is likely to capture the adverse effects of cognitive aging reasonably well.

Studies like ours that examine the effects of age also face the classic age-cohort-period identification problem (e.g., Heaton (1997), Ameriks and Zeldes (2004)). A potential alternative interpretation of our evidence on cognitive aging is that it reflects birth cohort effects. While plausible, there are several reasons why cohort effects are unlikely to explain our main findings. First, it is difficult to conceive a hypothesis based on cohort effects that predicts the observed *opposite* effects of age in our "rules of thumb" and "skill" regressions. Put differently, cohort effects cannot easily explain why older investors would exhibit a greater propensity to follow common investment principles but exhibit a lower ability to apply them effectively. Second, cohort-based explanations for the observed sudden drop in performance at older age are unlikely to be convincing. Third, cohort effects cannot successfully account for the inverted U-shaped relation between age and investment skill. In contrast, all these findings are strongly consistent with the cognitive aging hypothesis and reflect the natural outcome of the joint aging and learning processes.

In spite of our novel identification strategy based on economic reasoning, we attempt to directly control for cohort effects using two distinct methods. First, we follow Poterba and Samwick (1997) and include cohort-range dummy variables in our cross-sectional regressions. We find that the cohort dummies have insignificant coefficient estimates in all our specifications. Second, we adopt the differencing method proposed in McKenzie (2006) to eliminate cohort effects. For each investor, we compute the change in performance between the first and the second halves of the sample period and examine whether the performance differential varies with age. In our graphical analysis, we find that the performance differential measure exhibits an inverted U-shaped pattern and similar to the age-skill relation, there is a sharp decline at very old age. This evidence is consistent with the cognitive aging hypothesis and does not suffer from potential contamination from cohort effects because eliminates the common cohort effects. Overall, these results indicates that cohort effects do not induce the observed negative age-skill relation.

Examining the economic costs of aging, we find that, on average, investors with greater cognitive decline earn about 3% lower risk-adjusted annual returns, and the performance differential is over 5% among investors with larger portfolios. We conduct several robustness tests and show that our results are not sensitive to our relatively short sample size, exceptional performance of certain styles and industries, the choice of skill measures, potential error in skill measurement, our inability to observe investors' full portfolios, choice of the risk adjustment methodology, specific market conditions, investors' lack of interest in relatively small portfolios, and the geographical concentration of our sample investors.

At a first glance, our evidence might appear puzzling, and perhaps surprising, because the finance literature on portfolio choice mainly attributes increasing risk aversion and the positive effects of experience to the aging process. The adverse effects of cognitive aging are typically ignored. Within this traditional portfolio choice paradigm, it is very difficult to conceive a hypothesis that posits a positive impact of experience and the negative impacts of age, age-income, age-education, and age-race/ethnicity interaction terms on investment skill. However, when interpreted in the appropriate context of the extant psychological evidence on cognitive aging, our findings appear intuitive and economically meaningful because they represent the natural outcome of the joint aging and learning processes.

The rest of the paper is organized as follows. In the next section, we develop the testable hypotheses and discuss related research. We describe the data in Section 3. In Section 4, we examine the stock preferences of older investors and test our first hypothesis that focuses on the positive effects of aging and experience. In Section 5, we test our unconditional and conditional hypotheses, which posit that stock investment skill deteriorates with age but improves with experience. In Section 6, we estimate the economic costs of aging. In Section 7, we conduct robustness checks and attempt to rule out alternative interpretations of our key findings. We conclude in Section 8 with a brief summary of the paper and potential implications of our results.

2. Hypothesis Development and Related Research

We develop our testable hypotheses by synthesizing the empirical evidence from the psychological research on aging, the literature on learning, and life-cycle models of investing.

The extant psychological evidence indicates that the decline in cognitive abilities is a normal consequence of biological aging and this phenomenon is observed across different countries and cultures (Craik and Salthouse (1992)).

Both physical and cognitive abilities, especially memory, decline with age (e.g., Horn (1968), Fair (1994, 2004), Salthouse (2000), Schroeder and Salthouse (2004)), where the decline begins at a relatively young age of 30 (Grady and Craik (2000)). Weakening memory slows down the information processing ability of individuals and leads to a decline in older people's ability to perceive conditional probabilities (Spaniol and Bayen (2005)). Furthermore, due to a decline in attentional ability, older people get distracted easily and they are unable to distinguish between relevant and irrelevant information. Thus, older people are likely to react to new information inappropriately because they are typically slower and relatively less effective at processing and integrating new information.

The psychological evidence also indicates that people are likely to experience a decline in their general intelligence level as they grow older. The aging process influences general intelligence through two distinct channels. First, general intelligence declines with age due to the adverse effects of aging on memory and attention (e.g., Lindenberger and Baltes (1994), Baltes and Lindenberger (1997)). Second, with aging, there is also a decline in the sensory (vision and hearing) functioning, which leads to a decline in general intelligence. The decline in intelligence is much steeper after the age of 70 (Lindenberger and Baltes (1997)), while the adverse effects are attenuated in people's area of expertise because of frequent practicing (Masunaga and Horn (2001)).

Furthermore, socioeconomic and demographic factors such as education, income, wealth, race/ethnicity, and gender can exacerbate the adverse effects of cognitive aging. People who are more educated, more resourceful (i.e., have higher income and are wealthier), and undertake intellectually stimulating jobs experience a slower decline in cognitive abilities because they are able to actively compensate for the adverse effects of aging (Arbuckle, Gold, and Andres (1986), Baltes and Lang (1997), Cagney and Lauderdale (2002)). In contrast, the age-related decline in cognitive abilities is steeper among older women (Shanan and Sagiv (1982)) as well as older African Americans and Hispanics (Avolio and Waldman (1986), Black (2004)).

While old age is likely to have an adverse effect on people's ability to make effective investment decisions, older investors are likely to have greater investment experience and greater awareness of the fundamental principles of investing. Their accumulated investing wisdom could help them make more efficient investment decisions. Theoretical models of portfolio choice (e.g., Bakshi and Chen (1994), Samuelson (1991), Campbell and Viceira (2002), Cocco, Gomes, and Maenhout (2005), Gomes and Michaelides (2005)) also posit that the riskiness of investor portfolios would decline with age due to decreasing investment horizon and increasing risk aversion.[6]

In addition to these channels, investors are likely to learn, and they might be less prone to behavioral biases as they grow older and become more experienced. The extant empirical evidence from the individual investor literature indicates that older investors exhibit a weaker disposition effect (Dhar and Zhu (2006)), hold relatively better diversified portfolios (Goetzmann and Kumar (2005)), and exhibit lower degree of over-confidence (Barber and Odean (2001)). Furthermore, these behavioral biases decline as investors learn and gain more experience (e.g., List (2003), Goetzmann and Kumar (2005), Feng and Seasholes (2005)). Older investors are also less prone to gambling type activities in the stock market (Kumar (2006)).

Overall, the consensus that emerges from cognitive aging and learning research suggests that, on the one hand, older investors are likely to make relatively more conservative choices and might possess relatively greater knowledge about the fundamental principles of investing. But on the other hand, effective application of those principles requires efficient processing of information, which they might lack.[7] Given the opposite predictions of aging and learning research, our study investigates empirically whether declining cognitive abilities or increasing investment experience has a stronger influence on investors' stock investment decisions. First, based on the evidence from learning research, we posit that:

[6]Theoretical models (e.g., Mossin (1968), Samuelson (1969), Merton (1969)) also predict that portfolio holdings of investors would not vary with age in an ideal economy where the following four conditions are satisfied: (i) asset returns are independently and identically distributed, (ii) investors have constant relative risk aversion preferences and these preferences do not change over time, (iii) investors do not earn labor income and hold only tradeable assets, and (iv) transaction costs are zero and markets are complete. See Ameriks and Zeldes (2004) for an excellent review of this literature.

[7]There is an interesting (though imperfect) analogy between the investment behavior of older investors we are trying to capture and the driving behavior of older people. Older drivers have more driving experience but they are unable to apply that skill effectively due to a decline in their physical abilities. In a similar manner, older investors might have greater knowledge about investing but they can still fail to apply them effectively due to decline in their general intelligence and information processing ability. The analogy suggests that just as older drivers face additional aging related risks, older investors are likely to expose their portfolios to uncompensated risks due to their declining cognitive abilities.

H1: *Investment knowledge increases with both age and experience.*

Next, based on the extant psychological evidence, we develop our *unconditional* hypothesis, which posits that:

H2: *Investment skill increases with experience due to the positive effects of learning but declines with age due to the adverse effects of cognitive aging.*

While support for the unconditional hypothesis would provide evidence consistent with the predictions of cognitive aging, the following *conditional* hypothesis would strongly reinforce that evidence:

H2cond: *The decline in investment skill is steeper among older investors who are less educated, earn lower income, and belong to a racial/ethnic minority group.*

In the following sections, we test these hypotheses using data from multiple sources.

3. Data and Sample Selection

The main data set for this study consists of all trades and end-of-month portfolio positions of investors at a major U.S. discount brokerage house for the 1991 to 1996 time period. This data set offers several advantages and is quite appropriate for examining the adverse effects of cognitive aging. First, because our retail database consists of detailed stock-level data, we are able to investigate whether portfolio characteristics (e.g., portfolio tilt toward value stocks, growth stocks, etc.) vary with age. Second, using detailed information about the composition of investor portfolios, we are able to obtain more direct measures of portfolio risk instead of relying on survey-declared risk-aversion proxies. This allows us to obtain relatively accurate risk-adjusted performance measures. Last, 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. Our sample is also tilted towards the relatively affluent class of investors who might be able to compensate for their declining information processing abilities more effectively. Thus, the adverse effects of cognitive aging on investment decisions we find are likely to be stronger in a more representative sample containing a greater proportion of lower income individuals.[8]

[8]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)).

Of course, ideally, a data set that captures the portfolio holdings and trades of a representative sample of individual investors over a long time period is needed to accurately measure the adverse effects of cognitive aging and to quantify cohort effects (e.g., Heaton (1997), Ameriks and Zeldes (2004)). In the absence of such an extensive dataset, our paper uses the richness of the cross-sectional information to examine the adverse effects of cognitive aging. And we use economic reasoning to rule out cohort based explanations for our findings. Even if a long panel data set were available, one might worry about time effects induced by the changing investment environment over long time periods. In other words, with a long panel, we might be able to better separate aging and cohort effects but it would be very difficult to isolate time effects. Thus, the relatively short brokerage sample offers some advantages over a long, panel data set.

There are 77,995 households in the retail database who 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. The average aggregate value of investor portfolios in our sample is about 2.18 billion and our sample investors executed about 1.9 million common stock trades during the six-year sample period. Overall, investors' stock holdings and trades encompass about 90% of stocks (9,011 stocks) from the Center for Research on Security Prices (CRSP) universe.

An average investor holds a four-stock portfolio (median is three) with an average size of \$35,629 (median is \$13,869). For a subset of households, demographic information such as age, income, wealth, occupation, marital status, gender, etc. is available, where most of the demographic information is self-reported at the time the brokerage account is opened.[9] Further details on the investor database are available in Barber and Odean (2000).

Table I, Panel A reports summary statistics for five groups of investors grouped as age cohorts. Because our primary focus is on the investment behavior of older investors, in Panel B, we also provide summary statistics for five groups of older investors (age ≥ 60) grouped as age cohorts. A typical investor in our sample has held a brokerage account for about ten years, and as expected, investment experience increases with age. More importantly,

[9]Because the demographic information is available for only a subset of investors in the sample (e.g., both age and income measures are available for only 31,260 investors), the number of observations in our cross-sectional regressions depends upon the subset of demographic variables included. See Barber and Odean (2001, Section II.A) for additional details about the available demographic information.

we find that consistent with the prior evidence (e.g., Poterba (2001)), the mean portfolio size increases monotonically with age and there is no evidence that older investors reduce their exposure to equity as their investment horizon decreases. In fact, older investors have greater proportional investment in the stock market, both when measured as a proportion of their total wealth and their annual income.

The cross-sectional variations in wealth and income in our sample also match well with corresponding cross-sectional variations in the more representative Survey of Consumer Finances (SCF) data. For instance, consistent with the evidence in Poterba (2001), we find that the wealth level peaks within the age range of 65-69. Additionally, we find that the annual income peaks within the age range of 47-52, which is also consistent with the predictions of the life-cycle models. Overall, these comparisons with the SCF data suggest that our sample of older retail investors is reasonably representative of the older households in the U.S.[10]

To enrich our analysis, we complement the individual investor data with demographic data from the 1990 U.S. Census.[11] We use the Census data to identify the racial/ethnic profile and the educational background of investors. To identify the racial/ethnic composition of investors, for each zip code, we compute the proportion of individuals in the following four racial/ethnic groups: (i) Caucasian, (ii) African American, (iii) Hispanic, and (iv) Others. Using the zip code of each investor, we assign her the appropriate zip code-level racial/ethnic profile. Similarly, we use the Census data to infer the education level of an investor. Investors who live in more educated zip codes are assumed to be more educated, where the proportion of the zip code population that holds a bachelor's or higher degree is used to identify the educational status of that zip code.[12]

Several other data sets are used in this study. We use a representative household-level data set from the 2005 wave of the Survey of Health, Aging, and Retirement in Europe (SHARE) to estimate a model of cognitive abilities.[13] For each stock in the sample, we obtain

[10]See Ivković, Poterba, and Weisbenner (2005) and Ivković, Sialm, and Weisbenner (2007) for additional discussions on the representativeness of our individual investor data.

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

[12]Because we use the zip code-level Census data and assign to each investor the racial/ethnic and educational profile of her zip code, strictly speaking, the race and the education level measures of an investor indicates the dominant race and the educational status of the people in her zip code. However, we avoid these lengthy descriptors such as "investor who lives in a zip code dominated by African Americans". Instead, we broad labels such as Hispanic investor, highly educated investor, older African American investor, etc. to refer to an investor.

[13]The SHARE data are available at http://www.share-project.org/. See Christelis, Jappelli, and

the quarterly cash dividend payments, monthly prices, returns, and market capitalization data from CRSP and quarterly book value of common equity data from COMPUSTAT. We obtain the monthly time-series of the three Fama-French factors and the momentum factor from Professor Kenneth French's data library.[14] Last, we obtain characteristic-based benchmarks from Professor Russ Wermer's web site.[15]

4. When Do Older Investors Make Better Investment Decisions?

To find support for our first hypothesis (H1), we examine whether the knowledge and experience accumulated over time manifest themselves in investors' portfolio holdings and trading decisions.

4.1. Age and Equity Portfolio Risk

In our first formal analysis, we examine whether older investors follow the common theoretical prescription and hold relatively less risky portfolios. Specifically, we examine the style preferences of five age-based investor groups to determine whether older investors tilt their portfolios toward relatively less risky stocks. Since our focus is on the investment behavior of older investors, we also examine the style preferences of five groups of investors sorted on age, where the minimum age is 60.

To measure the style preferences of an investor group, first, we combine the portfolios of all investors in that group and construct a group-level portfolio (p). Next, for portfolio p, at the end of each month t, we compute the *actual* weights (in percent) assigned to various style portfolios (w_{spt}), where the subscript s refers to a style portfolio. The following six stock characteristics are used to measure investors' style preferences: (i) stock volatility or total risk, (ii) dividend yield, (iii) market beta, estimated using past 60 months of data, (iv) firm size, (v) book-to-market (B/M) ratio, and (vi) past 12-month return or momentum. We also construct the aggregate market portfolio by combining the entire universe of stocks available on CRSP and compute the *expected* weights (in percent) assigned to various style

Padula (2006) for details.

[14]The data library is available at `http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/`.

[15]The data are available at `http://www.smith.umd.edu/faculty/rwermers/ftpsite/Dgtw/coverpage.htm`.

portfolios(w_{smt}).[16] Lastly, we compute the unexpected (or excess) portfolio weight allocated to a style in the group-level portfolio, which is the difference between the actual and the expected style weights ($w_{spt} - w_{smt}$). The unexpected style weights in a given period provide a measure of the group's instantaneous style preferences and the means of the monthly unexpected style weights indicate the style preferences of a group during a chosen time-period.

Age-dependent style preference estimates are reported in Table II. We find that older and younger investors exhibit distinct style preferences. Both younger (age quintile 1) and older (age quintile 5) investors prefer small stocks but older investors exhibit a weaker preference for small stocks (see set (4)). Older (younger) investors over-weight small stocks by 15% (17.54%) and under-weight large-cap stocks by 20.02% (22.96%). Similarly, consistent with the evidence in Graham and Kumar (2006), we find that older investors, especially those who are above 75, exhibit stronger preference for high dividend yield stocks.[17] Overall, our evidence on age-dependent style preferences indicates that, even though older investors do not reduce their exposure to equity (see Table I), within the equity asset class, they prefer stocks that are relatively less risky.

For greater accuracy, we estimate panel regression models and examine the characteristics of age based group portfolios in a multivariate setting. In these regressions, the excess weight assigned to a stock in the aggregate group portfolio is the dependent variable and the mean return, idiosyncratic volatility, skewness, kurtosis, and the price of the stock are used as the primary independent variables.[18] The return moments are calculated using the past 60 months of data and the idiosyncratic volatility measure is the variance of the residual obtained by fitting a four-factor model to the monthly stock returns series.

Additionally, the following control variables are employed: (i) market beta, which is also estimated using past 60 months of data, (ii) firm size, (iii) book-to-market ratio, (iv) short-

[16] If investors in a group were to randomly select stocks, where the probability of picking a stock is proportional to its size, the weight of a style in the group portfolio would be approximately equal to the weight of the style in the aggregate market portfolio. Alternatively, if investors as a group exhibit mean-variance preferences even when individually they do not hold such preferences, they would hold the market portfolio. In either case, the set of weights in the aggregate market portfolio serves as an appropriate benchmark.

[17] These differences in stock preferences are obviously not independent of one another. Our intent here is simply to illustrate that older and younger investors prefer different types of stocks.

[18] 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.

term momentum (past one-month stock return), (v) longer-term momentum (past twelve-month stock return), (vi) an S&P500 dummy which is set to one if the stock belongs to the S&P500 index, and (vii) monthly volume turnover. To account for potential auto correlation and cross correlation in errors, we use the non-parametric approach of Driscoll and Kraay (1998) and obtain the corrected standard errors for our estimates. This methodology provides a unified approach for simultaneously correcting the standard errors for cross-sectional correlation, serial auto correlation, and cross serial correlation in a panel setup.[19]

The panel regression estimates are presented in Table III. The independent variables have been standardized (mean = 0, standard deviation = 1) to facilitate comparisons among the coefficient estimates. We also ensure that multi-collinearity is not contaminating our results. We estimate the panel regression model for three age-based categories: (i) younger age group containing investors in the 20-38 age range, (ii) older age group consisting of investors in the 60-94 age range, and finally, (iii) within the older investor group, the oldest age group consisting of investors in the 75-94 age range. Additionally, we estimate two panel regressions to examine the differences in the stock preferences of groups (i) and (ii), and (i) and (iii).

Focusing on the differential regression estimates (columns (4) and (5)), we find that older investors favor relatively less risky stocks. Specifically, older investors' preferences for stocks with higher idiosyncratic volatility, higher market beta, lower market capitalization, lower prices are weaker than those of younger investors. Older investors also exhibit weaker preference for stocks with higher skewness, which indicates they are less likely to chase extreme positive returns. Furthermore, our estimates indicate that investors' preferences for less risky stocks increase with age because the differences in stock preferences, as reflected by the magnitudes of the coefficient estimates, are stronger when we consider the 75-94 age group (see column (5)).[20]

In sum, the sorting results and panel regression estimates indicate that the average risk exposures of investors' stock portfolios decrease with age. Consistent with our first hypothesis (H1), the evidence indicates that experienced and prudent investors reduce the riskiness of

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[19] We find that the coefficient estimates are very similar and the t-statistics are of higher magnitude when we estimate Fama and MacBeth (1973) cross-sectional regressions and use the Pontiff (1996) method to compute serial correlation adjusted standard errors. We choose to report the conservative t-statistics obtained using the Driscoll and Kraay (1998) methodology.

[20] The results are remarkably similar when we use other age categories. Specifically, we examined the robustness of our results using the following three age groups: (i) 20-40 (weak retirement motive), (ii) 41-65 (strong retirement motive), and (iii) above 65 (retired).

their portfolios as they grow older.

4.2. Do Investors Accumulate More Knowledge About Investing As They Grow Older?

To examine whether older investors exhibit greater knowledge about investing, we concentrate on a few important dimensions of portfolio decisions that reflect "rules of thumb" in investing. The set of decisions we consider is guided by the availability of data. First, we examine whether older investors are more likely to recognize the potential benefits of diversification. Next, we examine whether older investors trade less frequently because they realize that active trading in efficient markets is a futile exercise. Last, we examine whether older investors are more likely to engage in year-end tax-loss selling, since it requires financial awareness but does not necessarily require skill.[21]

We estimate several "rule of thumb" cross-sectional regressions, where the dependent variable is a measure of investment decision that reflects a specific investing "rule of thumb". The measures are obtained for each investor using their decisions during the entire sample period. For each investment decision, we estimate both unconditional and conditional regression models. In the unconditional regressions, the independent variables are only age and investment experience. *Age* corresponds to the head of the household and *Investment Experience* is the number of days between the account opening date and December 31, 1996.[22] Most investors (about 88%) opened their brokerage accounts prior to the start of the sample period and all accounts were opened before 1992.

In the conditional regressions, several demographic variables and portfolio characteristics are employed as control variables: *Income* represents the annual household income.[23] *Education* represents the proportion of people in investor's zip code that has attained a bachelor's or higher educational degree. The *Male Dummy* is set to one if the head of the household is male, and the *Retired* dummy is set to one if the head of the household is retired. *Portfolio Size* is the average market capitalization of the household portfolio, *Portfolio Turnover* is the average of monthly buy and sell turnovers, and *Portfolio Dividend Yield* is the average

[21]Optimal trading behavior in presence of taxes requires skill (e.g., Constantinides (1983, 1984), Ivković, Poterba, and Weisbenner (2005)). However, such optimal response to taxes would lead to higher risk-adjusted performance, which our risk-adjusted performance measures would capture (see Section 5).

[22]The date is arbitrarily chosen and the choice does not influence any of our results.

[23]We have information about both the income and the wealth of investors. We use the income measure in our empirical analysis because it is available for a larger subset of investors in the sample. Our results are very similar when we use wealth instead of income.

dividend yield of the household portfolio.[24] The *RMRF* (market factor), *SMB* (small-minus-big factor), *HML* (high-minus-low factor), and *UMD* (up-minus-down or momentum factor) exposures are the factor loadings of an investor's portfolio and they capture the risk characteristics of the portfolio. The factor loadings are obtained by fitting a four-factor time-series model to the monthly portfolio returns series of each investor over the period the investor is active. Last, *Mutual Fund Holdings* is the proportion of the equity portfolio allocated to mutual funds.

The "rule of thumb" cross-sectional regression estimates are presented in Table IV, where the t-statistics are computed using robust and zip code level clustered standard errors. As before, to ensure that extreme values are not affecting our results, we winsorize all variables at their 0.5 and 99.5 percentile levels. The independent variables have been standardized so that each variable has a mean of zero and a standard deviation of one.

In the first two regressions, to examine whether older investors are more aware of the potential benefits of diversification, we use the number of stocks in the portfolio as the dependent variable (columns (1) and (2)). Our intent here is not to show that older investors hold more diversified stock portfolios. Given that we cannot observe the entire portfolios of investors, the number of stocks is likely to be a very noisy measure of diversification. Nonetheless, the number of stocks in an investor portfolio is likely to indicate whether or not an investor exhibits a preference for diversification.

Our results from the unconditional model indicate that older and more experienced investors hold portfolios containing more stocks. The coefficient estimates are significantly positive for both *Age* and *Investment Experience*, even in the presence of various control variables. The (unreported) coefficient estimates for the control variables are also broadly consistent with our expectations. For instance, the positive coefficient estimate for *Mutual Fund Holdings* indicates that investors who exhibit stronger preference for diversification in their stock portfolios also hold more mutual funds. Overall, consistent with our first hypothesis, the evidence indicates that the portfolio choices of older and more experienced investors are more likely to conform to one of the key principles of investing, namely, portfolio diversification.

[24] Because we use sample period averages for many of our variables, there is an issue of endogeneity that could affect some of our estimates. To minimize potential endogeneity affecting our coefficient estimates, we experimented with portfolio characteristics measures (e.g., the portfolio size) from the first month the investor enters the sample. We find that the coefficient estimates are virtually unchanged when we use those alternative measures. For consistency, we use the full sample based measures for all portfolio variables.

Next, we examine whether older investors follow one of the key recommendations of the efficient market hypothesis, which posits that investors should not trade actively to improve performance because such an exercise would be futile. In the next two regression specifications (columns (3) and (4)), we use the monthly portfolio turnover as the dependent variable.[25] Again, consistent with our first hypothesis, we find that both older and more experienced investors exhibit lower turnover rates. The coefficient estimates are significantly negative for both *Age* and *Investment Experience*, even in the presence of various control variables. The negative coefficient estimate for *Age* and the positive coefficient estimate for the *Male Dummy* are consistent with the evidence in Barber and Odean (2001), who find that older (male) investors trade relatively less (more) frequently. These estimates indicate that the trading behavior of older investors are more likely to conform to another key principle of investing, namely, less frequent trading.

While these cross-sectional regression estimates are consistent with our first hypothesis, one might argue that a stronger preference for diversification and lower portfolio turnover do not necessarily imply greater investment knowledge but reflect "passive" investing by older investors. To address this potential concern, we use another knowledge measure that is more likely to capture investor's knowledge about investing. Specifically, we examine whether older investors exhibit greater propensity to engage in year-end tax-loss selling.

We estimate a regression model where the proportion of "losers" (stock investments where an investor suffers a loss) sold in the month of December is used as a dependent variable.[26] The regression estimates indicate that both older and more experienced investors are more willing to sell their losers in December. The coefficient estimates are significantly positive for both *Age* (estimate = 0.016, t-stat = 5.696) and *Investment Experience* (estimate = 0.006, t-stat = 2.311), even in the presence of various control variables. Again, in unreported results, we find that most control variables have the expected signs. For instance, investors who hold larger portfolios and trade more often are likely to sell more losers in December. This evidence indicates that the trading behavior of older investors are likely to reflect yet another investing rule of thumb: "Sell your losers in December".

[25] The monthly portfolio turnover rate is the average of purchase and sales turnover rates. The purchase 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 sales turnover rate is defined in an analogous manner.

[26] The estimates are similar when we examine the proportion of losses realized in both November and December.

Given that the coefficient estimates of *Age* and *Investment Experience* have similar signs in all cross-sectional regression specifications, one might suspect that the two variables capture identical aspects of investors' investment decisions. But we find that age and investment experience measures are weakly correlated (correlation = 0.142). Furthermore, when we estimate a cross-sectional regression with portfolio dividend yield as the dependent variable, we find that the coefficient estimate for *Age* is positive but the coefficient estimate for *Investment Experience* is negative (see Table IV, column (5)). The positive coefficient estimate for *Age* is consistent with the evidence in Graham and Kumar (2006), who show that older investors are likely to prefer high yield stocks for consumption reasons. However, the negative estimate for *Investment Experience* is new and it indicates that, all else equal, more experienced investors prefer lower yield stocks. In the current context, more importantly, the estimates indicate that the age and experience variables capture two distinct aspects of investors' investment decisions.

Taken together, our "rule of thumb" cross-sectional regression results indicate that older investors make more conservative stock investment choices and their choices reflect greater knowledge about investing. This evidence supports our first hypothesis (H1), which posits that investment knowledge increases with both age and experience.

5. When do Older Investors Make Worse Investment Decisions?

While older investors, especially those who are more experienced, exhibit a greater propensity to follow common investment "rules of thumb", how effectively can they apply those principles? To gather support for our second hypothesis (H2 and H2cond) that posits opposite effects of age and experience, we estimate "skill" cross-sectional regressions, where a measure of investment skill is employed as the dependent variable.

We focus on two specific investment skills: "diversification skill" and the stock selection ability. Our conjecture is that although older investors hold portfolios with larger number of stocks, they might not exhibit "diversification skill" because the ability to perceive correlations accurately might decline with age.[27] Furthermore, investors' stock selection skill could

[27] Goetzmann, Li, and Rouwenhorst (2005) show that the total portfolio variance can be reduced by increasing the number of stocks in the portfolio and by a proper selection of stocks such that the average correlation among stocks in the portfolio is lower. Variance reduction through proper stock selection reflects "skill" while addition of stocks in the portfolio without a reduction in the average portfolio correlation reflects a "passive" form of diversification.

decline with age because the adverse effects of cognitive aging could influence people's ability to efficiently process new information. In contrast, both diversification and stock selection skills are likely to improve with investment experience.

5.1. Age, Investment Experience, and Investment Skill

We use the monthly Sharpe ratio to measure diversification skill and the monthly portfolio alpha to measure stock selection skill. The alpha measure is the intercept from the four-factor time-series model, where the portfolio returns is the dependent variable and the four commonly used risk factors (*RMRF*, *SMB*, *HML*, and *UMD*) are employed as dependent variables. We also employ the mean characteristic-adjusted monthly portfolio return obtained using the Daniel, Grinblatt, Titman, and Wermers (1997) methodology as an alternative measure of investment skill. The DGTW characteristic-adjusted return of a stock is the difference between the raw monthly stock return and the return from a matching size, book-to-market, and momentum matched benchmark portfolio return. Both investment skill measures captures the ability of investors to generate excess returns from their portfolio decisions, after accounting for the known differences in their style and risk preferences (see Table II).

Before presenting the skill regression estimates, we graphically illustrate the univariate relation between age and investment skill. Figure 1 shows the variation in the mean characteristic-adjusted portfolio returns with age. Two features of the plot are noteworthy. First, the investment performance exhibits an inverted U-shape with a peak around 40 years. The hump shape reflects the combined effects of experience and aging. Second, there is an abrupt and significant drop in performance around the age of 70. This nonlinear effect supports our cognitive aging hypothesis and is consistent with the psychological evidence that finds a steeper cognitive decline after the age of 70. Overall, the graphical evidence reveals that a complex set of interactions among age, experience, and investment skill determine portfolio performance.

The skill regressions allow us to better quantify these interactions. In the first set of regressions, we test our unconditional hypothesis, where the only independent variables are *Age* and *Investment Experience*. The cross-sectional regression estimates for the unconditional models are presented in Table V (columns (1), (3), and (5)). In all our regression specifications, we use robust, clustered standard errors to account for potential cross-sectional dependence within zip codes.

In the Sharpe ratio regression (column (1)), *Age* has a negative but statistically insignificant coefficient estimate (estimate = -0.001, t-stat = -0.935) while *Investment Experience* has a significantly positive coefficient estimate (estimate = 0.011, t-stat = 11.644).[28] In the alpha regression (column (3)), *Age* has a significantly negative coefficient estimate (estimate = -0.042, t-stat = -5.047) and *Investment Experience* has a negative but statistically insignificant estimate (estimate = -0.010, t-stat = -1.184). Last, in the characteristic-adjusted return regression (column (5)), *Age* has a significantly negative coefficient estimate (estimate = -0.044, t-stat = -7.293) while *Investment Experience* has a significantly positive coefficient estimate (estimate = 0.037, t-stat = 6.053).[29] These coefficient estimates are consistent with our main hypothesis and indicate that *Age* has opposite effects in "rule of thumb" and "skill" regressions.

The coefficient estimates in the skill regressions are significant in economic terms. For instance, the estimate for *Age* in the alpha regression indicates that, holding experience fixed, a one standard deviation shift in the age of an investor would correspond to an annual, risk-adjusted performance decline of $0.042 \times 12 = 0.504\%$. The mean age of investors in our sample is 50 and the standard deviation is about 12. Thus, when an investor aged 30 becomes older and crosses the retirement age of 65 (a three standard deviation change in age), she is likely to suffer an annual performance decline of 1.512% on a risk-adjusted basis.

Collectively, the graphical evidence and the results from our unconditional tests indicate that, investment skill varies inversely with age and positively with investment experience. This evidence is consistent with our unconditional hypothesis (H2) but the strengths of age-skill and experience-skill relations are rather weak.[30]

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[28]Consistent with our evidence, using household-level data from Sweden, Calvet, Campbell, and Sodini (2005) show that older investors make cautious but relatively less efficient investment choices. Also, see Campbell (2006).

[29]Our results might appear inconsistent with the evidence in the Barber and Odean (2001) study, who find a *positive* relation between age and net performance. When we use a cross-sectional regression specification similar to theirs with portfolio turnover as an additional control variable (to capture the adverse effects of trading) and without *Investment Experience* as one of the independent variables, we also find a positive relation between age and portfolio performance.

[30]In a different context, Chevalier and Ellison (1999) find that, keeping experience and other characteristics constant, older mutual fund managers exhibit worse performance than younger managers. They find this evidence puzzling and attribute it to managers' career concerns. However, the evidence is also consistent with our unconditional hypothesis, which posits that skill varies inversely with age and positively with experience.

To gather stronger support for the second hypothesis, we consider additional proxies for cognitive aging. Our choice is motivated by the psychological evidence, which finds that people who are more educated, more resourceful, and undertake intellectually stimulating jobs are able to better compensate for their declining cognitive abilities (Arbuckle, Gold, and Andres (1986), Baltes and Lang (1997), Cagney and Lauderdale (2002)). Analogous to the psychological evidence, we expect that the adverse effects of cognitive aging would be weaker among wealthier, higher income, and more educated investors. Older investors who are more educated and more resourceful (i.e., investors with higher income and greater wealth) might be able to better compensate for their declining information processing abilities.

5.2. An Empirical Model of Cognitive Abilities

Before estimating extended specifications of skill regressions, we further ensure that the additional cognitive aging proxies employed in the regression specification are appropriate. We estimate a model of cognitive abilities using a representative European household data set. The data contain three direct measures of cognitive abilities: (i) verbal ability, (ii) quantitative ability, and (iii) memory. The three cognitive measures are positively correlated but the maximum correlation is below 0.50. Using these measures, we obtain a composite (equal-weighted) measure of cognitive abilities. The European household data also contain demographic variables that are available in our individual investor data set. We consider several regression specifications, where one of direct measures of cognitive abilities is the dependent variable and the main determinants of cognitive abilities identified in the psychological literature are the independent variables.

The cognitive abilities regression estimates are reported in Table VI. Consistent with the psychological evidence, we find that cognitive abilities decline with age and are positively associated with education, wealth, and income. Furthermore, the decline is steeper among individuals who are considerably older (age > 70), are less educated, and have lower income. It is interesting that two facets of cognitive abilities that are more relevant for investment decisions, namely, the quantitative ability and memory, exhibit a sharper decline with age. The decline in verbal ability that might be less relevant for investment decisions is relatively less severe. In sum, the cognitive abilities model estimates indicate that demographic variables such as age, income, wealth, education, and their interactions are likely to capture the adverse effects of cognitive aging reasonably well.

5.3. Conditional Deterioration in Investment Skill

To quantify the influence of cognitive aging on investment decisions more accurately, we estimate an extended skill regression specification. This specification includes additional cognitive aging proxies that are suggested by our empirical model of cognitive abilities. Specifically, we interact age with income and education, where both the *Age*Low Income* and *Age*Low Education* interaction terms are defined after standardizing the age variable. We also consider an *Over 70 Dummy* to capture the sudden drop in investment performance identified in Figure 1.[31]

The psychological evidence (e.g., Avolio and Waldman (1986), Black (2004)) suggests that the age-related decline in cognitive abilities is steeper among ethnic/racial minorities (African Americans and Hispanics).[32] In light of this evidence, we use two additional interaction terms, one for Hispanics and another for African-Americans. The *Hispanic* variable is set to one for investors who live in zip codes where the ratio of the populations of Hispanics to Whites is in the upper quintile.[33] The *African American* variable is defined in an analogous manner. We interact both race/ethnicity variables with *Age*.

We also consider several independent variables to control for the known determinants of performance and investment skill. We include a *Male Dummy* as a control variable because previous studies have shown that gender influences net investment performance (Barber and Odean (2001)). The *Retired Dummy* allows us to control for the significant lifestyle changes at the time of retirement, which could alter investment behavior.[34] We employ several portfolio characteristics as control variables because investors' risk preferences are likely to vary with age. This set includes portfolio size, portfolio dividend yield, and the four factor exposures ($RMRF$, SMB, HML, and UMD coefficient estimates) of the investor

[31]We also considered a quadratic age term in our regression specifications. The Age^2 variable has an insignificant coefficient estimate, which is not surprising because other variables like income and wealth also capture the hump shape.

[32]In our sample, zip codes with higher concentration of minorities are primarily located in California, Illinois, Maryland, New York, and Texas.

[33]When we use the continuous race/ethnicity variables, which are likely to be noisier, the interaction term estimates are similar, though somewhat weaker. Note that although we use zip code-level measures of education and race/ethnicity, our coefficient estimates are consistent. See Wooldridge (2002) for details.

[34]The abrupt changes in lifestyle at the time of retirement are known to affect consumption behavior (e.g., Banks, Blundell, and Tanner (1998), Bernheim, Skinner, and Weinberg (2001)).

portfolio.[35] Last, the *Portfolio Turnover* measure serves as an approximate control for the effects of transaction costs on portfolio performance.

The skill regression estimates for the conditional models are also reported in Table V (columns (2), (4), and (6)). Consistent with our hypotheses, we find that the age-skill and experience-skill relations become stronger and appear more transparent in the conditional models. In the Sharpe ratio regression (column (2)), both *Age* and *Investment Experience* have significant coefficient estimates, where the loading on *Age* is negative (estimate = -0.014, t-stat = -3.355) and the loading on *Investment Experience* is positive (estimate = 0.010, t-stat = 9.450). We interpret the negative coefficient estimate on *Age* as an adverse effect of cognitive aging, while the positive coefficient estimate on *Investment Experience* suggests that greater experience leads to greater diversification skill.

Our results from the Sharpe ration regression indicate that the coefficient estimate on *Income* is positive but statistically insignificant. However, the *Age*Low Income* interaction term has a negative coefficient estimate, which indicates that the adverse effects of aging are stronger among older investors with lower income. In addition, we find that *Education* has a significantly positive coefficient estimate (estimate = 0.002, t-stat = 1.882) and the *Age*Low Education* interaction term has a marginally negative coefficient estimate. These results indicate that while education and investment experience leads to more effective diversification, as investors grow older, their ability to diversify effectively decreases.

When we estimate the conditional skill regression with the four-factor alpha as the dependent variable, the results are remarkably similar to the Sharpe ratio regression estimates. Both *Age* and *Investment Experience* have significant coefficient estimates, where the loading on *Age* is negative (estimate = -0.051, t-stat = -4.735) and the loadings on *Investment Experience* and *Education* are positive (the estimates are 0.020 and 0.014, and the t-statistics are 2.283 and 2.527, respectively). Furthermore, the *Over 70 Dummy* has a negative and significant coefficient estimate (estimate = -0.025, t-stat = -2.073). We also find that the *Age*Low Income* and *Age*Low Education* interaction terms have negative coefficient estimates, though the latter is not statistically significant.

When we use the mean characteristic-adjusted monthly returns to measure risk-adjusted

[35]Since we use risk-adjusted measures of portfolio performance as dependent variables in our regression specifications, these control variables are not necessary. We employ these control variables to be conservative. They would adjust for residual risk differences that the standard risk adjustment models might not be able to capture.

performance, consistent with our alpha regression estimates, we find that age and investment experience maintain their opposite signs and the interaction terms have similar estimates (see column (6)).[36] The coefficient estimate for *Age* is -0.054 with a t-statistic of -2.945 and coefficient estimate for *Investment Experience* is 0.027 with a t-statistic of 3.891. Furthermore, both *Age*Low Income* and *Age*Low Education* interaction terms have the expected negative and significant coefficient estimates (the estimates are -0.014 and -0.005 with t-statistics of -1.996 and -2.719, respectively).

While we use robust, clustered standard errors in our skill regressions to account for potential cross-sectional dependence, for additional robustness, we estimate a panel regression specification using the monthly characteristic-adjusted returns. We use the Driscoll and Kraay (1998) methodology to account for potential cross-sectional correlation, serial autocorrelation, and cross serial correlation. We find that the panel regression results are qualitatively very similar (see column (7)) to the cross-sectional regression estimates.

The coefficient estimates in the skill regressions are easy to interpret in economic terms. They allow us to quantify the performance decline that can be attributed solely to the adverse effects of cognitive aging. For instance, the coefficient estimate of *Age* in column (4) indicates that, all else equal, a one standard deviation shift in the age of an investor who does not belong either to the lower income, lower education, or ethnic minority groups would be associated with an annual, risk-adjusted performance decline of $0.051 \times 12 = 0.612\%$. This indicates that when an investor aged 30 becomes older and crosses the retirement age of 65 (a three standard deviation change in age), she is likely to suffer an annual performance decline of 1.836% on a risk-adjusted basis.

Examining the race/ethnicity interactions, we find that *Age*Hispanic* interaction term has a significantly negative coefficient estimate in all four regression specifications. For instance, in the alpha regression (column (4)), the coefficient estimate of the interaction term is -0.034, with a t-stat of -3.516. In economic terms, this implies that an older investor who also earns lower income and belongs to the Hispanic ethnic group would experience an annual, risk-adjusted performance decline of $(0.051 + 0.025 + 0.034) \times 12 = 1.320\%$. Furthermore, a jump in age from 30 to 65 for an investor with these attributes would correspond to an annual performance decline of 3.96% on a risk adjusted basis. In contrast, we find that the

[36]The correlation between the four-factor alpha and the characteristic-adjusted performance measures is positive (0.592) but not extremely high.

*Age*African American* interaction term has insignificant coefficient estimates.

In unreported results, we find that the coefficient estimates of our control variables have the expected signs. For instance, in the alpha regression, the *Portfolio Dividend Yield* has a strongly negative estimate, which indicates that investors who focus excessively on high dividend yield stocks exhibit weaker stock selection ability. Nonetheless, these investors are able to reduce the total risk of their portfolios, thereby increasing the Sharpe ratio (see column (2)). Additionally, investors who hold larger portfolios exhibit better stock selection ability because portfolio size is likely to be a proxy for greater resources and it may also reflect greater investment experience.[37] We also find that the coefficient estimate for *Retired Dummy* is statistically insignificant, which suggests that the abrupt lifestyle change at the time of retirement does not have an incremental negative effect on investment skill.

Overall, the skill regression estimates support our unconditional hypothesis (H2), which posits that investment skill increases with experience due to the positive effects of learning, but declines with age due to the adverse effects of cognitive aging. The evidence also supports our conditional hypothesis (H2cond), which posits that the decline in skill is steeper among less educated and less wealthy older investors who belong to minority groups.

5.4. Additional Evidence: Cognitive Aging and Learning

Do older investors learn less effectively due to cognitive aging? To gather additional support for our main hypothesis, we examine whether the speed and effectiveness of learning depends upon age. We embed two interaction variables in one of our skill regression specifications (column (6) in Table V): *Below 30 * Low Experience* and *Over 70 * Low Experience*. In untabulated results, we find that lack of experience has stronger adverse effects on older investors. The coefficient estimate for the *Over 70 * Low Experience* dummy is negative and significant (estimate = -0.041, t-stat = -4.068) while the coefficient estimate of the *Below 30 * Low Experience* dummy is statistically insignificant (estimate = 0.005, t-stat = 0.546). This evidence is consistent with our conditional hypothesis and indicates that learning is impaired by the adverse effects of cognitive aging.

[37]To eliminate potential concerns about reverse causality (portfolio size is larger because of better portfolio performance and not vice versa), we use the portfolio size from the first month the investor enters the sample.

5.5. *Sub Sample Estimates Without the Extreme Performers*

To examine whether the exceptionally superior or poor performance of certain types of stocks or industries are influencing our estimates, we exclude $k\%$ investors from both the tails and re-estimate the skill regressions. When $k = 5$, our estimates remain qualitatively similar. For instance, the coefficient estimates for *Age* and *Investment Experience* are -0.047 (t-stat $= -3.031$) and 0.035 (t-stat $= 4.609$), respectively. Furthermore, the interaction terms have the expected negative and significant estimates.

5.6. *Evidence from Other Related Settings*

While our study focuses on investors' stock investment decisions to test the cognitive aging hypothesis, footprints of cognitive aging are observed in other related settings as well. For instance, the evidence in Bailey, Kumar, and Ng (2006) corroborates our findings and supports our main hypotheses. While that paper does not focus on the implications of cognitive aging, they find that both older and more experienced investors exhibit a stronger propensity to invest in foreign securities. Those investors are more likely to participate and, conditional upon participation, they hold larger foreign equity portfolios. Thus, older and more experienced investors follow another commonly prescribed investment advice: "Diversify internationally." However, the empirical evidence in that paper also reveals that while both older and more experienced investors experience reduction in the portfolio volatility due to their foreign investments, only experienced investors are able to improve the Sharpe ratios of their portfolios. This evidence indicates that older investors are more likely to attempt to exploit the potential benefits of foreign investments but, conditional upon participation, they appear less skillful in their decisions.

We obtain very similar results when we evaluate investors' mutual fund investment decisions. In untabulated results, we find that both older and experienced investors are more likely to invest in mutual funds. Furthermore, older investors exhibit a greater propensity to invest in index funds while experienced investors exhibit a stronger preference for other types of funds. Thus, older investors are more likely to follow yet another common investment rule of thumb: "Invest in well-diversified mutual funds." However, consistent with our cognitive aging hypothesis, we also find that only investors with greater experience earn higher risk-adjusted returns from their increased participation rates in mutual funds. This evidence shows that in yet another setting older investors follow the commonly prescribed investment principle but are relatively less effective in applying that rule.

5.7. Identification Strategy for Separating Cognitive Aging, Time, and Cohort Effects

Studies like ours that examine the effects of age are plagued with the classic age-cohort-period identification problem (e.g., Heaton (1997), Ameriks and Zeldes (2004)). The main concern is that in addition to age-induced cognitive aging effects that we are mainly interested in, age could capture birth cohort or time effects. Because the three effects are strongly correlated, it is usually difficult to isolate their effects without a data set that tracks the portfolio choices of the same set of individuals over a very long period of time. Fortunately, time effects are unlikely to play a significant role during the relatively short six-year sample period. Thus, we largely assume that time effects are small and do not contaminate our results.

More importantly, there are several reasons why cohort effects are unlikely to explain our findings. First, we use a combination of "rules of thumb" and "skill" regressions to identify the adverse effects of cognitive aging, where our main hypothesis predicts opposite effects of age in the two contexts. But just like the effects of experience, any cohort-based hypothesis would predict a similar influence of age in both regressions. Common social experiences such as the quality of education, socioeconomic environment when growing up, or common first hand experience of salient events (e.g., the depression or the stock market crash) that are often associated with cohort effects cannot successfully explain the opposite signs of age in rules of thumb and skill regressions.

For instance, consider the effects of the quality of education on investment decisions. The cohort of older investors might have experienced lower quality educational environments and one might argue that older investors would have stale and relatively less accurate knowledge about investment concepts such as diversification. But we have shown earlier that older investors exhibit greater knowledge about investing and their investment choices are more aligned with several other common investing rules of thumb. Only when we examine their diversification "skill", we find that older investors make relatively worse choices. Furthermore, older investors trade less, they are more likely to engage in tax-loss selling and, in general, exhibit a greater propensity to follow investing "rules of thumb." Yet, they earn lower risk-adjusted returns.

These findings are consistent with our cognitive aging hypothesis but it is almost impossible to conceive a hypothesis based on cohort effects that posits opposite effects of age in rules of thumb and skill regressions. It is also very difficult to attribute the opposite effects of age in the two contexts to time effects. Therefore, the coefficient estimates of age with opposite signs in the rules of thumb and skill regressions not only provides evidence consistent with our main hypothesis, they also help alleviate potential concerns about time or cohort effects contaminating our results.

Second, as shown in Figure 1, cohort-based explanations for the abrupt and sudden drop in performance at older age are unlikely to be very convincing. Third, cohort effects cannot successfully account for the inverted U-shaped relation between age and investment skill. In contrast, all these findings are strongly consistent with the cognitive aging hypothesis and reflect the natural outcome of the joint aging and learning processes.

In spite of our novel identification strategy based on economic reasoning, we follow Poterba and Samwick (1997) and attempt to directly control for cohort effects in our cross-sectional regressions by using cohort-range dummy variables. We consider five cohort ranges: Below 35, 35-45, 45-55, 55-65, and above 65. In untabulated results, we find that the age-range dummies have negative but insignificant coefficient estimates in all our specifications. More importantly, the coefficient estimates of age, experience, and other interaction variables that provide evidence in support of our main hypothesis remain significant. In fact, the coefficient estimate of *Age* (see column (6) in Table V) becomes stronger (coefficient $= -0.082$, t-stat $= -3.129$).

We also find that the change in performance between the first and the second halves of the sample period exhibits an inverted U-shaped pattern (see Figure 1). The older investors experience a greater decline in performance and similar to the age-skill relation, there is a sharp decline at very old age. This evidence is consistent with the cognitive aging hypothesis and does not suffer from potential contamination from cohort effects because differencing eliminates the common cohort effects (McKenzie (2006)). Overall, these results indicates that cohort effects are not the main driver of the negative age-skill relation.

To further ensure the robustness and the accuracy of our identification strategy, we identify a scenario where cohort effects do not make a meaningful prediction but the cognitive aging hypothesis makes a sharp prediction. Specifically, we assume that portfolio size is a proxy for task difficulty and examine the effect of portfolio size on portfolio performance differential that we attribute to cognitive aging. When an investor actively manages a larger portfolio that requires greater attention and cognitive capacity, the cognitive aging hypothesis predicts that the possibility of making mistakes would be greater among older investors. Consequently, the performance differential between younger and older investors would increase with portfolio size. In contrast, there is no obvious birth cohort based prediction for the variation in performance differential with portfolio size.

When we include *Portfolio Size * Age* interaction variable in the skill regression specification (column (6) in Table V), it has a significantly negative coefficient estimate (estimate $= -0.032$, t-stat $= -3.987$), while the estimates of other variables in the model remain almost unchanged. Thus, consistent with the cognitive aging hypothesis, older investors exhibit greater risk-adjusted performance when they hold larger portfolios that are more difficult to manage.

6. Economic Costs of Cognitive Aging

6.1. A Portfolio Based Approach

To quantify the economic costs associated with cognitive aging more accurately, we conduct portfolio-based, time-series tests. An additional advantage of the portfolio-based analysis is that it is insensitive to concerns about potential cross-sectional dependence in portfolio performance.

We proceed as follows: First, we follow the standard imputation methodology (e.g., Skinner (1987), Ziliak (1998), Browning and Leth-Petersen (2003)) and use the previously estimated model of cognitive abilities (see Section 5.2 and Table VI) to obtain an imputed cognitive ability measure for each investor. We regress this imputed cognitive ability measure on investment experience and obtain a residual cognitive ability measure that is orthogonal to experience. Next, we sort investors into deciles based on their residual cognitive ability measures, where group 1 consists of investors with low cognitive ability and group 10 consists of investors with high cognitive abilities. Last, we examine the average performance of investors in the ten cognitive ability categories and estimate the economic costs of aging.

We find that investors in the lowest cognitive ability decile earn a mean monthly return of 0.984%, investors in the highest cognitive ability decile earn a mean monthly return of 1.264%, and the annualized performance differential of 3.360% ($12 \times (1.264 - 0.984)$) is statistically significant (t-stat = 2.181). The performance differentials are of similar magnitudes when we measure the risk-adjusted performance using the four-factor alpha (annualized performance differential = 3.240%, t-stat = 2.762) or the characteristic-adjusted returns (annualized performance differential = 3.363%, t-stat = 2.827). These performance estimates indicate that the economic costs of cognitive aging are significant.

Examining the factor exposures of the cognitive ability sorted portfolios, we find that high cognitive ability investors hold relatively riskier, smaller, and growth-oriented portfolios. For instance, the four factor exposures ($RMRF$, SMB, HML, and UMD) for the lowest cognitive ability decile portfolio are 1.083, 0.571, 0.314, and -0.218, respectively. In contrast, for the highest cognitive ability decile portfolio, the corresponding factor exposures are 1.219, 0.677, 0.112, and -0.299, respectively. These factor exposure estimates are statistically significant and the factor estimate differences between the high and the low cognitive ability decile portfolios are also significant. This evidence is consistent with the evidence on investors' style preferences, conditional upon age (see Section 4.1 and Table II).

To examine whether the economic costs of aging are also economically significant for investors who hold larger portfolios, we compute the risk-adjusted performance measures, conditional upon portfolio size.[38] The results are shown in Figure 2. We find that the economic cost of cognitive aging increases with portfolio size. As portfolio size increases, high (quintile 5) cognitive ability investors perform better, low (quintile 1) cognitive ability investors do worse, and the performance gap becomes wider. When portfolio size is below $10,000, the annualized characteristic-adjusted return differential is 1.725% and it increases to 5.012% when the portfolio size is above $50,000. When we use the four-factor alpha as the performance measure, the cognitive aging related performance differentials for small, mid-sized, and large portfolios are 2.148%, 2.407%, and 4.613%, respectively.

Collectively, the results from portfolio-based time-series tests indicate that investors who do not experience the adverse effects of cognitive aging (as predicted by our empirical model of cognitive abilities) earn superior risk-adjusted returns. Importantly and somewhat surprisingly, the economic costs of cognitive aging are larger among investors who hold larger portfolios. Those investors are less likely to hold significant positions outside their brokerage

[38]The results are very similar when we compute conditional performance measures using the ratio of the mean portfolio size to the annual income as the conditioning variable.

accounts, especially during the sample period when the median number of brokerage accounts varied between one and two.[39] The performance differentials measured in percentage terms might not appear alarming. But because older investors hold larger portfolios, the economic costs are even more significant when measured in dollar terms.

6.2. *Identifying the Components of Stock Selection Ability*

To better understand how high cognitive ability investors generate superior portfolio performance, we use the Daniel, Grinblatt, Titman, and Wermers (1997) and Wermers (2003) decomposition to estimate the three components of stock selection skill: 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.

As before, we sort investors into five or ten categories based on their residual cognitive ability measures and compute the CS, CT, and AS measures for each of the quintile or decile portfolios. We find that high cognitive ability investors exhibit greater ability to pick stocks within the styles. When we consider five portfolios, the annual CS measures for the lowest and the highest cognitive ability quintile portfolios are -0.496% and 0.660%, respectively, and the difference of 1.156% is significant. As expected, the performance differential is stronger ($= 1.920\%$) when we consider decile portfolios.

Examining the CT estimates for the cognitive ability sorted portfolios, we find that CT estimates are uniformly negative for all portfolios. Thus, both high and low cognitive ability investors lack characteristic timing abilities. However, the low cognitive ability investors have more negative CT measure and exhibit worse timing abilities. For instance, the annual CT measure for the lowest and the highest decile portfolios are -2.001% and -1.156%, respectively, and the difference is positive ($= 0.845\%$).

The AS estimates for the cognitive ability sorted portfolios exhibit less variation and are quite similar. Nevertheless, the performance difference between the highest and the lowest cognitive ability categories is positive. When we consider quintile portfolios, the annual AS differential is 0.292% and when we consider decile portfolios, the differential is 0.429%.

[39] According to the 1992 Survey of Consumer Finances (SCF), the median U.S. household held only one brokerage account (mean = 1.57) in 1992 (about 62% of households had only one brokerage account) and the 1995 SCF indicates that the median number of brokerage accounts increased to two (mean = 2.62) in 1995.

Overall, the performance differentials between the highest and the lowest cognitive ability investor categories with quintile and decile portfolios are 1.949% and 3.195%, respectively.

6.3. Adverse Effects of Aging or Just Unlucky?

While we have used multiple risk-adjusted performance measures to obtain "style adjusted" portfolio performance, given our relatively short sample size, one might argue that the performance differences reflect systematic age-induced style differences rather than the adverse effects of cognitive aging. For instance, the style or industries (e.g., the technology sector) favored by investors with higher cognitive abilities might have yielded exceptional returns during the six-year sample period. Thus, it is possible that older investors do not have poor stock picking skills but rather the styles chosen by them performed poorly during the sample period due to chance.

To address these potential concerns, we extend the performance measurement period both backward and forward by k-months using investors' portfolio compositions in January 1991 and November 1996, respectively. The extended period performance estimates are shown in Figure 3. We find that the performance differential between high and low cognitive ability investors is significant even during the extended sample periods. For $k = 24, 36, 48$, and 60, the characteristic-adjusted annual performance differentials are 2.232%, 2.901%, 2.543%, and 2.351%, respectively. While these estimates are lower than the in-sample performance differential estimate of 3.363%, they are economically significant and indicate that our performance results cannot be attributed to the exceptional performance of certain style or industries during the six-year sample period.

7. Alternative Explanations and Additional Robustness Tests

In this section, we conduct a wide array of tests to examine the robustness of our results and attempt to further rule out alternative interpretations of our findings. The results are summarized in Table VII, where for brevity, we only report the estimates for the variables that are most closely related to our hypotheses.

7.1. Investment Skill Measure using Investors' Trades

Although our skill measures capture different dimensions of investment skill, they are not orthogonal to each other. For additional robustness, we compute a skill measure that is not strongly correlated with our previous skill measures. An additional advantage of this skill measure is that it does not depend upon our ability to observe investors' entire financial portfolios.

Our choice is motivated by Odean (1999) and Barber and Odean (2001), who use a similar measure to identify the stock selection ability of investors. Specifically, we use the mean k-day post-trade buy-sell return differential ($PTBSD(k)$) as a measure of investment skill. The trading based performance measure reflects the belief that investors who have superior stock selection ability are likely to buy stocks that perform better than the stocks they sell. We choose two different values of k ($k = 5$ and 10), because using the same dataset as ours, Coval, Hirshleifer, and Shumway (2002) show that the trading performance of individual investors declines after about two weeks. The maximum correlation between the $PTBSD$ measures and the previously employed skill measures is only 0.012 in absolute terms.

The skill regression estimates with trading based skill measures are summarized in Panel A. Similar to the results from previous skill measures, we find that the *Age* and *Investment Experience* have opposite signs, both when $PTBSD(5)$ and $PTBSD(10)$ are used as dependent variables. The interaction terms mostly have the expected signs, though their estimates are statistically weaker. Thus, older investors trade less (see Table IV) but when they do trade, they make worse buy and sell decisions. The stocks they purchase underperform the stocks they sell by a larger magnitude. This evidence provides additional and independent support to our unconditional (H2) and conditional (H2cond) hypotheses.

7.2. Cognitive Aging and Market Timing Skill

Next, we examine investors' market timing abilities using the two Graham-Harvey performance metrics (Graham and Harvey (1996), Graham and Harvey (1997)). We re-estimate the skill regression and the results are reported in Panel B. Again, we find that, in both instances, age and investment experience maintain their opposite signs. Moreover, the interaction term estimates are very similar to the respective estimates in the alpha regression (see Table V, column (4)). Thus, consistent with our main hypothesis, market timing skill improves with experience but deteriorates with age due to the adverse effects of cognitive aging.

7.3. Split Sample Tests

The 1991 to 1996 sample period encapsulates two distinct market conditions: (i) a relatively flat market during the first half of the sample period, following the 1990 NBER recession, and (ii) an increasing market during the second half of the sample period, representing the start of the "bubble" period. One might be concerned that the negative age-skill relation we find results from the relatively conservative (i.e., less risky) investments by older investors during bullish market conditions. To examine whether the adverse effects of cognitive aging are significant during both periods of weak and strong stock market performance, we estimate the skill regression for the 1991 to 1993 and the 1994 to 1996 sub periods using the characteristic-adjusted portfolio returns. We use the characteristic-adjusted performance measures because the four-factor alpha estimates would be noisier with only three years of data.

The skill regression estimates for the two sub samples are summarized in Panel C. We find evidence of adverse effects of cognitive aging and positive effects of learning during both time-periods. Both age and experience variables have significant coefficient estimates. Interestingly, the age-race/ethnicity interaction terms have statistically insignificant coefficient estimates in the full-sample regression but they have the expected negative signs during the 1994 to 1996 sub period. Overall, the sub sample estimates indicate that the negative age-skill relation we find cannot be attributed to the bullish market conditions during the latter part of the sample period.

7.4. Differential Skill in Identifying Superior Local Stocks

Ivković and Weisbenner (2005) show that, on average, the local stock investments of individual investors perform better than their non-local investments. To examine whether the negative age-skill relation hold in both local and non-local settings, we compute the four-factor alpha for each investor's local portfolio. The local portfolio represents the part of the portfolio that contains stock investments in firms located within a 100 mile radius of investor's location.[40] We re-estimate the skill regressions using the local alpha measure as the dependent variable. The correlation between the local and the total alpha measures is positive (0.513) but not very high.

The skill regression estimates are reported in Panel D. Again, consistent with our main conjecture, we find that age and investment experience estimates have opposite signs. Moreover, the age-race/ethnicity interaction terms have negative coefficient estimates. The *Age*Low Income* and *Age*Low Education* interaction terms have the expected negative signs but those estimates are not statistically significant. The local alpha regression estimates indicate that older investors also experience the adverse effects of cognitive aging even with their local stock investment decisions.

7.5. Do Skill Differences Reflect Noisy Risk Adjusted Performance Estimates?

One might be concerned that our alpha measure is noisy due to the relatively short estimation period and because investors in our sample hold relatively concentrated portfolios with fewer stocks. To address this potential concern, we re-estimate the cross-sectional skill regression for two sub samples: (i) only consider investors with statistically significant (t-statistic $\geq$ 1.95) alpha estimates, and (ii) only consider investors who have at least 60 months of returns data. These skill regression estimates are also reported in Panel D. For both sub samples, we find that the coefficient estimates are consistent with our unconditional (H2) and conditional (H2cond) hypotheses. In fact, the adverse effects of cognitive aging are stronger (the age coefficient estimates are more negative) in both sub samples.

7.6. Investment Skill Measure with Controls for Liquidity and Industry Exposures

To ensure that our results are not influenced by the exceptional performance of certain styles or industries during the relatively short six-year sample-period, we measure investment skill using extended sample periods (see Section 6.3). To further alleviate such concerns, we follow the Pástor and Stambaugh (2002) and Pástor and Stambaugh (2003) methodologies and compute portfolio alphas after employing controls for industry exposures and liquidity. We estimate skill regressions using this eight-factor alpha. The results are reported in Panel D.

[40]Following Ivković and Weisbenner (2005), we choose the 100-mile cutoff to define local and non-local portfolio components, but the results are similar when we use a 250-mile cutoff.

We find that *Age* is still negatively related to investment skill (coefficient estimate = -0.047, t-stat = -3.745), while *Investment Experience* is still positively related to investment skill (coefficient estimate = 0.022, t-stat = 2.314). Furthermore, the interaction terms maintain their negative coefficient estimates.

For additional robustness, we follow an alternative approach to control for the effects of industries. For each investor, we compute the mean portfolio weight allocated to the 48 Fama-French industries (Fama and French (1997)) and employ them as additional independent variables in the skill regressions. As expected, we find that many of these industry weights have large and significant coefficient estimates. For instance, technology stocks in the electronic equipment industry has a strong positive coefficient estimate (estimate = 0.114, t-stat = 10.254) while utilities industry has a strong negative coefficient estimate (estimate = -0.152, t-stat = -12.773). However, the age, experience, and relevant interaction variables still maintain their signs and statistical significance. Thus, the exceptional performance of one or more industries does not seem to considerably influence our skill regression estimates.

7.7. Lack of Skill or Lack of Effort?

One might argue that the negative skill-aging relation we find is not too surprising or economically meaningful because the portfolios we analyze represent investors' "play money" accounts meant primarily for gambling and entertainment purposes. The bulk of investors' actual investments including their retirement accounts are held elsewhere, which we cannot observe.

To examine whether the weaker investment skill of older investors can be attributed to their lack of interest in their brokerage portfolios, we consider a sub sample of investors who hold larger portfolios in comparison to their income levels. Specifically, we re-estimate the skill regressions for the sub sample of investors whose mean portfolio size to annual income ratio (i.e., SIR) is greater than or equal to 1.23 (the top two-third of investors). These equity portfolios are unlikely to represent investors' "play money" accounts and are unlikely to be ignored.

The skill regression estimates for the large portfolio sub sample are summarized in Panel E. We find that the sub sample coefficient estimates are similar to the full sample results. For instance, *Age* has a coefficient estimate of -0.053 (t-stat $= -4.759$) and *Investment Experience* has a coefficient estimate of 0.018 (t-stat $= 1.996$) in the alpha regression. Additionally, two of the four interaction terms have the expected negative signs.

7.8. Are the Results Driven by Investors Located in California?

Our results might be influenced by the strong concentration of investors from California because a considerable portion (27.25%) of our sample is located in California. To guard against this possibility, we exclude all investors who reside in California and re-estimate the skill regressions. The results for the non-Californian sub sample are summarized in Panel E. Again, we find that the sub sample coefficient estimates are similar to the full sample results and portray a similar picture. *Age* has a coefficient estimate of -0.044 (t-stat $= -2.797$) and *Investment Experience* has a coefficient estimate of 0.017 (t-stat $= 2.651$) in the alpha regression.

Collectively, our additional robustness test results indicate that the empirical support for the unconditional (H2) and conditional (H2cond) hypotheses is strong and the results are remarkably consistent with the extant psychological evidence. Our findings are not sensitive to the choice of skill measures, potential error in skill measurement, choice of the risk adjustment methodology, specific market conditions, investors' lack of interest in relatively small brokerage portfolios, and the geographical concentration of our sample investors.

8. Summary and Implications of Our Research

This is the first study to examine the potential role of cognitive aging on the stock investment decisions of older investors. We investigate whether older individual investors make better investment choices because of greater investment experience or whether their investment skill deteriorates with age due to the adverse effects of cognitive aging. This is an important issue that has implications for how individual investors should structure their portfolios over time, the type of investment advice they should seek over their lifetime, and the potential effects of changes in government policy on investment generated retirement income.

Our evidence indicates that older and more experienced investors hold less risky portfolios, exhibit stronger preference for diversification, trade less frequently, and exhibit greater propensity for year-end tax-loss selling. Thus, their choices reflect greater knowledge about investing. But consistent with the cognitive aging hypothesis, we also find that older investors have worse investment skill, where the skill deteriorates sharply around the age of 70. Examining the economic costs of aging, we find that older investors earn about 3-5% lower returns annually on a risk-adjusted basis. Collectively, our evidence indicates that older investors' portfolio choices reflect greater knowledge about investing but their investment skill deteriorates with age due to the adverse effects of cognitive aging.

These results could potentially be used to improve the investment decisions of older investors. We do not prescribe that older investors should stop making independent investment decisions. Rather, based on the evidence, our hope is that older people would recognize the adverse effects of cognitive aging and would try to compensate for those effects, perhaps by seeking advice from a financial advisor or some other qualified investment professional. An investment refresher course that highlights the adverse effects of cognitive aging and suggests effective compensating mechanisms might also be helpful. This may especially be a wise decision if an investor holds portfolios larger than those examined in this study. Furthermore, the performance results indicate that while most investors in our sample would benefit from holding a passive index fund, the potential benefits of passive investing are likely to be greater for older investors.

In broader terms, our findings could help us better understand the stock market participation puzzle. Theoretical models typically have the greatest difficulty in explaining the participation rates in the extreme age categories (e.g., Gomes and Michaelides (2005)). Based on our findings, we conjecture that younger investors would stay away from the stock market due to their lack of investment experience, while older investors would be less willing to participate due to a perception of declining cognitive abilities. A theoretical model that synthesizes the positive effects of experience and adverse effects of cognitive aging may provide a fresh perspective into the stock market participation and the broad asset allocation decisions over the life-cycle.

Our empirical evidence also provides specific guidance for refining asset pricing models that incorporate the effects of aging. Previous theoretical models have examined the aggregate effects of aging on the stock market behavior (e.g., Bakshi and Chen (1994), Poterba (2001), Goyal (2004)) through the channel of risk aversion. Our results indicate that age is likely to influence asset returns through an additional channel. Specifically, if older investors become aware of their declining investment skill, the perceived costs for stock market participation would increase, and those investors would demand a higher premium for investing in the stock market. In this scenario, stock market returns could increase as the population ages, even when there is no substantial increase in people's risk aversion. Additionally, our evidence on the stock preferences of older investors provide guidance about the segments of the market (e.g., high dividend yield and less risky stocks), where the effects of aging on stock returns are likely to be stronger.

We conclude the paper with a caveat. Although our results are strongly consistent with the cognitive aging hypothesis, some amount of caution must be exercised while interpreting this evidence because we cannot directly measure the degree of cognitive decline among older investors. In addition, because we use a relatively short six-year panel to identify the adverse effects of cognitive aging, in spite of our numerous attempts to rule out alternative explanations for our results based on cohort and time effects, some concerns might remain. Nevertheless, given the remarkable similarities between our results and the evidence from psychological research on aging, the footprints of cognitive aging in investment decisions appear strong and quite difficult to ignore.

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Table I

Summary Statistics: Age Sorted Investor Groups

This table reports the summary statistics for age sorted investor groups. Portfolio size is the mean portfolio size of the investors in the group during the sample period. Income is the annual household income and wealth is the self-reported net worth reported at the account opening date. SIR is the portfolio size to income ratio, and SWR is the portfolio size to wealth ratio. Investment experience is the number of years between the account opening date and December 31, 1996. In Panel A, we report the measures for the five age quintiles. We further divide the 60-94 age group (the highest age quintile) into quintiles and present the summary statistics in Panel B. In Panel A (Panel B), there are 5,404 (1,351) observations in each group. The retail investor data are from a large U.S. discount brokerage house for the period from 1991 to 1996.

Panel A: All Investors

Age Group	Portfolio Size	Income	Wealth	SIR	SWR	Experience
Q1 (20-38)	$23,372	$90,146	$196,765	0.414	0.283	8.46
Q2 (39-46)	$23,372	$98,619	$243,081	0.377	0.246	9.68
Q3 (47-52)	$29,270	$101,086	$247,701	0.462	0.304	9.92
Q4 (53-59)	$32,543	$93,363	$296,595	0.554	0.298	10.01
Q5 (60-94)	$49,274	$70,700	$360,403	1.096	0.346	10.49
Mean	$31,566	$90,782	$268,909	0.581	0.295	9.71

Panel B: Investors With Age 60 or Above

Age Group	Portfolio Size	Income	Wealth	SIR	SWR	Experience
Q1 (60-62)	$37,652	$87,134	$340,955	0.599	0.293	9.85
Q2 (63-64)	$39,678	$74,890	$356,931	0.765	0.322	10.39
Q3 (65-70)	$48,416	$72,833	$409,153	1.040	0.313	10.33
Q4 (71-74)	$48,556	$67,574	$350,882	0.984	0.338	10.45
Q5 (75-94)	$64,526	$64,111	$334,917	1.469	0.464	10.87

Table II

Age and Equity Style Preferences

This table reports the style preferences of age sorted investor groups. The following six stock characteristics are used to measure style preferences: (i) stock volatility or total risk, (ii) dividend yield, (iii) market beta, estimated using past 60 months of data, (iv) firm size, (v) book-to-market (B/M) ratio, and (vi) past 12-month return or momentum. The top three and the bottom three deciles are used to define the extreme style portfolios (i.e., the high and the low portfolios). The style preference measure for a group of investors is the unexpected portfolio weight (= actual weight − expected weight) allocated to a style in the group-level portfolio. To compute actual style weights, we combine the portfolios of all investors in the group and construct a group-level portfolio (p). For portfolio p, at the end of each month t, we compute the *actual* percentage weights assigned to various style portfolios (w_{spt}) such as small-cap stocks, value stocks, etc. The subscript s represents a style portfolio. Additionally, we construct the aggregate market portfolio by combining the entire universe of stocks available on CRSP and compute the expected percentage weights assigned to various style portfolios(w_{smt}). The difference ($w_{spt} - w_{smt}$) provides a measure of an investor group's style preferences. The sample-period means of actual monthly style weights are reported in the table. For brevity, only the weights for the two extreme style categories are reported. In Panel A, we report the actual style weights for the five age quintiles, and in Panel B, we further divide the 60-94 age group (the highest age quintile) into quintiles and present the style weights. The expected portfolio or style weights are also reported in the first row of Panel A. The retail investor data are from a large U.S. discount brokerage house for the period from 1991 to 1996.

Table II (Continued)

Age and Equity Style Preferences

Panel A: Aggregate Percentage Portfolio Weights For All Investors

Age	(1):Total Risk		(2):Div Yield		(3):Mkt Beta		(4):Size		(5):B/M		(6):Momentum	
Group	Low	High	Low	High	Low	High	Small	Large	Growth	Value	Low	High
Exp Wts	76.19	2.15	34.63	24.13	11.74	28.87	4.59	81.45	53.50	11.86	13.54	25.03
20-38	**42.34**	**18.63**	**30.41**	**30.84**	**11.25**	**44.35**	**22.13**	**58.49**	**50.05**	**20.24**	**29.61**	**27.01**
39-46	42.84	18.61	28.97	30.70	11.66	42.26	23.08	56.85	48.61	21.10	29.73	26.30
47-52	44.20	17.64	27.49	32.82	12.27	41.08	22.28	57.87	47.66	21.60	28.66	26.30
53-59	45.13	18.25	26.41	35.01	13.20	39.55	23.00	57.59	47.49	22.32	28.58	25.93
60-94	**53.55**	**15.13**	**21.29**	**42.47**	**17.07**	**32.82**	**19.59**	**61.43**	**44.25**	**24.10**	**26.89**	**22.97**

Panel B: Aggregate Percentage Portfolio Weights For Investors With Age 60 or Above

Age	(1):Total Risk		(2):Div Yield		(3):Mkt Beta		(4):Size		(5):B/M		(6):Momentum	
Group	Low	High	Low	High	Low	High	Small	Large	Growth	Value	Low	High
60-62	**46.06**	**18.73**	**25.44**	**35.10**	**15.04**	**37.27**	**23.11**	**57.18**	**46.52**	**23.15**	**28.52**	**25.58**
63-64	51.38	16.43	22.33	39.68	15.17	35.69	20.52	60.27	45.50	23.11	27.25	24.13
65-70	50.90	16.13	23.56	38.91	16.26	34.15	20.84	59.47	45.98	23.26	27.96	23.32
71-74	55.18	13.89	19.76	46.06	18.26	31.28	19.25	61.67	42.83	25.29	26.20	22.53
75-94	**57.34**	**13.77**	**19.54**	**46.93**	**18.80**	**30.01**	**17.23**	**64.57**	**41.95**	**25.31**	**25.66**	**21.62**

Table III

Age and Stock Preferences: Panel Regression Estimates

This table reports the panel regression estimates for different age-based investor groups, where the excess weight assigned to a stock in the aggregate group portfolio is the dependent variable. Three aggregate group portfolios are considered: the aggregate portfolio of younger (age range 20-38), older (age range 60-94), and very old (age range 75-94) investors. 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 mean return, idiosyncratic volatility, skewness, kurtosis, and the price of the stock is used as independent variables. Additionally, the following control variables are employed: (i) market beta, which is estimated using past 60 months of 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) an S&P500 dummy which is set to one if the stock belongs to the S&P500 index, and (vii) monthly volume turnover. The t-statistics for the coefficient estimates are shown in smaller font below the estimates. To account for potential autocorrelation and cross correlation in errors, we use the non-parametric approach of Driscoll and Kraay (1998) and obtain corrected standard errors. To ensure that extreme values are not affecting our results, we winsorize all variables at their 0.5 and 99.5 percentile levels. The independent variables have been standardized so that each variable has a mean of zero and a standard deviation of one. The individual investor data are from a large U.S. discount brokerage house for the period from 1991 to 1996.

Table III (Continued)

Age and Stock Preferences: Panel Regression Estimates

	Age Groups				
Variable	(1):20-38	(2):60-94	(3):75-94	(2)−(1)	(3)−(1)
Mean Return	−0.118	−0.146	−0.134	−0.016	−0.021
	−14.295	−14.293	−13.406	−1.747	−2.356
Idiosyncratic Volatility	0.139	0.128	0.116	**−0.046**	**−0.050**
	24.124	18.095	16.753	−7.138	−7.880
Skewness	0.052	0.018	−0.019	**−0.037**	**−0.060**
	11.604	3.254	−3.538	−7.266	−12.018
Kurtosis	−0.075	−0.047	−0.015	0.040	0.060
	−15.670	−7.984	−2.523	7.513	11.314
Stock Price	−0.033	−0.054	−0.055	−0.014	−0.013
	−11.268	−14.903	−15.520	−1.213	−0.859
Market Beta	0.095	0.033	0.007	**−0.068**	**−0.081**
	29.707	8.383	1.881	−19.061	−22.980
Log(Firm Size)	−0.128	−0.104	−0.007	**0.026**	**0.115**
	−31.992	−21.011	−1.348	3.415	26.088
Book-To-Market Ratio	−0.058	−0.025	−0.032	0.039	0.033
	−19.793	−6.940	−9.199	11.965	10.172
Past 1-Month Stock Return	0.003	0.009	0.010	0.002	0.004
	0.882	2.209	2.448	0.685	1.009
Past 12-Month Stock Return	0.001	0.025	0.016	0.014	0.006
	0.134	4.607	2.996	2.789	1.286
S&P500 Dummy	0.008	0.067	−0.005	−0.010	−0.011
	4.534	20.810	−2.537	−5.039	−5.682
Monthly Turnover	0.062	−0.003	0.053	**−0.017**	**−0.025**
	23.627	−1.564	16.851	−5.876	−8.604
Month Fixed Effects	Yes	Yes	Yes	Yes	Yes
Number of Observations	113,269	113,269	113,269	113,269	113,269
Adjusted R^2	0.056	0.031	0.011	0.010	0.024

Table IV

Age, Investment Experience, and Investment Decisions: "Rule of Thumb" Cross-Sectional Regression Estimates

This table reports the estimates for cross-sectional regressions, where a measure of investment choice reflecting a "rule of thumb" is the dependent variable. We consider four different measures: (i) average number of stocks in the portfolio (NSTKS), (ii) portfolio turnover (TURN), (iii) proportion of "losers" (stock investments where an investor has experienced a loss) realized in the month of December (TAX), and (iv) portfolio dividend yield (PDY). All measures are obtained for each investor using their choices during the sample period. **Independent variables:** *Age* corresponds to the head of the household and *Investment Experience* is the number of days between the account opening date and December 31, 1996. The *Over 70 Dummy* is set to one if the investor is at least 70 years old. *Income* is the total household income. *Education* represents the proportion of people in investor's zip code who has attained a bachelor's or higher educational degree. The *Male Dummy* is set to one if the head of the household is male, and the *Retired* dummy is set to one if the head of the household is retired. *Portfolio Size* is the average market capitalization of the household portfolio, *Portfolio Turnover* is the average of monthly buy and sell turnovers, and *Portfolio Div Yield* is the average dividend yield of the household portfolio. **Control variables:** The *RMRF, SMB, HML,* and *UMD Exposures* are the factor loadings of an investor's portfolio. These loadings are obtained by fitting a four-factor time-series model to the monthly portfolio returns series of each investor over the period the investor is active. *Mutual Fund Holdings* is the proportion of the equity portfolio allocated to mutual funds. **Other details:** The t-statistics for the coefficient estimates are shown in smaller font below the estimates. Robust, clustered standard errors are used to account for potential cross-sectional dependence within zip codes. To ensure that extreme values are not affecting our results, we winsorize all variables at their 0.5 and 99.5 percentile levels. The independent variables have been standardized so that each variable has a mean of zero and a standard deviation of one. The individual investor data are from a large U.S. discount brokerage house for the period from 1991 to 1996. The zip code-level education data are from the 1990 U.S. Census.

Table IV (Continued)

Age, Investment Experience, and Investment Decisions: "Rule of Thumb" Cross-Sectional Regression Estimates

Variable	(1):NSTKS	(2):NSTKS	(3):TURN	(4):TURN	(5):TAX	(6):PDY
Intercept	4.308	4.392	5.344	4.121	0.157	1.773
	18.967	20.715	27.395	11.525	14.211	18.467
Age	**0.476**	**0.186**	**−0.407**	**−0.183**	**0.016**	**0.116**
	20.150	7.454	−7.347	−4.355	5.696	10.537
Investment Experience	**0.517**	**0.423**	**−0.223**	**−0.177**	**0.006**	**−0.013**
	21.294	19.113	−3.922	−4.749	2.311	−2.285
Income		0.020		−0.100	0.003	−0.035
		2.019		−2.665	1.329	−3.520
Education		−0.035		−0.014	−0.004	−0.001
		−1.878		−0.376	−1.685	−0.127
Male Dummy		0.013		0.157	0.006	−0.040
		1.345		4.115	2.655	−0.969
Retired Dummy		0.005		0.006	−0.001	0.032
		0.210		0.168	−0.333	3.265
Portfolio Size		1.642		0.282	0.075	0.116
		30.266		7.154	22.960	11.218
Portfolio Turnover		−0.399			0.093	−0.066
		−17.697			28.848	−6.589
Portfolio Dividend Yield		0.152		−0.286	−0.003	
		5.922		−6.589	−1.221	
(For brevity, the coefficient estimates of control variables are suppressed.)						
Number of Investors	27,716	19,906	27,716	19,906	19,906	19,906
Adjusted R^2	0.044	0.252	0.035	0.158	0.120	0.282

Table V

Determinants of Investment Skill: Cross-Sectional Regression Estimates

This table reports the estimates for cross-sectional regressions, where a measure of individual skill is the dependent variable. We consider three skill measures: (i) the monthly Sharpe ratio (SR), (ii) the four factor alpha (Alpha), and (iii) the average characteristic-adjusted monthly portfolio return (CharAdj). The four factor alpha is obtained by fitting a four-factor time-series model to the monthly portfolio returns series of each investor over the period the investor is active. In column (7), we present panel regression estimates, where the skill measure is the monthly characteristic-adjusted returns. **Independent variables:** *Age* corresponds to the head of the household and *Investment Experience* is the number of days between the account opening date and December 31, 1996. *Income* is the total household income and *Low Income* dummy is set to one for investors with an annual household income of $40,000 or below. *Education* represents the proportion of people in investor's zip code who has attained a bachelor's or higher educational degree. *Low Education* dummy is set to one for investors who are in the lowest education level quintile. The *Male Dummy* is set to one if the head of the household is male, and the *Retired* dummy is set to one if the head of the household is retired. The *African American* (*Hispanic*) variable is the ratio of the population of African-Americans (Hispanics) and Whites in the investor's zip code. **Control variables:** *Portfolio Size* is the average market capitalization of the household portfolio, *Portfolio Turnover* is the average of monthly buy and sell turnovers, and *Portfolio Div Yield* is the average dividend yield of the household portfolio. The *RMRF, SMB, HML,* and *UMD Exposures* are the factor loadings of an investor's portfolio. The factor exposures are not used as control variables in specification (7). **Other details:** The t-statistics for the coefficient estimates are shown in smaller font below the estimates. Robust, clustered standard errors are used to account for potential cross-sectional dependence within zip codes. To ensure that extreme values are not affecting our results, we winsorize all variables at their 0.5 and 99.5 percentile levels. The independent variables have been standardized so that each variable has a mean of zero and a standard deviation of one. The individual investor data are from a large U.S. discount brokerage house for the period from 1991 to 1996. The zip code-level education and race/ethnicity data are from the 1990 U.S. Census.

Table V (Continued)

Determinants of Investment Skill: Cross-Sectional Regression Estimates

	SR		Alpha		Char Adj		
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)Panel
Intercept	0.101	0.102	−0.341	−0.340	0.006	−0.001	0.031
	13.173	9.568	−14.285	−13.099	0.699	−0.101	0.448
Age	−0.001	**−0.014**	−0.042	**−0.051**	−0.044	**−0.054**	**−0.063**
	−0.935	−3.355	−5.047	−4.735	−7.293	−2.945	−2.257
Investment Experience	0.011	**0.010**	−0.010	**0.020**	0.037	**0.027**	**0.028**
	11.644	9.450	−1.184	2.283	6.053	3.891	2.289
Over 70 Dummy		−0.007		−0.025		−0.020	−0.022
		−1.483		−2.073		−2.163	−2.886
Income		0.001		0.001		0.011	0.004
		0.824		0.062		1.112	0.470
Low Income Dummy		−0.002		−0.004		−0.009	−0.011
		−1.223		−0.275		−0.773	−1.004
*Age * Low Income*		−0.002		−0.025		−0.014	−0.022
		−2.033		−2.674		−1.996	−2.242
Education		0.002		0.014		0.017	0.013
		1.882		2.527		2.717	2.089
Low Education Dummy		−0.002		−0.012		−0.014	−0.015
		−1.809		−1.813		−1.798	−1.401
*Age * Low Education*		−0.001		−0.003		−0.005	−0.004
		−1.789		−1.250		−2.719	−2.242
Male Dummy		−0.001		−0.001		−0.006	−0.021
		−0.550		−0.108		−0.945	−1.306
Retired Dummy		0.001		0.007		0.004	−0.010
		0.072		0.760		0.504	−0.957
Hispanic Dummy		−0.002		−0.003		0.009	−0.007
		−0.350		−0.650		0.220	−1.072
African American Dummy		−0.005		−0.016		−0.012	−0.003
		−1.038		−1.403		−1.133	−0.879
*Age * Hispanic*		−0.004		−0.034		−0.025	−0.017
		−3.568		−3.516		−3.111	−2.876
*Age * African American*		0.002		0.010		0.009	−0.007
		0.437		0.588		1.108	−1.035
(For brevity, the coefficient estimates of control variables are suppressed.)							
Number of Investors	27,716	19,906	27,716	19,906	27,716	19,906	1,186,835
Adjusted R^2	0.015	0.055	0.014	0.254	0.028	0.090	0.061

Table VI

Determinants of Cognitive Abilities

This table reports the cross-sectional regression estimates, where the dependent variable is a measure of cognitive ability. The independent variables are the main determinants of cognitive ability identified in the psychological literature and available in our individual investor sample. 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 Income* dummy is set to one for investors who are in the lowest income quintile. *Low Education* dummy is set to one for investors who are in the lowest education level category. *Over 70 Dummy* is set to one for individuals with age over 70. The t-statistics for 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 so that each variable has a mean of zero and a standard deviation of one. The household data are from the 2005 wave of the Survey of Health, Aging, and Retirement in Europe (SHARE).

	Cognitive ability measure is:			
Variable	Verbal	Quantitative	Memory	Combined
Intercept	−0.001	−0.005	−0.003	0.001
	−0.080	−0.754	−0.571	0.118
Wealth	0.049	0.020	0.012	0.031
	8.038	3.271	1.963	5.628
Income	0.047	0.053	0.002	0.041
	7.818	8.482	0.372	7.230
Education	**0.365**	**0.313**	**0.312**	**0.398**
	25.991	16.255	17.306	25.216
Age	**−0.129**	**−0.160**	**−0.239**	**−0.211**
	−13.178	−15.718	−24.088	−23.039
Retired Dummy	−0.081	−0.065	−0.011	−0.056
	−11.393	−10.394	−1.182	−9.953
Over 70 Dummy	−0.010	−0.036	−0.021	−0.032
	−1.932	−3.186	−2.902	−3.199
Age × Low Income	**−0.086**	**−0.055**	**−0.066**	**−0.084**
	−12.142	−7.460	−9.196	−12.794
Age × Low Education	0.001	**−0.014**	**−0.030**	**−0.024**
	0.108	−2.500	−4.140	−3.060
Number of Individuals	22,153	21,777	21,904	22,215
Adjusted R^2	0.249	0.211	0.245	0.341

Table VII

Robustness Test Results:
Skill Regression Estimates using Sub Samples and Alternative Skill Measures

This table reports the estimates for cross-sectional regressions, where a portfolio performance measure is the dependent variable. For brevity, we only report the estimates for the variables that are related to our main hypotheses. The estimates for the control variables are suppressed. In Panel A, we use a trading based skill measure, which is defined as the k-day post-trade buy-sell return differential ($PTBSD(k)$), $k = 5, 10$. In Panel B, we consider the two Graham-Harvey performance measures (GH_1 and GH_2). In GH_1, the S&P 500 futures index is levered up or down to match the volatility of the investor portfolio. GH_1 is the difference between the mean return on the newsletter portfolio and the mean return on the volatility-matched market portfolio. GH_2 is computed by levering up or down each investor's portfolio to match the volatility of the S&P500 futures index. GH_2 is the difference between the mean return on the volatility-matched portfolio and the return on the S&P500 futures index. In both cases, the volatilities are computed for the time-period in which an investor is active and the appropriate portfolio is levered up or down by combining it with T-bills. In Panel C, we measure investment skill using characteristic-adjusted portfolio returns and following Daniel and Titman (1997) methodology. In Panel D, we use the four-factor alpha as a measure of investment skill, where we use both the total alpha and the local alpha measures. To compute the total four-factor alpha for an investor portfolio, we use all stocks in the investor's portfolio and to compute the local four-factor alpha, we only consider the part of the investor portfolio that contains stock investments in firms located within a 100 mile radius of investor's location. In Panel D, we also report estimates using the total portfolio four-factor alpha for two sub samples: (i) only consider investors with statistically significant (t-statistic ≥ 1.95) alpha estimates, and (ii) only consider investors who have at least 60 months of returns data. Lastly, in this Panel, we report the skill regression estimates, where an eight-factor alpha is the dependent variable. To compute the eight-factor alpha, we use the four commonly used risk factors (*RMRF*, *SMB*, *HML*, and *UMD*), three industry factors (Pástor and Stambaugh (2003)), and a liquidity factor (Pástor and Stambaugh (2003)). Last, in Panel E, we report the cross-sectional regression estimates for the following two sub samples: (i) investors with large portfolios relative to income and (ii) investors who are located outside California. The independent variables have been defined previously in Table V. **Other details:** The t-statistic for the coefficient estimates are shown in smaller font below the estimates. Robust, clustered standard errors are used to account for potential cross-sectional dependence within zip codes. To ensure that extreme values are not affecting our results, we winsorize all variables at their 0.5 and 99.5 percentile levels. The independent variables have been standardized so that each variable has a mean of zero and a standard deviation of one. The individual investor data are from a large U.S. discount brokerage house for the period from 1991 to 1996. The zip code-level education and race/ethnicity data are from the 1990 U.S. Census.

Table VII

Robustness Test Results: Skill Regression Estimates using Sub Samples and Alternative Skill Measures

Panel A: Skill Measurement using Trading Based Skill Measures

Robustness Test	Age	Inv Exper	Age*Hisp	Age*AfrAm	Age*LowInc	Age*LowEdu
PTBSD(5)	−0.081	0.054	−0.018	−0.037	0.015	−0.041
	−2.682	2.134	−1.704	−1.446	0.581	−1.253
PTBSD(10)	−0.153	0.082	−0.016	−0.018	−0.038	−0.071
	−3.790	2.430	−1.469	−1.537	−1.882	−1.621

Panel B: Skill Measurement using Market Timing Performance Metrics

Robustness Test	Age	Inv Exper	Age*Hisp	Age*AfrAm	Age*LowInc	Age*LowEdu
Graham-Harvey 1	−0.023	0.036	−0.042	0.011	−0.020	−0.009
	−1.912	3.469	−4.002	1.071	−1.883	−1.672
Graham-Harvey 2	−0.010	0.004	−0.010	0.006	−0.005	−0.002
	−2.710	2.359	−3.124	0.827	−1.434	−1.536

Panel C: Regression Estimates using Characteristic-Adjusted Skill Measures

Robustness Test	Age	Inv Exper	Age*Hisp	Age*AfrAm	Age*LowInc	Age*LowEdu
1991-93 Sub Sample	−0.041	0.035	0.001	0.011	−0.011	−0.010
	−4.739	3.769	0.520	1.137	−2.050	−1.850
1994-96 Sub Sample	−0.034	0.030	−0.021	−0.014	−0.005	−0.007
	−2.064	3.672	−2.767	−1.903	−1.698	−1.740

Table VII(Continued)

Robustness Test Results:
Skill Regression Estimates using Sub Samples and Alternative Skill Measures

Panel D: Skill Measurement using Multifactor Alphas

Robustness Test	Age	Inv Exper	Age*Hisp	Age*AfrAm	Age*LowInc	Age*LowEdu
Four-Factor Alpha						
Local	−0.039	0.026	−0.037	−0.021	−0.008	−0.009
	−2.738	2.504	−3.408	−1.921	−0.757	−0.702
Significant	−0.053	0.037	−0.025	0.003	−0.016	−0.009
	−5.656	10.305	−3.235	0.662	−2.101	−1.884
Min 60 Months of Returns	−0.062	0.031	−0.034	0.010	−0.009	−0.010
	−3.247	5.019	−2.751	0.585	−2.746	−2.040
Eight-Factor Alpha						
Full Sample	−0.047	0.022	−0.023	0.009	−0.017	−0.004
	−3.745	2.314	−3.652	1.124	−2.668	−1.439

Panel E: Sub Sample Estimates using Four-Factor Alphas

Skill Measure	Age	Inv Exper	Age*Hisp	Age*AfrAm	Age*LowInc	Age*LowEdu
Investors With Large Portfolios	−0.053	0.018	−0.032	0.007	−0.032	0.001
	−4.759	1.996	−3.268	0.768	−3.099	0.088
Investors Outside California	−0.044	0.017	−0.029	0.016	−0.032	−0.003
	−2.797	2.651	−2.732	0.532	−3.006	−1.197

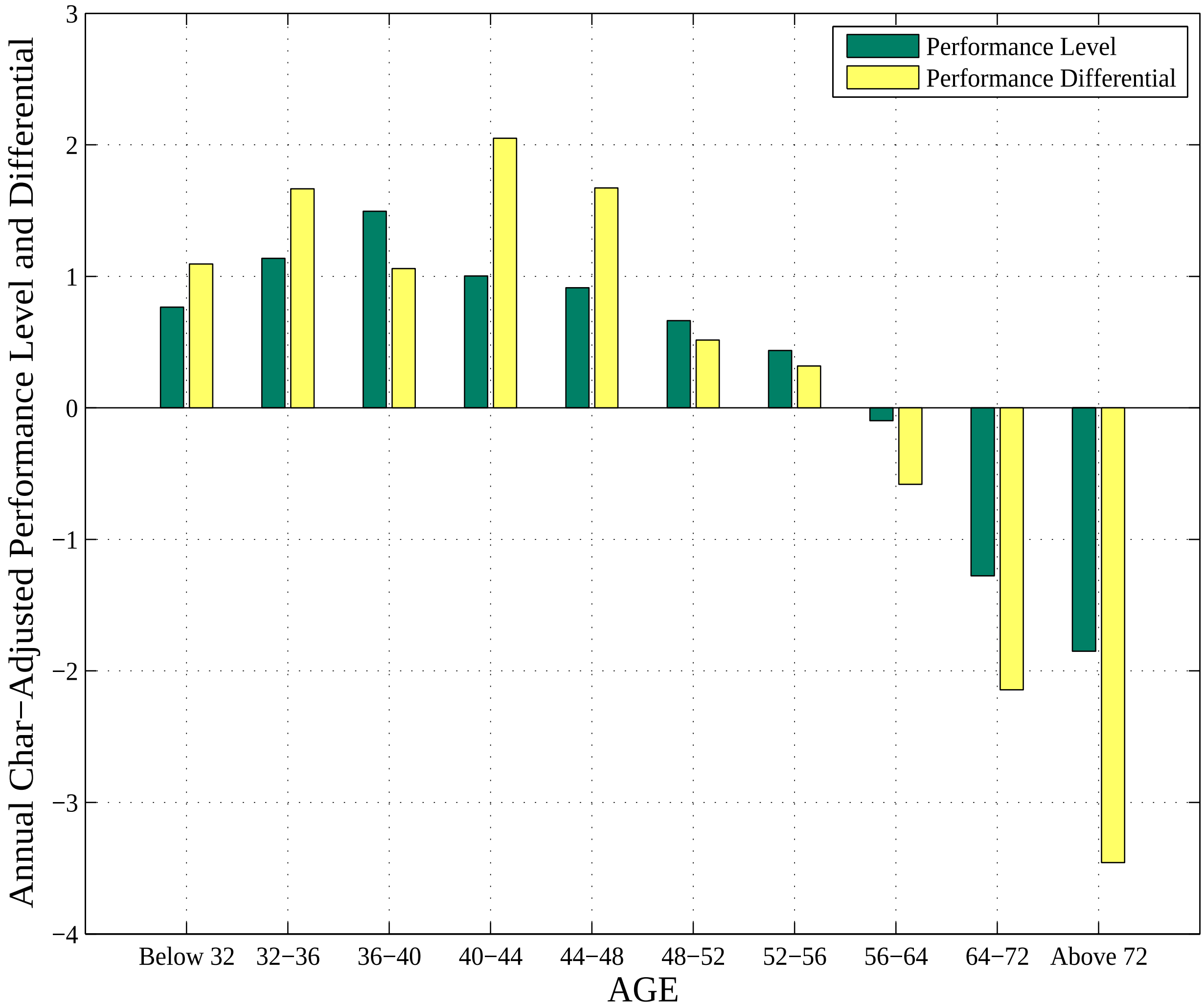

Figure 1. Age, portfolio performance, and change in performance. This figure shows the risk-adjusted performance level (annualized characteristic-adjusted percentage returns) and the performance differential, conditional upon age. The performance differential is the change in the performance between the last two and the first two years of the sample period. The individual investor data are from a large U.S. discount brokerage house for the period from 1991 to 1996.

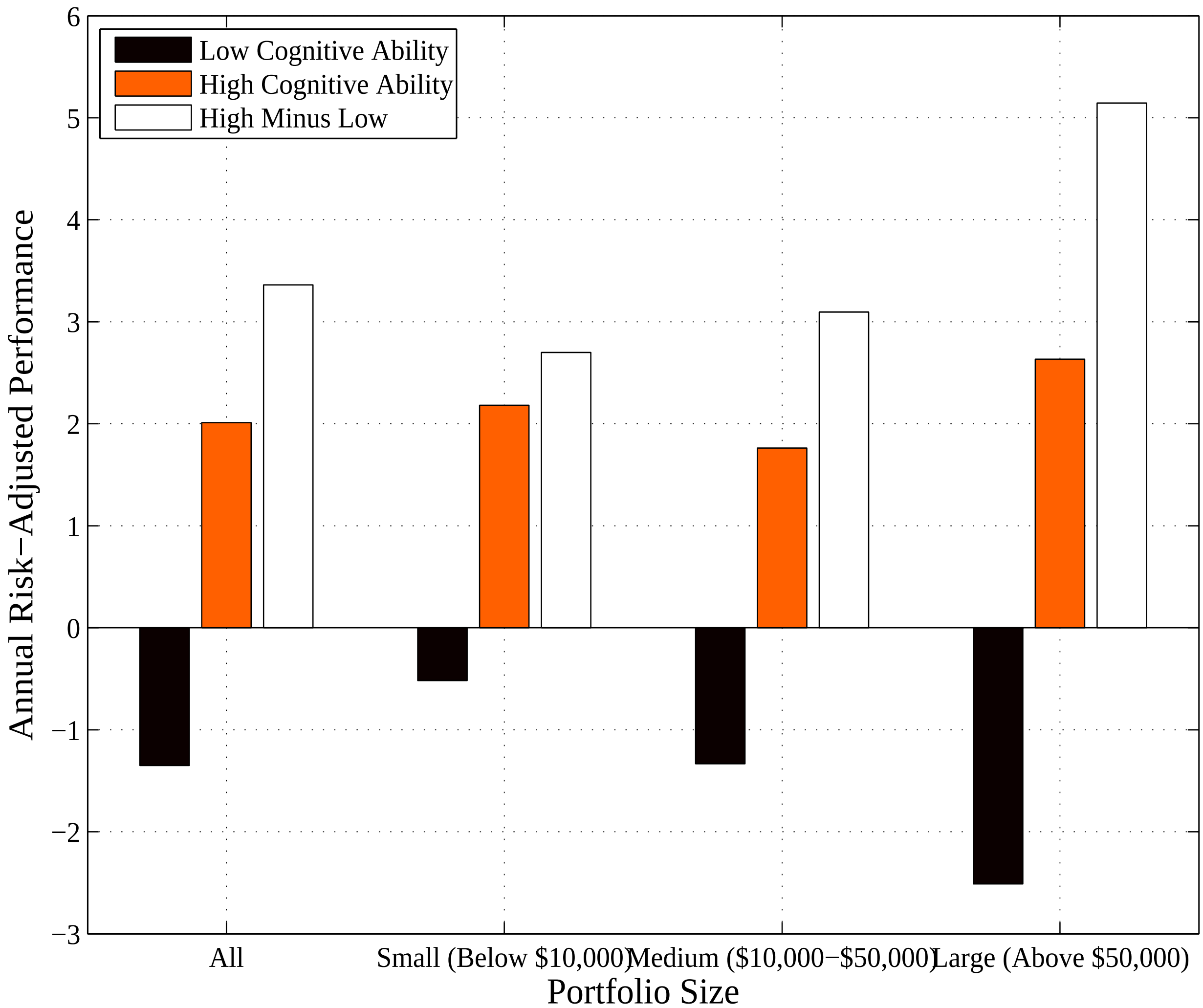

Figure 2. Cognitive aging, portfolio size, and portfolio performance. This figure shows the risk-adjusted performance (annualized characteristic-adjusted percentage returns), conditional upon portfolio size and investors' predicted cognitive abilities. The empirical model of cognitive abilities estimated in Table VI is used to obtain the predicted cognitive ability measures. We regress the predicted cognitive ability measure on investment experience and obtain a residual cognitive ability measure that is orthogonal to experience. The individual investor data are from a large U.S. discount brokerage house for the period from 1991 to 1996.

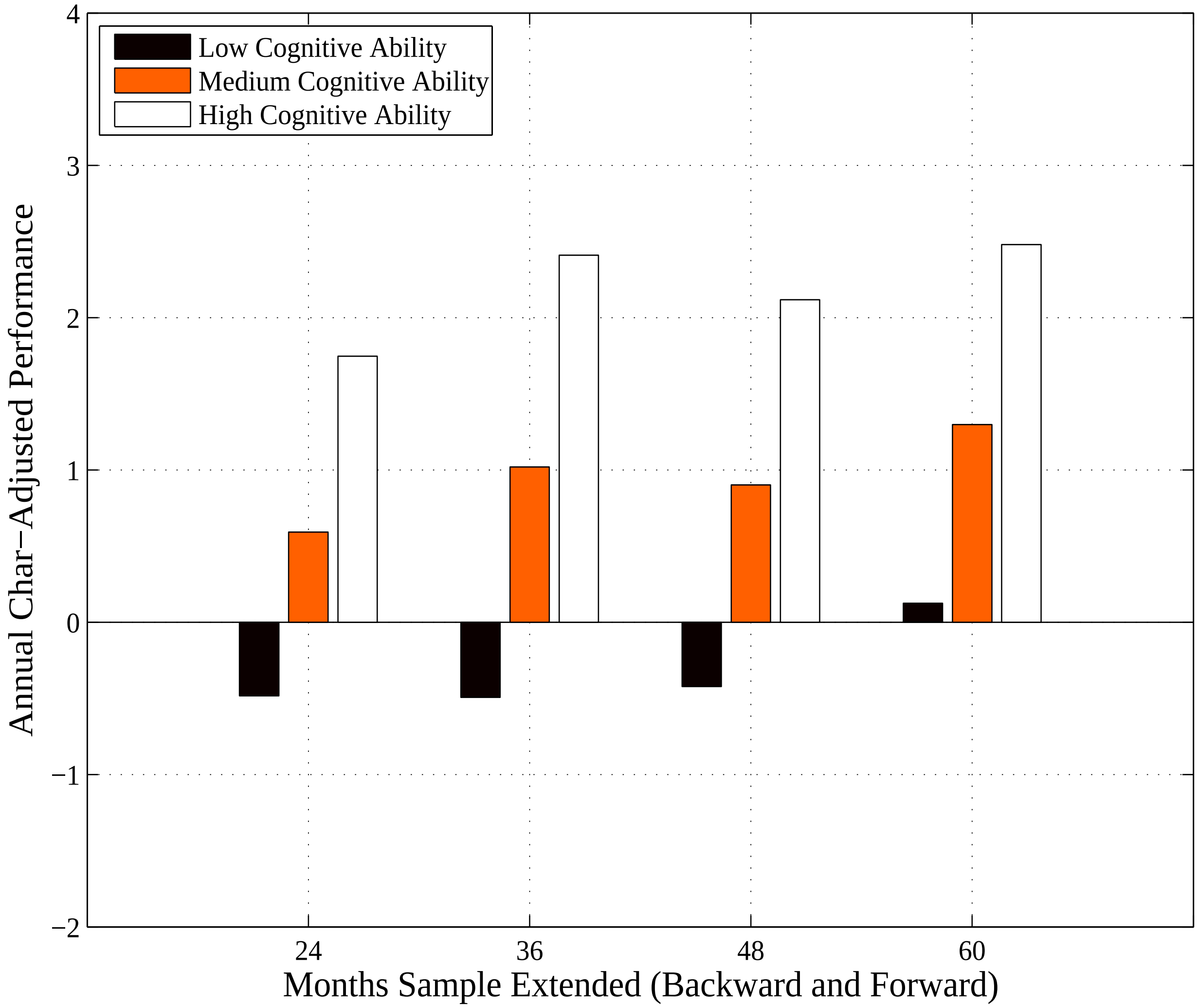

Figure 3. Cognitive aging and portfolio performance for extended sample periods. This figure shows the risk-adjusted performance (annualized characteristic-adjusted percentage returns) for extended sample periods, conditional upon the level of cognitive aging. The sample period is extended by k-months in both backward and forward directions using the portfolio weights in January 1991 and November 1996, respectively. The individual investor data are from a large U.S. discount brokerage house for the period from 1991 to 1996.