DO OLDER INVESTORS MAKE BETTER INVESTMENT DECISIONS?

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Abstract—This paper examines the investment decisions of older individual investors. We find that older and experienced investors are more likely to follow rules of thumb that reflect greater investment knowledge. However, older investors are less effective in applying their investment knowledge and 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 aging dominate the positive effects of experience. These results indicate that older investors' portfolio decisions reflect greater knowledge about investing, but investment skill deteriorates with age due to the adverse effects of cognitive aging.

I.   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 quality of life after retirement. The popular media have often raised the concern that older people would not be able to generate the annual income necessary to sustain the preretirement quality of life. 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 postretirement income and, therefore, one of the main determinants of their postretirement quality of life.

In this study, we focus on an important but previously unexplored determinant of the stock investment decisions of older investors: cognitive aging. We examine whether older people make better investment choices as they gain more investment knowledge and 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. 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 evidence from cognitive aging and learning research indicates that aging and learning processes operate jointly. In particular, studies in cognitive aging demonstrate that both physical and cognitive abilities, especially memory, decline with age (Horn, 1968; Fair, 1994, 2004; Salthouse, 2000; Schroeder & Salthouse, 2004). Further, 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 (List, 2003; Feng & Seasholes, 2005; Dhar & Zhu, 2006; Goetzmann & Kumar, 2008).

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 would hinder the effective application of those principles. If the adverse effects of aging dominate the positive effects of experience, older investors' portfolios would underperform common performance benchmarks. 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.

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 investment rule of thumb or a measure of investment skill. The key explanatory 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.[2] 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 attempt to separate the positive effects of experience from the negative effects of cognitive aging.

[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] 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 had 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.

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, exhibit greater propensity for year-end tax-loss selling, and exhibit weaker behavioral biases. 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. These results suggest that older investors exhibit a greater propensity to use common investment rules of thumb, but they appear less skillful in successfully implementing those rules.[3]

To gather additional support for our main hypothesis, we seek guidance from the psychology literature that examines the conditional effects of cognitive aging. The evidence from this literature 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, et al., 1986; Baltes & Lang, 1997; Cagney & Lauderdale, 2002). The evidence also suggests that the age-related decline in cognitive abilities is steeper for African Americans and Hispanic minority groups (Avolio & Waldman, 1986; Black, 2004).

Motivated by these findings in cognitive psychology, we use age-income, age-education, age-race, and age-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 adverse effects of cognitive aging directly, our results are open to alternative interpretations. To further ensure that the variables we use to capture 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. There is a sharp decline after the age 70, and, moreover, the cognitive decline is steeper among older individuals who are also less educated and have lower income. These results 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.

Studies like ours that examine the effects of age also face the classic age-cohort-period identification problem (Deaton, 1997; Ameriks & 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 that 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 the 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 an older age are unlikely to be convincing. Third, cohort effects cannot successfully account for the inverted U-shaped relation between age and investment skill. Last, the performance differential between younger and older investors increase with portfolio size, which we interpret as a proxy for task difficulty. There is no obvious cohort-based explanation for this result. In contrast, all of these findings are strongly consistent with the cognitive aging hypothesis and reflect the natural outcome of the joint aging and learning processes.

To further account for the effects of birth cohorts, we perform an individual-level comparison and use the differencing method proposed in McKenzie (2006). 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. By differencing, we eliminate the common effects associated with cohorts. 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.

Examining the economic costs of aging, we find that, on average, investors with stronger aging effects earn about 3% lower risk-adjusted annual returns, and the performance differential is over 5% among older investors with large portfolios. These performance differentials remain economically significant even when we account for transaction costs and use net returns to measure performance. We conduct several robustness tests and show that our results are not sensitive to the 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 first glance, these empirical findings 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

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[3] In a related study, Agarwal et al. (2009) 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.

in the appropriate context of the 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 main testable hypotheses. We describe the data in section III, and in section IV, we test our first hypothesis that focuses on the positive effects of aging and experience. In section V, we test our unconditional and conditional hypotheses, which posit that stock investment skill deteriorates with age but improves with experience. In section VI, we estimate the economic costs of aging. In section VII, we conduct robustness checks and attempt to rule out alternative interpretations of our key findings. We conclude in section VIII with a brief summary of the paper and potential implications of our results.

II.   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 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 & Salthouse, 1992).

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

The psychological evidence also indicates that people are likely to experience a decline in the level of their general intelligence 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 (Lindenberger & Baltes, 1994; Baltes & Lindenberger, 1997). Second, sensory (vision and hearing) functioning worsens with age and is associated with lower levels of intelligence. The decline in intelligence is much steeper after the age of 70 (Lindenberger & Baltes, 1997), while these adverse effects are attenuated in people's area of expertise due to frequent practicing (Masunaga & Horn, 2001).

In addition to biological and psychological factors, socioeconomic and demographic factors such as education, income, wealth, race/ethnicity, and gender can exacerbate the adverse effects of cognitive aging. For example, people who are more educated, more resourceful (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, et al., 1986; Baltes & Lang, 1997; Cagney & Lauderdale, 2002). In contrast, the age-related decline in cognitive abilities is steeper among older women (Shanan & Sagiv, 1982) as well as older African Americans and Hispanics (Avolio & 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 (Bakshi and Chen, 1994; Campbell & Viceira, 2002; Cocco, Gomes, & Maenhout, 2005; Gomes & Michaelides, 2005) also posit that the riskiness of investor portfolios would decline with age due to decreasing investment horizon and increasing risk aversion.[4]

In addition to these channels, investors are likely to learn through the process of trading, and they might be less prone to behavioral biases as they grow older and become more experienced. The empirical evidence from the individual investor literature indicates that older investors exhibit a weaker disposition effect (Dhar & Zhu, 2006), hold less concentrated portfolios (Goetzmann & Kumar, 2008), and exhibit a lower degree of overconfidence (Barber & Odean, 2001). Furthermore, these behavioral biases decline as investors learn and gain more experience (List, 2003; Feng & Seasholes, 2005; Goetzmann & Kumar, 2008). Older investors are also less prone to gambling-type activities in the stock market (Kumar, 2009).

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.[5] Given the opposite predictions of aging and learning research, our paper investigates empirically whether declining

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[4] Some theoretical models (Mossin, 1968; Samuelson, 1969; Merton, 1969) also predict that portfolio holdings of investors would remain constant with age. See Ameriks & Zeldes (2004) for an excellent review of this literature.

[5] 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 may accumulate more driving knowledge because of their greater driving experience, but they may not be able to apply that knowledge effectively due to a decline in their physical abilities. In a similar manner, older investors would have greater knowledge about investing, but they may still fail to apply them effectively due to a decline in their general intelligence and information-processing abilities. The analogy suggests that just as older drivers face additional aging-related risks on the road, older investors are likely to expose their portfolios to noncompensated risks due to the adverse effects of cognitive aging.

cognitive abilities or increasing investment experience has a stronger influence on investors' stock investment decisions.

Overall, we test three hypotheses. First, based on the evidence from learning studies, we posit that:

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

Next, based on the 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, in the absence of a direct measure 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.

III. 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. There are 77,995 households in the retail database who hold common stocks and trade a variety of other securities, including mutual funds, options, and American depository receipts (ADRs). In this study, we focus on the investment behavior of 62,387 investors who have traded common stocks. For a subset of households, demographic information such as age, income, wealth, occupation, marital status, and gender is available. The demographic measures were compiled by Infobase a few months after the end of the sample period (June 1997). The total wealth is reported at the account opening date.[6]

An average investor holds a four-stock portfolio (median is three) with an average size of $35,629 (median is $13,869). 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

TABLE 1.—SUMMARY STATISTICS: AGE SORTED INVESTOR GROUPS

Age Group	Portfolio Size	Income	Wealth	SIR	SWR	Experience
A: All Investors						
Q1 (20–38)	$23,372	$90,146	$196,765	0.414	0.283	5.46
Q2 (39–46)	23,372	98,619	243,081	0.377	0.246	7.68
Q3 (47–52)	29,270	101,086	247,701	0.462	0.304	8.92
Q4 (53–59)	32,543	93,363	296,595	0.554	0.298	9.01
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	8.71
B: Investors Age 60 or Above						
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

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 ratio of portfolio size to income, and SWR is the ratio of portfolio size to wealth. Investment experience is the number of years between the account opening date and December 31, 1996. In panel A (panel B), there are 5,404 (1,351) observations in each group.

sample period. Investors' stock holdings and trades encompass about 90% of stocks (9,011 stocks) from the Center for Research on Security Prices (CRSP) universe. (Further details on the investor database are available in Barber and Odean, 2000.)

Table 1, 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 provide summary statistics for five groups of older investors (age 60 or older) 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 important, we find that consistent with the prior evidence (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, when measured as both 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 to 69. Additionally, we find that the annual income peaks within the age range of 47 to 52, which is also consistent with the predictions of the life cycle models. These comparisons with the SCF data suggest that our sample of older retail investors is reasonably representative of the older households in the United States.[7]

To enrich our analysis, we complement the individual investor data with demographic data from the 1990 U.S. Census. We use the census data to identify the racial/ethnic profile and educational background of investors. To identify the racial/ethnic composition of investors, for each ZIP code,

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

[7] See Ivković et al. (2005) and Ivković, Sialm, and Weisbenner (2008) for additional discussions on the representativeness of the brokerage data.

we compute the proportion of individuals in the following four racial/ethnic groups: Caucasian, African American, Hispanic, and others. Using the ZIP of each investor, we assign 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.

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. We use data from the 2005 Dutch DNB Household Survey for some of our robustness checks. For each stock in the sample, we obtain the quarterly cash dividend payments, monthly prices, returns, and market capitalization data from the Center for Research on Security Prices (CRSP) and quarterly book value of common equity data from COMPUSTAT. We obtain the monthly time series of the three Fama-French factors and the momentum factor from Kenneth French's data library. Finally, we obtain characteristic-based performance benchmarks from Russ Wermers's Web site.[8]

IV.   Age, Experience, and Investment Knowledge

In this section, we gather support for our first main hypothesis (H1). Specifically, we examine whether the knowledge and experience accumulated over time are reflected in investors' portfolio holdings and trading decisions.

A.   Age and Equity Portfolio Risk

In our first formal test, we investigate whether older investors tilt their portfolios toward relatively less risky stocks. We estimate panel regression models to 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.[9] The group portfolio is constructed by combining the portfolios of all investors who belong to the group. The return moments are calculated using the past sixty 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, we consider the following control variables to characterize investors' stock preferences: (a) market beta, which is also estimated using the past sixty months of data; (b) firm size; (c) book-to-market ratio; (d) short-term momentum (past one-month stock return); (e) longer-term momentum (past twelve-month stock return); (f) an S&P500 dummy that is set to 1 if the stock belongs to the S&P500 index; (g) monthly volume turnover; and (h) annual dividend yield.

We account for potential autocorrelation and cross-correlation in errors using the nonparametric 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 correlation, and cross serial correlation in a panel setup. To ensure that extreme values are not affecting our results, we winsorize all variables at their 0.5 and 99.5 percentile levels. Further, to facilitate comparisons among the coefficient estimates, the independent variables are standardized so that each variable has a mean of 0 and a standard deviation of 1.

The panel regression estimates are presented in table 2. We estimate the panel regression model for three age-based categories: (a) younger age group containing investors in the 20 to 38 age range; (b) older age group consisting of investors in the 60 to 94 age range; and (c) within the older investor group, the oldest age group consisting of investors in the 75 to 94 age range. Additionally, we estimate two panel regressions to examine the differences in the stock preferences of groups a and b, and groups a and c.

Focusing on the differential regression estimates (see 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, and lower prices are weaker than those of younger investors. In addition, older investors exhibit weaker preference for stocks with higher skewness, which indicates they are less likely to chase extreme positive returns. Our estimates also indicate that investors' preferences for less risky stocks increase with age. The differences in the stock preferences of younger and older investors, as reflected by the magnitudes of the coefficient estimates, are stronger when we consider the 75 to 94 age group to identify older investors (see column 5).[10]

Collectively, the 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 their portfolios as they grow older.

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[8] The U.S. Census data are available at http://www.census.gov/main/www/cen1990.html. The SHARE data are described in Christelis, Jappelli, and Padula (2010) and are available at http://www.share-project.org/. Kenneth French's data library is available at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/. Russ Wermers's data library is available at http://www.smith.umd.edu/faculty/rwermers/ftpsite/Dgtw/coverpage.htm.

[9] 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.

[10] 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: 20–40 (weak retirement motive), 41–65 (strong retirement motive), and above 65 (retired).

TABLE 2.—AGE AND STOCK PREFERENCES: PANEL REGRESSION ESTIMATES

Variable	Age Groups			(2) − (1)	(3) − (1)
	(1): 20–38	(2): 60–94	(3): 75–94		
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	0.053	0.046	0.039
	(4.534)	(20.810)	(16.851)	(5.039)	(5.682)
Monthly turnover	0.062	−0.003	−0.005	−0.051	−0.062
	(23.627)	(−1.564)	(−2.537)	(−5.876)	(−8.604)
Dividend yield	0.006	0.018	0.030	0.015	0.021
	(0.450)	(3.470)	(3.701)	(2.455)	(2.818)
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

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. The group portfolio is formed by combining the portfolios of all investors who belong to the group. 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 price of the stock are used as independent variables. Additionally, the following stock characteristics are employed as control variables: (a) market beta, which is estimated using the past sixty months of data; (b) firm size; (c) book-to-market ratio; (d) short-term momentum (past one-month stock return); (e) longer-term momentum (past twelve-month stock return); (f) an S&P500 dummy, which is set to 1 if the stock belongs to the S&P500 index; (g) monthly volume turnover; and (h) the annual dividend yield. The t-statistics for the coefficient estimates are shown in the row below the estimates in parentheses, where we use the nonparametric approach of Driscoll and Kraay (1998) to obtain corrected standard errors. We winsorize all variables at their 0.5 and 99.5 percentile levels, and the independent variables are standardized.

B. Do Investors Accumulate More Knowledge as They Grow Older?

To examine whether older investors possess greater knowledge about investing, we concentrate on several important dimensions of portfolio decisions that reflect common investment rules of thumb. The set of decisions that 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 these investors trade less frequently because they realize that they would not be able to improve performance through active trading. 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.[11]

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.

[11] Optimal trading behavior in presence of taxes requires skill (Constantinides, 1983, 1984; Ivković et al., 2005). However, such optimal response to taxes would lead to higher risk-adjusted performance, which our risk-adjusted performance measures are likely to capture (see section V).

The measures are obtained for each investor using his or her 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.

In the conditional regressions, the following demographic variables and portfolio characteristics are employed as control variables. *Income* represents the annual household income; *education* represents the proportion of people in investor's ZIP code that has attained a bachelor's or higher educational degree; *male dummy* is set to 1 if the head of the household is male; *retired dummy* is set to 1 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 dividend yield of the household portfolio. 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 characterize the riskiness of

the portfolio. The factor loadings are obtained by fitting a four-factor time-series model to the monthly portfolio return series of each investor for the period in which the investor is active. Last, *mutual fund holdings* is the proportion of the equity portfolio that is allocated to mutual funds.

The rule-of-thumb cross-sectional regression estimates are presented in table 3, where the *t*-statistics are computed using robust and ZIP code–level clustered standard errors. As before, we winsorize all variables at their 0.5 and 99.5 percentile levels and the independent variables are standardized. In the first two regressions, we use the number of stocks in the portfolio as the dependent variable to examine whether older investors are more aware of the potential benefits of diversification (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's equity portfolio is likely to indicate whether an investor exhibits a preference for diversification and at least attempts to diversify.[12]

Our results from the unconditional model indicate that older and more experienced investors hold portfolios containing a greater number of stocks. The coefficient estimates are significantly positive for both age and investment experience, even in the presence of various control variables. The 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: portfolio diversification.

Next, we examine whether older investors follow one of the key recommendations of the efficient market hypothesis, which posits that investors cannot improve performance through active trading. In the next two regression specifications (columns 3 and 4), we use monthly portfolio turnover as the dependent variable.[13] 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 & Odean (2001), who find that older (male) investors trade relatively less (more)

frequently. These estimates indicate that the trading behavior of older investors is more likely to conform to another key principle of investing: less frequent trading.

While these cross-sectional regression estimates are consistent with our first hypothesis, one might conjecture that a stronger preference for diversification and lower portfolio turnover does not necessarily imply greater investment knowledge but merely reflects "passive" investing by older investors. For example, an older investor might hold more stocks in her portfolio not because she has a preference for diversification, but because she has accumulated a large number of stocks during a long investing period. To address this potential concern, we use a knowledge measure that is more likely to capture an investor's knowledge about investing. Specifically, we examine whether older investors exhibit a greater propensity to engage in year-end tax-loss selling.

We estimate a regression model in which the proportion of "losers" (stock investments in which an investor suffers a loss) sold in the month of December is used as a dependent variable. The regression estimates indicate that both older and more experienced investors are more willing to sell their losers in December (see column 5). 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, 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 reflects yet another investing rule of thumb: "Sell your losers in 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 column 6). 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 important, the estimates indicate that the age and experience variables capture two distinct aspects of investors' portfolio choices and trading decisions.

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[12] We obtain similar results when we use other measures (such as normalized portfolio variance) to capture the preference for diversification. Also, see the results in table 5 of Goetzmann & Kumar (2008).

[13] 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.

C.   Other Rules of Thumb

While it is very difficult to perform a comprehensive analysis of rules of thumb recommended by investment advisers, we study whether older and experienced investors exhibit

TABLE 3.—RULE-OF-THUMB CROSS-SECTIONAL REGRESSION ESTIMATES

Variable	(1) NSTKS	(2) NSTKS	(3) TURN	(4) TURN	(5) TAX	(6) PDY
A: Main Rules-of-Thumb Regression Estimates						
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)	
Portfolio RMRF exposure		−0.020		0.509	0.009	−0.215
		(−0.821)		(12.291)	(3.149)	(−19.833)
Portfolio SMB exposure		0.304		0.828	0.021	−0.814
		(10.491)		(17.023)	(6.684)	(−20.737)
Portfolio HML exposure		0.052		−0.609	−0.011	0.666
		(1.903)		(−13.152)	(−3.695)	(19.019)
Portfolio UMD exposure		0.051		0.132	−0.001	−0.116
		(2.129)		(3.242)	(−0.071)	(−10.827)
Mutual fund holdings		0.127		0.215	0.010	0.027
		(6.276)		(5.885)	(3.987)	(2.723)
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

Dependent Variable	Intercept	Age	Experience
B: Other Rules-of-Thumb Regression Estimates			
(1) Number of asset classes	2.545	0.139	0.073
	(24.956)	(13.035)	(6.871)
(2) Mutual fund portfolio expense ratio × 100	0.856	−0.026	−0.013
	(11.668)	(−9.371)	(−4.601)
(3) Weight in foreign stocks × 100	3.575	0.672	1.384
	(17.925)	(3.053)	(4.224)
(4) Adjusted disposition effect × 100	1.780	−7.849	−1.467
	(3.527)	(−6.632)	(−2.235)
(5) Local bias × 100	29.493	−0.822	−0.434
	(11.590)	(−3.866)	(−2.511)
(6) Margin account dummy	0.577	−0.023	0.007
	(20.744)	(−8.178)	(2.531)
(7) Short-sell dummy	0.096	−0.017	0.015
	(18.239)	(−4.330)	(8.125)
(8) Option trade dummy	0.089	−0.018	0.019
	(15.697)	(−8.735)	(9.701)
C: Logit Estimates Using the Dutch DNB Data			
(1) Mutual fund participation dummy	−5.587	0.022	0.473
	(−12.552)	(4.851)	(4.746)
(2) All asset classes participation dummy	−9.788	0.053	0.613
	(−7.186)	(3.819)	(2.067)

This table reports the estimates from cross-sectional regressions, where a measure of investment choice reflecting a rule of thumb is the dependent variable. In panel A, we consider four measures: (a) average number of stocks in the portfolio (NSTKS), (b) portfolio turnover (TURN), (c) proportion of "losers" (stock investments where an investor has experienced a loss) realized in the month of December (TAX), and (d) portfolio dividend yield (PDY). All measures are obtained for each investor using his or her choices during the sample period. In panel B, we consider (a) number of asset classes in which the investor has at least one trade during the sample period, (b) the sample-period expense ratio of the investor's mutual fund portfolio, (c) the proportion of equity portfolio invested in foreign stocks, (d) local bias, measured as the proportion of equity portfolio that is invested in stocks within a 100-mile radius, (e) the peer-group adjusted disposition effect (ADE) measure, defined as the difference between an investor's actual propensity to realize gains and the expected propensity to realize gains (see Kumar and Lim, 2008 for details), (f) margin fund dummy that is set to 1 if the investor holds a margin account, (g) short-sell dummy that is set to 1 if the investor holds a short position at least once during the sample period, and (h) option trade dummy that is set to 1 if the investor executes an option trade at least once during the sample period. In panel C, the dependent variable is either the mutual fund participation dummy (set to 1 if the investor holds any type of mutual fund) or the "all asset classes" participation dummy (set to 1 if the respondent holds stocks, bonds, and mutual funds) in the 2005 Dutch DNB Household Survey. The independent variables used in panels A and B are described in section IVB. In panel C, the independent variables are age, self-reported knowledge of financial markets (proxy for investment experience), income, education level, gender, and retirement dummy. The *t*-statistics for the coefficient estimates are shown in the rows below the estimates in parentheses, where robust, clustered standard errors are used to account for potential cross-sectional dependence within ZIP codes. We winsorize all variables at their 0.5 and 99.5 percentile levels and the independent variables are standardized. In panel C, we estimate a logit model and do not standardize the variables. We report the *z*-statistics for the coefficient estimates based on robust standard errors. In panels A and B, the individual investor data are from a large U.S. discount brokerage house for the period from 1991 to 1996. In panel C, we use the 2005 Dutch DNB Household Survey data.

a greater propensity to follow other commonly prescribed rules of thumb. The results from these additional empirical tests are summarized in table 3, panel B. First, we examine whether older investors exhibit a higher propensity to spread their positions across multiple asset classes. We also investigate whether older investors are more likely to diversify using low-expense mutual funds and foreign stocks.

Consistent with the evidence on diversification preference, the estimates from test 1 show that both older and experienced investors invest in a greater number of asset classes. We also find that both older and experienced investors hold mutual funds with lower expense ratios and hold a larger proportion of foreign stocks in their equity portfolios (see tests 2 and 3).[14] For example, the expense ratio differential between a 30-year-old and a 65-year-old investor is 0.078%, which is about 9.10% higher than the mean expense ratio of sample investors (= 0.857%). Similarly, older investors allocate 2.02% more weight to foreign stocks than younger investors do. This is more than 50% higher than the sample mean foreign stock weight of 3.87%. These results indicate that older investors are more likely to follow two other common investment rules of thumb: "Invest in well-diversified, low-expense mutual funds" and "Diversify internationally."[15]

Next, in tests 4 and 5, we examine whether both older and experienced investors exhibit weaker behavioral biases such as the disposition effect and local or familiarity bias. We find that consistent with the greater investment knowledge hypothesis, older and experienced investors are less likely to hold on to their losers (they exhibit a weaker disposition effect) and exhibit a relatively lower propensity to hold local stocks (exhibit a weaker local bias).[16]

Last, we examine whether older investors shy away from relatively sophisticated trading strategies such as margin trading, short selling, and option trading (see tests 6 to 8). We find that older investors are less likely to hold a short position or trade options. In contrast, experienced investors are more likely to hold short positions, and they also exhibit a greater propensity to trade options. Investors with greater experience are also more likely to have a margin trading account. These findings suggest that experience might be a proxy for financial sophistication and could be positively correlated with investment skill.

D. Evidence from the Dutch DNB Data

To further examine the robustness of our rules-of-thumb regression results, we consider data from another country. We use the Dutch DNB data and examine whether older and experienced investors exhibit stronger diversification motives. The DNB data contain information about the aggregate holdings in stocks, bonds, and mutual funds but do not provide information about the types of assets investors hold or trade. We also have information about the respondent's age, income, education, gender, self-reported knowledge of financial markets (our proxy for investment experience), self-reported cognitive ability measures, and other demographic variables.

Using the mutual fund participation dummy as a proxy for the intent to diversify, we estimate a logit model, where the mutual fund participation dummy is the dependent variable and the various demographic variables including age, experience, and cognitive ability are the independent variables.[17] The results are reported in table 3, panel C. Consistent with the results from the U.S. brokerage data, we find that older and more knowledgeable Dutch investors exhibit a higher probability of holding mutual funds (see test 1). The results are similar when we use an alternative measure to capture investors' diversification motives: an "all asset classes" dummy that is set to 1 if an investor holds stocks, bonds, and mutual funds. We find that both age and experience have significantly positive coefficient estimates (see test 2).

When we include the cognitive ability index as an additional dependent variable, in untabulated results, we find that higher levels of cognitive ability increase the mutual fund participation probability (estimate = 0.321, z-statistic = 2.225). High-cognitive-ability investors also exhibit a greater propensity to invest in all asset classes, although the coefficient estimate is only marginally significant (estimate = 0.577, z-statistic = 1.671). These results indicate that like cognitive abilities, age and experience are positively correlated with investment knowledge.

Overall, 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. Furthermore, the evidence indicates that investors with greater experience appear more sophisticated and could be skilled.

V. Cognitive Aging and Investment Skill

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? In this section, we examine the relation of age, investment experience, and investment skill and gather support for our second set of hypotheses, H2 and

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[14] In untabulated results, we find that both older and experienced investors are more likely to invest in mutual funds. However, older investors exhibit a greater propensity to invest in index funds, while experienced investors exhibit a stronger preference for other types of funds.

[15] See Bailey, Kumar, and Ng (2008) for additional results on the relation between age and foreign stock holdings. Bailey, Kumar, and Ng (2009) provide additional evidence on the effect of age on the mutual fund choices of individual investors.

[16] The disposition effect evidence is also reported in Dhar & Zhu (2006), although they do not focus on the opposite effects of cognitive aging and investment experience.

[17] The cognitive ability index is constructed using self-reported measures of ability on a five-point scale—specifically, the Cognitive Ability Index = (Memory − do not get abstract idea + rich vocabulary + use difficult words)/4. It is positively correlated with the experience measure but negatively correlated with age.

Figure 1.—Age, Portfolio Performance, and Change in Performance
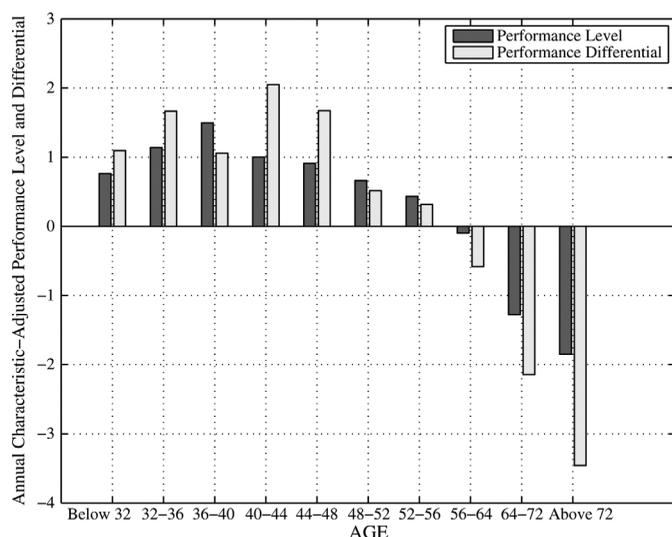
This figure shows the risk-adjusted performance level (annualized characteristic-adjusted percentage return) and the performance differential, conditional on age. The performance differential is the change in the performance between the last three and the first three years of the sample period.

H2cond, which posit opposite effects of age and experience on investment skill.

A. Graphical Evidence: Univariate Results

Figure 1 shows the univariate relation between age and investment skill, as captured by the Daniel et al. (1997) characteristic-adjusted performance measure. Two features of the plot are noteworthy. First, the investment performance exhibits an inverted U-shape with a peak at around 42 years. The hump shape reflects the combined effects of experience and aging. This evidence is consistent with the findings in Agarwal et al. (2009), who find a similar pattern in the borrowing rates of households in various credit markets. Second, there is an abrupt and significant drop in investment performance around the age of 70. This nonlinear effect supports our cognitive aging hypothesis and is consistent with the evidence from studies in psychology that document a steeper cognitive decline after the age of 70. Overall, the graphical evidence reveals that the interactions between the aging and learning processes determine the risk-adjusted performance of investor portfolios.

B. Opposite Effects of Age and Experience

We attempt to uncover these interactions by estimating "skill" regressions. In these cross-sectional regressions, a measure of investment skill is employed as the dependent variable. We focus on two specific investment skill measures: the diversification skill and the stock selection ability. Our conjecture is that although older investors hold portfolios with larger numbers of stocks, they might not possess diversification skill because the ability to perceive correlations

accurately would decline with age.[18] Furthermore, investors' stock selection skill could decline with age because the adverse effects of cognitive aging would influence their ability to efficiently process new information. In contrast, both diversification skill and stock selection abilities would improve with investment experience.

We use the monthly Sharpe ratio to measure diversification skill and the monthly portfolio alpha to measure stock selection skill. For each investor, the realized portfolio return series during the full sample period is used to compute the two performance measures. The Sharpe ratio measure is defined as $SR_p = (\mu_p - r_f)/\sigma_p$, where μ_p is the average realized portfolio return, σ_p is the standard deviation of the portfolio return series, and r_f is the risk-free rate of return. The alpha measure is the intercept obtained by fitting a four-factor time-series model to the portfolio return series. The factor model includes the market (RMRF), size (SMB), value (HML), and momentum (UMD) factors. We also employ the mean characteristic-adjusted monthly portfolio return measure computed using the Daniel et al. (1997) methodology as an alternative measure of investment skill.[19] Both investment skill measures capture the ability of investors to generate excess returns from their portfolio decisions, after accounting for the known differences in their stock preferences (see table 2).

In the first set of skill regressions, we test our unconditional hypothesis. The only independent variables in these regression specifications are age and investment experience. The cross-sectional regression estimates for the unconditional models are presented in table 4, panel A (columns 1, 3, and 5). In all our regression specifications, we use robust, clustered standard errors to account for potential cross-sectional dependence in performance within ZIP codes.

In the Sharpe ratio regression (column 1), age has a negative but statistically insignificant coefficient estimate (estimate = −0.001, t-statistic = −0.935), while investment experience has a significantly positive coefficient estimate (estimate = 0.011, t-statistic = 11.644).[20] In the alpha regression (column 3), age has a significantly negative coefficient estimate (estimate = −0.042, t-statistic = −5.047), and investment experience has a positive but statistically insignificant estimate (estimate = 0.010, t-statistic = 1.184). In the characteristic-adjusted return regression (column 5), age has a significantly negative coefficient estimate

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[18] 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.

[19] Even when we consider other performance benchmarks that include industry and liquidity factors, our key results remain qualitatively similar. See section VIIA.

[20] Consistent with our evidence, using household-level data from Sweden, Calvet, Campbell, and Sodini (2007) show that older investors make cautious but relatively less efficient investment choices. Also see Campbell (2006).

TABLE 4.—INVESTMENT SKILL CROSS-SECTIONAL REGRESSION ESTIMATES

	SR (1–2)		Alpha (3–4)		Characteristic Adjusted (5–8)				Difference (9)
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
				A: Baseline Specifications					
Intercept	0.101	0.102	−0.341	−0.340	0.006	−0.001	0.031	0.001	0.006
	(13.173)	(9.568)	(−14.285)	(−13.099)	(0.699)	(−0.101)	(0.448)	(0.005)	(0.193)
Age	−0.001	−0.014	−0.042	−0.051	−0.044	−0.054	−0.063	−0.045	−0.077
	(−0.935)	(−3.355)	(−5.047)	(−4.735)	(−7.293)	(−2.945)	(−2.257)	(−4.636)	(−3.388)
Investment experience	0.011	0.010	0.010	0.020	0.037	0.027	0.028	0.026	0.028
	(11.644)	(9.450)	(1.184)	(2.283)	(6.053)	(3.891)	(2.289)	(3.938)	(3.103)
Over-70 dummy		−0.007		−0.025		−0.020	−0.022	−0.014	−0.019
		(−1.483)		(−2.073)		(−2.163)	(−2.886)	(−2.592)	(−2.167)
Income		0.001		0.001		0.011	0.004	−0.001	0.018
		(0.824)		(0.062)		(1.112)	(0.470)	(−0.108)	(2.013)
Low-income dummy		−0.002		−0.004		−0.009	−0.011	−0.010	−0.008
		(−1.223)		(−0.275)		(−0.773)	(−1.004)	(−0.155)	(−0.218)
Age × Low Income		−0.012		−0.025		−0.014	−0.022	−0.023	−0.006
		(−2.033)		(−2.674)		(−1.996)	(−2.242)	(−2.367)	(−1.791)
Education		0.011		0.014		0.017	0.013	0.013	0.014
		(1.882)		(2.527)		(2.717)	(2.089)	(2.129)	(1.529)
Low-education dummy		−0.010		−0.012		−0.014	−0.015	−0.011	−0.025
		(−1.809)		(−1.813)		(−1.798)	(−1.401)	(−1.636)	(−1.510)
Age × Low Education		−0.011		−0.003		−0.005	−0.004	−0.004	−0.005
		(−1.789)		(−1.250)		(−2.719)	(−2.242)	(−1.843)	(−1.942)
Male dummy		−0.001		−0.001		−0.006	−0.021	−0.011	−0.013
		(−0.550)		(−0.108)		(−0.945)	(−1.306)	(−1.816)	(−0.772)
Retired dummy		0.001		0.007		0.004	−0.010	0.002	−0.006
		(0.072)		(0.760)		(0.504)	(−0.957)	(0.391)	(−0.818)
Hispanic dummy		−0.002		−0.003		0.009	−0.007	−0.018	−0.008
		(−0.350)		(−0.650)		(0.220)	(−1.072)	(−1.667)	(−0.309)
African American dummy		−0.005		−0.016		−0.012	−0.003	−0.014	0.006
		(−1.038)		(−1.403)		(−1.133)	(−0.879)	(−1.084)	(0.517)
Age × Hispanic		−0.004		−0.034		−0.025	−0.017	−0.020	−0.036
		(−3.568)		(−3.516)		(−3.111)	(−2.876)	(−2.524)	(−2.488)
Age × African American		0.002		0.010		0.009	−0.007	−0.008	−0.013
		(0.437)		(0.588)		(1.108)	(−1.035)	(−1.562)	(−1.876)
			(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	19,906	18,367
Adjusted R^2	0.015	0.055	0.014	0.254	0.028	0.090	0.061	0.086	0.055

	Skill			Skill Difference	
Variable	(1) Alpha	(2) Characteristic Adjusted	(3) Net Characteristic Adjusted	(4) Characteristic Adjusted	(5) Net Characteristic Adjusted
		B: Specifications with Quadratic Age			
Intercept	−0.368	−0.016	−0.013	0.008	−0.017
	(−18.877)	(−0.656)	(−1.089)	(0.190)	(−1.099)
Age	−0.044	−0.064	−0.061	−0.079	−0.073
	(−4.316)	(−6.287)	(−4.521)	(−3.371)	(−3.066)
Age^2	−0.027	−0.018	−0.020	−0.044	−0.032
	(−2.922)	(−1.838)	(−2.157)	(−2.356)	(−2.624)
Investment experience	0.030	0.036	0.029	0.039	0.041
	(2.940)	(6.001)	(4.965)	(3.163)	(3.760)
Over-70 dummy	−0.024	−0.026	−0.019	−0.017	−0.014
	(−2.296)	(−2.028)	(−2.614)	(−2.899)	(−1.834)
		(For brevity, other coefficient estimates are suppressed.)			

The dependent variable is either a measure of investment skill or skill difference across the two halves of the sample period. The following measures of investment skill are considered: the monthly Sharpe ratio (SR), the four-factor alpha (Alpha), and the average characteristic-adjusted monthly portfolio return. The four-factor alpha is obtained by fitting a four-factor time-series model to the monthly portfolio return series of each investor over the period the investor is active. All independent variables are defined in section VC. In column 7 of panel A, we present panel regression estimates, where the skill measure is the monthly characteristic-adjusted returns. In this specification, the factor exposures are excluded from the set of control variables. In column 8 of panel A, the skill measure is the average net, characteristic-adjusted return. The t-statistics for the coefficient estimates are shown in the rows below the estimates in parentheses, where robust, clustered standard errors are used to account for potential cross-sectional dependence within ZIP codes. We winsorize all variables at their 0.5 and 99.5 percentile levels, and the independent variables are standardized.

(estimate $= -0.044$, t-statistic $= -7.293$), while investment experience has a significantly positive coefficient estimate (estimate $= 0.037$, t-statistic $= 6.053$). These coefficient estimates are broadly consistent with our second main hypothesis and indicate that age has opposite effects in rule of thumb and skill regressions.

The coefficient estimates in the skill regressions are also significant in economic terms. For instance, the estimate for age in the alpha regression indicates that, holding experience fixed, a 1-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 3-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), although the strengths of age-skill and experience-skill relations are not very strong.[21]

C. Model of Cognitive Abilities and Skill Regression Specification

We consider additional proxies for cognitive aging to gather stronger support for the second hypothesis. Our choice is motivated by previous studies in cognitive psychology, which demonstrate that individuals who are more educated, more resourceful, and undertake intellectually stimulating jobs are better able to compensate for their declining cognitive abilities (Arbuckle, et al., 1986; Baltes & Lang, 1997; Cagney & 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, with higher income and greater wealth, might be able to better compensate for their declining information processing abilities.

To ensure that the additional cognitive aging proxies employed in the skill regression specification are appropriate, we estimate a model of cognitive abilities using a representative European household data set and show that our cognitive aging proxies are strongly correlated with direct measures of cognitive abilities. We choose the European data set because it contains three direct measures of cognitive abilities: verbal ability, quantitative ability, and 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 psychology literature are the independent variables.

The cognitive abilities regression estimates are reported in table 5. Consistent with the evidence from psychology, we find that cognitive abilities decline with age and are positively associated with education, wealth, and income. Furthermore,

TABLE 5.—DETERMINANTS OF COGNITIVE ABILITIES

Variable	Cognitive Ability Measure Is:			
	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

The dependent variable is a measure of cognitive ability. The combined cognitive ability measure is the equal-weighted measure of the verbal, quantitative, and memory measures. 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 preprimary to post-tertiary; the low-income dummy is set to 1 for investors who are in the lowest income quintile; the low-education dummy is set to 1 for investors who are in the lowest education-quintile; the over-70 dummy is set to 1 for individuals over 70 years old. The t-statistics for the coefficient estimates are shown in the rows below the estimates in parentheses. We winsorize all values at their 0.5 and 99.5 percentile levels, and the independent variables have been standardized. The household data are from the 2005 wave of the Survey of Health, Aging, and Retirement in Europe (SHARE).

the decline is steeper among individuals who are considerably older (over 70 years old), are less educated, and have lower income. It is interesting that two facets of cognitive abilities that are more relevant for investment decisions, 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. Collectively, the cognitive abilities model estimates indicate that demographic variables such as age, income, wealth, and education, and their interactions, are likely to capture the adverse effects of cognitive aging reasonably well.

Motivated by this evidence from our cognitive abilities model, we consider an extended skill regression model with multiple cognitive aging proxies and attempt to capture the influence of cognitive aging on investment decisions more accurately. 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.

The evidence from research in cognitive psychology (Avolio & Waldman, 1986; Black, 2004) suggests that the age-related decline in cognitive abilities is steeper among ethnic/racial minorities (African Americans and Hispanics). 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 1 for investors who live in ZIP codes where the ratio of the populations of Hispanics to

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[21] 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.

whites is in the upper quintile. The African American variable is defined in an analogous manner. We interact both race/ethnicity variables with age.

Similar to the unconditional skill regressions, we consider several independent variables to control for the known determinants of portfolio 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 & Odean, 2001). The retired dummy allows us to control for the significant lifestyle changes at the time of retirement, which could alter investment behavior. 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 portfolio. Last, the portfolio turnover measure at least partially accounts for the effects of transaction costs on portfolio performance.

D. Intent to Diversify versus Actual Diversification Skill

The diversification skill regression estimates for the conditional model is reported in table 4, panel A, column 2. Consistent with our second hypothesis, we find that the age-skill and experience-skill relations become stronger and appear more transparent in the conditional model. In the Sharpe ratio regression, both age and investment experience have significant coefficient estimates, where the loading on age is negative (estimate $= -0.014$, t-statistic $= -3.355$) and the loading on investment experience is positive (estimate $= 0.010$, t-statistic $= 9.450$). We interpret the negative coefficient estimate on age as the adverse effect of cognitive aging, while the positive coefficient estimate on investment experience indicates that greater experience leads to greater diversification skill.

Our results from the Sharpe ratio regression indicate that the coefficient estimate of income is positive but statistically insignificant. However, the Age $\times$ 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-statistic $= 1.882$) and the Age $\times$ Low Education interaction term has a marginally negative coefficient estimate. These results indicate that while education and investment experience lead to more effective diversification, investors' ability to diversify effectively decreases as they grow older.

Our results are similar when we use the average correlation among stocks in the portfolio as an alternative measure of diversification skill. If investors diversify effectively, all else equal, they would hold stocks that have lower correlations among them. When the average stock correlation is the dependent variable in the skill regression, in untabulated results, we find that age has a significantly positive coefficient estimate (estimate $= 0.006$, t-statistic $= 3.032$), investment

experience has a significantly negative coefficient estimate (estimate $= -0.004$, t-statistic $= -3.903$), and other coefficient estimates are very similar to the Sharpe ratio regression estimates. This evidence indicates that although both older and experienced investors attempt to diversify, only experienced investors demonstrate an ability to achieve effective diversification and possess diversification skill.

We obtain similar results when we evaluate investors' mutual fund choices. The rules-of-thumb regressions in section IVC indicate that older investors are more likely to follow the rule: "Invest in well-diversified, low-expense mutual funds." However, consistent with our cognitive aging hypothesis, we find, in untabulated results, that older investors do not earn higher risk-adjusted returns from their increased participation rates in mutual funds. After accounting for other factors, age is negatively related and experience is positively related to risk-adjusted mutual fund performance. 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.[22]

The evidence from other related studies reinforces our diversification skill results. In particular, Bailey, Kumar, and Ng (2008) show that both older and experienced investors exhibit strong intentions to diversify using foreign stocks, but only the experienced investors benefit from their diversification attempts. This evidence indicates that older investors are more likely to attempt to exploit the potential benefits of foreign investments, but, conditional on participation, they appear less skillful in their decisions.

E. Conditional Deterioration in Stock Selection Abilities

When we estimate the conditional skill regression with the four-factor alpha as the dependent variable (a measure of stock selection skill), the results are remarkably similar to the Sharpe ratio regression estimates. These results are reported in table 4, panel A, column 4. We find that both age and investment experience have significant coefficient estimates, where the loading on age is negative (estimate $= -0.051$, t-statistic $= -4.735$) 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). Further, the over-70 dummy has a negative and significant coefficient estimate (estimate $= -0.025$, t-statistic $= -2.073$). We also find that the Age $\times$ Low Income and Age $\times$ Low Education interaction terms have negative coefficient estimates, though the latter is not statistically significant.

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

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[22] Also, see Bailey et al. (2009) for additional evidence on a negative relation between age and mutual fund performance.

column 6).[23] The coefficient estimate of Age is -0.054 with a t-statistic of -2.945, and the coefficient estimate of Investment Experience is 0.027 with a t-statistic of 3.891. In addition, 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 month-t characteristic-adjusted portfolio return as the dependent variable. As before, we use the Driscoll and Kraay (1998) methodology to account for potential cross-sectional correlation, serial correlation, and cross-serial correlation. We find that the panel regression results reported in column 7 are qualitatively very similar to the cross-sectional regression estimates.

In untabulated 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 have 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 proxy for greater resources, and it may also reflect greater investment experience.[24] We also find that the coefficient estimate of the 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.

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 1-standard-deviation shift in the age of an investor who does not belong to either 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 3-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 the Age × Hispanic interaction term has a significantly negative coefficient estimate in all four regression specifications. For instance, in the alpha regression, the coefficient estimate of the interaction term is -0.034, with a t-statistic 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 $(0.051 + 0.025 + 0.034) \times 12 = 1.320\%$. For an investor with these attributes, a jump in age from 30 to 65 would correspond to an annual performance decline of 3.960% on a risk-adjusted basis. In contrast, we find that the Age × African American interaction term has insignificant coefficient estimates.

F. Stock Selection Skill Regression Estimates Using Net Returns

Because older investors have lower turnover rates (see section IVB), their net performance after accounting for transaction costs might not be significantly worse than younger investors. Using the Barber and Odean (2000) method, we account for trading commissions, bid-ask spread, and the potential market impact of investors' trades and measure the net portfolio returns of each investor portfolio. We reestimate the skill regression using characteristic-adjusted net returns. The results are reported in column 8 of table 4, panel A.

Even when we use net portfolio return to measure skill, age and investment experience maintain their opposite signs and relative magnitudes. As expected, we find that the adverse effects of aging are weaker when we use net returns, but the performance decline that can be attributed to aging remains economically significant. For instance, when an investor aged 30 becomes older and crosses the retirement age of 65 (a 3-standard-deviation shift in age), she is likely to suffer a net annual performance decline of $0.045 \times 12 \times 3 = 1.620\%$. If this investor also earns lower income and belongs to the Hispanic ethnic group, she would experience a net annual risk-adjusted performance decline of $(0.045 + 0.023 + 0.020) \times 12 \times 3 = 3.168\%$.[25]

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.

G. 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 varies with age. We embed two interaction variables in one of our skill regression specifications (column 6 in

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

[24] 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.

[25] The results are very similar when the skill measure is the four-factor alpha computed using net returns. The coefficient estimate of age is -0.057 (t-statistic $= -5.366$) while the coefficient estimate of investment experience is 0.030 (t-statistic $= 4.380$). The interaction terms have the expected signs too. For brevity, we do not tabulate those results.

TABLE 6.—ROBUSTNESS TEST RESULTS

Robustness Test	Age	Experience	Age × Hisp	Age × AfrAm	Age × LowInc	Age × LowEdu
(1) 5-day PTBSD	−0.081	0.054	−0.018	−0.037	0.015	−0.041
	(−2.682)	(2.134)	(−1.704)	(−1.446)	(0.581)	(−1.253)
(2) 10-day PTBSD	−0.153	0.082	−0.016	−0.018	−0.038	−0.071
	(−3.790)	(2.430)	(−1.469)	(−1.537)	(−1.882)	(−1.621)
(3) GH_1 measure	−0.023	0.036	−0.042	0.011	−0.020	−0.009
	(−1.912)	(3.469)	(−4.002)	(1.071)	(−1.883)	(−1.672)
(4) GH_2 measure	−0.010	0.004	−0.010	0.006	−0.005	−0.002
	(−2.710)	(2.359)	(−3.124)	(0.827)	(−1.434)	(−1.536)
(5) Alternative exp. measure	−0.054	0.033	−0.024	−0.004	−0.028	−0.003
	(−3.690)	(2.390)	(−2.087)	(−0.458)	(−1.836)	(−1.381)
(6) Internet users subsample	−0.063	0.048	−0.022	−0.005	−0.025	−0.014
	(−3.168)	(2.653)	(−1.795)	(−1.161)	(−1.893)	(−1.349)
(7) 1991–93 subsample	−0.041	0.035	0.001	0.011	−0.011	−0.010
	(−4.739)	(3.769)	(0.520)	(1.137)	(−2.050)	(−1.850)
(8) 1994–96 subsample	−0.034	0.030	−0.021	−0.014	−0.005	−0.007
	(−2.064)	(3.672)	(−2.767)	(−1.903)	(−1.698)	(−1.740)
(9) Local four-factor alpha	−0.039	0.026	−0.037	−0.021	−0.008	−0.009
	(−2.738)	(2.504)	(−3.408)	(−1.921)	(−0.757)	(−0.702)
(10) Eight-factor alpha	−0.047	0.022	−0.023	0.009	−0.017	−0.004
	(−3.745)	(2.314)	(−3.652)	(1.124)	(−2.668)	(−1.439)
(11) 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)
(12) Exclude investors from 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)

This table reports the skill regression estimates using the baseline specification from table 4, panel A. The dependent variable is an investment skill measure. For brevity, we report only the estimates for the variables related to our main hypotheses. The estimates for the control variables are suppressed. In tests 1 and 2, 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 tests 3 and 4, we consider the two Graham-Harvey market timing measures (GH_1 and GH_2). To compute 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 of the investor portfolio and the mean return of 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 of the volatility-matched portfolio and the return of the S&P500 futures index. In both cases, the volatilities are computed for the time period in which an investor is active and the investor portfolio is levered up or down by combining it with T-bills. In test 5, we use an alternative experience measure defined using self-reported investment experience and knowledge measures. In test 6, we consider only a subsample of investors who have used the Internet to execute trades. Tests 7 and 8 estimate the skill regression for two subperiods, where the mean characteristic-adjusted portfolio return is the skill measure. In test 9, we use the local four-factor alpha as a measure of investment skill. To compute the local four-factor alpha, we consider the performance of the local part of the investor portfolio that contains stock investments in firms located within a 100-mile radius of investor's location. In test 10, the skill measure is the eight-factor alpha. It is the intercept from an eight-factor model that contains the four commonly used risk factors (RMRF, SMB, HML, and UMD), three industry factors (Pástor & Stambaugh, 2002), and a liquidity factor (Pástor & Stambaugh, 2003). In test 11, we consider a subsample of investors with large portfolios relative to income. Last, in test 12, we exclude investors who are located in California. We use the four-factor alpha as the measure of investment skill in tests 5, 6, 11, and 12. The t-statistics for the coefficient estimates are shown in the rows below the estimates in parentheses, where robust, clustered standard errors are used to account for potential cross-sectional dependence within ZIP codes.

table VI, panel A): 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-statistic = −4.068) while the coefficient estimate of the Below 30 × Low Experience dummy is statistically insignificant (estimate = 0.005, t-statistic = 0.546). This evidence is consistent with our conditional hypothesis and indicates that learning is impaired by the adverse effects of cognitive aging.

H. Subsample Estimates without the Extreme Performers

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 (for example, 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 they have chosen performed poorly during the sample period due to chance.

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 top and the bottom tails of the performance distribution and reestimate the skill regressions. Even when we choose $k = 5$, our estimates remain qualitatively similar to the baseline estimates reported in table IV, panel A, column 4. For instance, the untabulated results indicate that the coefficient estimates for age and investment experience are −0.047 (t-statistic = −3.031) and 0.035 (t-statistic = 4.609), respectively. Additionally, the interaction terms have the expected negative and significant estimates.

I. Adverse Effects of Cognitive Aging or Cohort Effects?

Studies like ours that examine the effects of age are plagued with the classic age-cohort-period identification problem (Deaton, 1997; Ameriks & 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. We also find that our main results hold for the 1991–1993 and 1994–1996 subsamples (see table 6), which indicates that time effects are not the primary drivers of our findings.

Focusing on cohort effects, we conjecture that cohort effects are unlikely to explain our findings for several reasons. 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 firsthand experience of salient events (for example, the Great 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. 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.

Although our results so far seem inconsistent with cohort-based explanations, we conduct several tests to directly account for the effects of birth cohorts. In the first test, we follow Poterba and Samwick (1997) and define cohort-range dummy variables, where we consider five cohort ranges: Below 35, 35 to 45, 45 to 55, 55 to 65, and above 65 years of age. In untabulated results, we find that the age range dummies have negative but insignificant coefficient estimates in all our specifications. More important, 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 4, panel A) becomes stronger (coefficient = −0.082, t-statistic = −3.129).

Next, we perform an individual-level performance comparison and 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).

The age-performance differential relation is qualitatively similar when we consider a multivariate estimation framework and account for other factors that might influence the subperiod performance differential. Specifically, we estimate a cross-sectional regression in which the performance differential between the two halves of the sample period is the dependent variable and the set of independent variables includes the demographic characteristics used in the skill regression. We find that age and investment experience have opposite signs in the skill difference regression (see table 4, panel A, column 9). This evidence indicates that older investors experience a decline in performance, while the performance of investors with greater experience improves.

When we consider a quadratic age term to capture the hump shape of the age-performance relation, we find qualitatively similar results. These results are reported in panel B of table 4. When the dependent variable is one of the performance measures, both age and age^2 have negative and significant coefficient estimates (see columns 1–3). This evidence indicates that the inverted U-shape relation between age and investment skill is strong and significant even when we account for other demographic factors and portfolio characteristics that may be correlated with skill. When the dependent variable is the subperiod performance differential, we again find that both age and age^2 have negative and significant coefficient estimates (see columns 4 and 5). In both specifications, we also find that the over 70 dummy is significantly negative, which is consistent with the sharp drop in performance level and performance differential documented in figure 1.

To further investigate whether our evidence reflects the adverse effects of cognitive aging or cohort effects, 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.

In our last-cohort related test, we include Portfolio Size × Age interaction variable in the skill regression specification (column 6 in table 4, panel A). We find that the interaction term has a significantly negative coefficient estimate (estimate = −0.032, t-statistic = −3.987), while the estimates of other variables in the model remain almost unchanged. Thus, consistent with the cognitive aging hypothesis, older investors exhibit worse risk-adjusted performance when they hold larger portfolios that are more difficult to manage.[26] This evidence, however, does not have a clear cohort–based explanation. Overall, the results from birth cohort–related robustness tests indicate that cohort effects are unlikely to successfully explain the observed negative relation between age and investment skill.

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[26] Also see figure 2. We find similar results when we use the number of stocks in the portfolio to quantify the difficulty level of managing a portfolio. The coefficient estimate is −0.030 and t-statistic = −3.008.

VI.   Economic Costs of Cognitive Aging

A.   A Portfolio-Based Approach

In this section, we quantify the economic costs associated with cognitive aging more accurately using portfolio-based, time-series tests. An additional advantage of this 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 (Skinner, 1987; Ziliak, 1998; Browning & Leth-Petersen, 2003) and use the previously estimated model of cognitive abilities (see section VC and table 5) 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 compute the average performance of investors in each of 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-statistic = 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-statistic = 2.762) or the characteristic-adjusted returns (annualized performance differential = 3.363%, t-statistic = 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, as are the factor estimate differences between the high- and the low-cognitive-ability decile portfolios. This evidence is consistent with our evidence on investors' stock preferences, conditional upon age (see section IVA and table 2).

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 on portfolio size. The results are shown in figure 2. We find that the economic cost of cognitive aging increases with portfolio size. As portfolio size
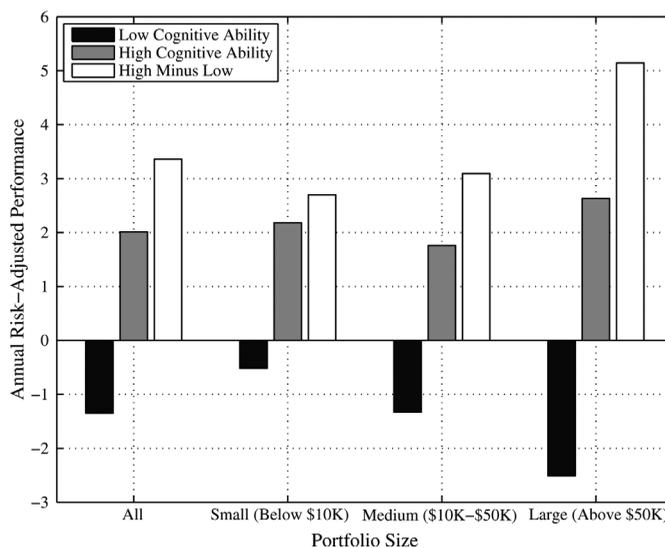
This figure shows the risk-adjusted performance (annualized characteristic-adjusted percentage return), conditional on portfolio size and investors' predicted cognitive abilities. The empirical model of cognitive abilities estimated in table 5 is used to obtain the predicted cognitive ability measures. We regress the predicted cognitive ability measure on investment experience and obtain a residual cognitive ability measure that is orthogonal to experience.

increases, high-cognitive-ability investors (quintile 5) perform better, low-cognitive-ability investors (quintile 1) 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, midsized, and large portfolios are 2.148%, 2.407%, and 4.613%, respectively.[27]

Collectively, the results from portfolio-based time-series tests indicate that investors who do not experience the adverse effects of cognitive aging earn superior risk-adjusted returns. Importantly and somewhat surprisingly, the economic costs of cognitive aging are larger (in both percentage and dollar terms) among investors who hold larger portfolios. Those investors are less likely to hold significant positions outside their brokerage accounts, especially during the sample period when the median number of brokerage accounts varied between one and two.[28] 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.

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[27] As before, we find qualitatively similar results when we use the number of stocks in the portfolio to quantify the difficulty associated with managing a portfolio.

[28] 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.

B. Identifying the Components of Stock Selection Ability

To better understand how high-cognitive-ability investors generate superior portfolio performance, we use the Daniel et al. (1997) 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.

First, we sort investors into five or ten categories based on their residual cognitive ability measures and construct an aggregate portfolio for each investor category by combining the portfolios of all investors who belong to the group. Then, for each of those aggregate portfolios, we compute the CS, CT, and AS measures. 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 cognitive-ability-sorted 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 measures 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 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%. Overall, the performance differentials between the highest- and the lowest-cognitive-ability sorted quintile and decile portfolios are 1.949% and 3.195%, respectively.

VII. Alternative Explanations and Robustness Checks

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 for our findings. The results are summarized in table 6, where for brevity, we report the estimates for only the six variables that are most closely related to our aging-related hypotheses.

A. Alternative Skill Measures

In the first set of tests, we consider other investment skill measures. First, we compute a trading-based skill measure that is not strongly correlated with our previous performance-based skill measures and does not depend on our ability to

observe investors' entire financial portfolios. This skill 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. 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. We choose two different values of k ($k = 5$ and 10), because using the same data set as ours, Coval, Hirshleifer, and Shumway (2005) show that the trading performance of individual investors declines after about two weeks. When $PTBSD(5)$ or $PTBSD(10)$ is used as a dependent variable in the skill regression, similar to the results from previous skill measures, we find that the age and investment experience have opposite signs (see tests 1 and 2 in table 6). The interaction terms mostly have the expected signs, though their estimates are statistically weaker. This evidence indicates that older investors trade less (see table 3), 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.

Next, we examine investors' market timing abilities using the two Graham-Harvey (1996, 1997) performance metrics. We reestimate the skill regression and find that in both instances, age and investment experience maintain their opposite signs (see tests 3 and 4). In addition, the interaction term estimates are very similar to the respective estimates in the alpha skill regression reported in table 4, column 4. These results are consistent with our second main hypothesis and indicate that market timing skill improves with experience but deteriorates with age due to the adverse effects of cognitive aging.

B. An Alternative Experience Measure

In our second robustness test, we define an alternative experience measure using our main investment experience proxy (number of days since account opening date) and self-reported measures of investment knowledge and experience. For a small subset of investors, we know whether investors believe that they have extensive, good, limited, or zero investment experience. A similar self-reported measure reflects their self-assessment of investment knowledge. Using these two self-reported measures, we construct an indicator variable that is set to 1 for investors who have either good or extensive investment knowledge or experience. We also define a second indicator variable that is set to 1 for investors who hold the brokerage account for at least five years. Our new experience measure is the sum of the two indicator variables.[29]

When we replace the investment experience proxy in the skill regression with this new experience variable, we still

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[29] We find similar results if we define the new experience measure as the interaction between the two indicator variables.

find that age has a significantly negative coefficient estimate (coefficient $= -0.054$, t-statistic $= -3.690$) and experience has a significantly positive coefficient estimate (coefficient $= 0.033$, t-statistic $= 2.390$). The other main variables in the skill regression specification maintain their original signs and significance levels (see test 5). This evidence indicates that our key results are robust and do not depend on the specific choice of the investment experience proxy.

C. Aging Effects or Informational Illiteracy?

In the third robustness test, we entertain another cohort-based explanation for the negative age-skill relation. Specifically, we examine whether older investors make worse investment decisions because they are slower to adopt new technology such as the Internet and not due to cognitive aging. It is possible that older investors who belong to a cohort from the radio and television era and are not as technologically savvy as the cohort of younger investors from the computers and Internet era. Consequently, older investors could experience higher search costs and make their decisions using stale and less accurate information signals.

We consider a subset of investors who are technologically savvy and have used the Internet to execute trades in their brokerage account. If the adverse effects of aging are visible even among this set of investors with relatively higher levels of informational literacy, it is unlikely that cohort-induced differences in technology adoption propensity can successfully explain our findings. When we use the four-factor alpha skill measure to estimate the skill regression using the subsample of Internet users only, we find that age and investment experience maintain their opposite signs (see test 6). Age has a coefficient estimate of -0.063 (t-statistic $= -3.168$), and experience has a coefficient estimate of 0.048 (t-statistic $= 2.653$). The other main variables in the skill regression specification maintain their original signs and significance levels. These results are qualitatively similar to our baseline estimates reported in table 4 and indicate that informational literacy associated with an age cohort is unlikely to be an appropriate explanation for our findings.

D. Split Sample Tests

In our fourth robustness test, we reestimate the skill regression for two subperiods. The 1991 to 1996 sample period encapsulates two distinct market conditions: a relatively flat market during the first half of the sample period, following the 1990 NBER recession, and 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 (that is, less risky) investments by older investors during bullish market conditions. To examine whether the adverse effects of cognitive aging are significant during periods of both weak and strong stock market performance, we estimate the skill regression for the 1991 to 1993 and the 1994

to 1996 subperiods 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 subsamples indicate that the adverse effects of cognitive aging and the positive effects of learning are present in both time periods (see tests 7 and 8). Both age and experience variables have significant coefficient estimates. Interestingly, the age-race/ethnicity interaction terms have statistically weak coefficient estimates in the full-sample regression but the expected negative signs during the 1994 to 1996 subperiod. Taken together, the subperiod 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.

E. Differential Skill in Identifying Superior Local Stocks

The fifth robustness test focuses on the performance of local investments. Ivković and Weisbenner (2005) show that, on average, the local stock investments of individual investors perform better than their nonlocal investments. To examine whether the negative age-skill relation holds in both local and nonlocal 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.[30] We reestimate 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 again consistent with our second main conjecture. We find that age and investment experience estimates have opposite signs, and the age-race/ethnicity interaction terms have negative coefficient estimates (see test 9). The Age $\times$ Low Income and Age $\times$ Low Education interaction terms have the expected negative signs, but those estimates are statistically insignificant. This evidence indicates that older investors experience the adverse effects of cognitive aging even in their local stock investment decisions.

F. Controls for Liquidity and Industry Exposures

In the next robustness test, we further 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 follow the Pástor & Stambaugh (2002, 2003) methodologies and compute portfolio alphas after employing controls for industry exposures and liquidity. We estimate skill regressions using this eight-factor alpha and find that age is still negatively related to investment skill

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

(estimate $= -0.047$, t-statistic $= -3.745$), while investment experience is still positively related to investment skill (estimate $= 0.022$, t-statistic $= 2.314$). Furthermore, the interaction terms maintain their negative coefficient estimates (see test 10).

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 & French, 1997) and employ them as additional independent variables in the skill regressions. In untabulated results, we find that many of these industry weights have large and significant coefficient estimates. For instance, technology stocks in the electronic equipment industry have a strong, positive coefficient estimate (estimate $= 0.114$, t-statistic $= 10.254$), while the utilities industry has a strong, negative coefficient estimate (estimate $= -0.152$, t-statistic $= -12.773$). However, the age, experience, and relevant interaction variables still maintain their signs and statistical significance. Thus, the exceptional performance of one or more industries during the sample period does not significantly influence our skill regression estimates.

G. Lack of Skill or Lack of Effort?

The seventh robustness test examines the "play money" hypothesis. One might argue that the negative skill-aging relation we find is not too surprising or economically very 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 subsample of investors who hold larger portfolios in comparison to their income levels. Specifically, we use the four-factor alpha skill measure and reestimate the skill regressions for the subsample of investors whose mean portfolio size to annual income ratio (the SIR) is greater than or equal to 1.23 (the top two-thirds of investors). These equity portfolios are unlikely to represent investors' play money accounts and are less likely to be ignored.

The skill regression estimates for the large portfolio subsample indicate that the subsample coefficient estimates are similar to the full sample results (see test 11). For instance, age has a coefficient estimate of -0.053 (t-statistic $= -4.759$) and investment experience has a coefficient estimate of 0.018 (t-statistic $= 1.996$) in the alpha regression. Additionally, two of the four interaction terms have the expected negative signs. Thus, our key results are unlikely to be successfully explained by the play money hypothesis.

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

In the eighth robustness test, we examine whether our results are influenced by the strong concentration of investors

from California because a considerable portion (27.25%) of our sample is located there. To guard against this possibility, we exclude all investors who reside in California and reestimate the skill regression using the four-factor alpha skill measure. The results for the non-Californian subsample are similar to the full sample results (see test 12). Age has a coefficient estimate of -0.044 (t-statistic $= -2.797$), and investment experience has a coefficient estimate of 0.017 (t-statistic $= 2.651$) in the alpha regression. This result indicates that the geographical concentration of our sample investors is unlikely to successfully explain the negative age-skill relation.

I. Is the Age on the Account Opening Date an Indicator of Skill?

In the last robustness test, we examine whether our main results are influenced by a sample selection bias. In particular, one might be concerned that investor's age on account opening date might be an indicator of skill. All else equal, investors who open the brokerage account at an older age would have lower investment skill. Thus, the investment skill differences between older and younger investors after accounting for experience might reflect not the adverse effects of cognitive aging but the sample selection bias.

To ensure that our results are not influenced by the potential sample selection bias, we compute the age of each investor on the account opening date ($=$ age in June 1997 $-$ investment experience) and estimate skill regressions for subsamples of younger, middle-aged, and older investors. We use the age on the account opening date to define the three subsamples. In untabulated results, we find that in both diversification skill and stock selection skill regressions, the age and experience variables maintain their opposite signs and magnitudes. This evidence indicates that our results do not reflect skill differences that can be attributed to investor's age on account opening date.

Collectively, the 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 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.

VIII.   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, exhibit greater propensity for year-end tax-loss selling, and exhibit weaker behavioral biases such as the disposition effect and familiarity bias. 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 a 3% to 5% lower annual return 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 adviser or some other qualified investment professional. An investment refresher course that highlights the adverse effects of cognitive aging and prescribes effective compensating mechanisms might also be helpful. This may especially be a wise decision for investors who hold portfolios larger than those examined in this study. Our performance results also 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 higher for older investors.

In broader terms, our empirical 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 (Gomes & 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 stock market behavior (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 provides guidance about the segments of the market (for example, stocks with high dividend yield and less risk), 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 difficult to ignore.

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