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IQ and Stock Market Participation

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ABSTRACT

Stock market participation is monotonically related to IQ, controlling for wealth, income, age, and other demographic and occupational information. The high correlation between IQ and participation exists even among the affluent. Supplemental data from siblings, studied with an instrumental variables approach and regressions that control for family effects, demonstrate that IQ's influence on participation extends to females and does not arise from omitted familial and nonfamilial variables. High-IQ investors are more likely to hold mutual funds and larger numbers of stocks, experience lower risk, and earn higher Sharpe ratios. We discuss implications for policy and finance research.

ONLY ABOUT 50% OF U.S. households invest in stocks, either directly or indirectly (via mutual funds in retirement and nonretirement accounts), and participation in Europe is even lower.[1] Traditional models in financial economics, which prescribe universal participation,[2] cannot easily explain these stylized facts, viewing them as a "participation puzzle." Rather, these facts lend support to the common sense view that limited wealth precludes savings, let alone

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[1] See Bucks, Kennickell, and Moore (2009) and Guiso, Sapienza, and Zingales (2008).

[2] For example, Arrow (1965) shows that investors at every risk-tolerance level optimally hold risky stock because the equity premium is positive and investor preferences are locally risk-neutral at zero risky investment.

investment in risky stocks. However, "common sense" does not explain the degree of nonparticipation among those who can afford to invest.

A vast and rapidly growing literature seeks to explain why those who can afford to save fail to participate.[3] Frictions associated with the direct costs of participation have been advanced as one possibility, but given how small these costs are, they are unlikely to explain the degree of nonparticipation observed. Nontraditional preferences can also help explain the participation puzzle, but these unorthodox preferences lack wide acceptance in the literature. Nonparticipants also might believe that stock markets offer lower returns to them than to participants because the latter have access to better information, technology, and professional advice—an explanation that links participation to both wealth and cognitive ability.

This paper studies cognitive ability as a driver of participation. Limited ability to process information, an indirect participation cost, is a widely advanced explanation for nonparticipation, but testing this hypothesis has been problematic. Resolving whether cognitive skill plays a significant role in participation has implications both for policy and for financial models. For example, if cognitive skill plays no role in participation, and decisions are optimally made, policies that force individuals to participate in the stock market (e.g., President Bush's Social Security reform proposal) reduce welfare.[4] By contrast, if cognitive skill influences participation, tax incentives and financial literacy programs may be less effective and cost more than retirement plan defaults that force workers to opt out of equity funds. Moreover, the standard aggregation theorems that simplify asset pricing models may not apply when variation in portfolios across investors does not exclusively arise from differences in risk aversion and wealth. Last, if many individuals stay out of the market for reasons unrelated to asset prices, empiricists can ignore nonparticipants' consumption and use stockholder consumption data to calibrate asset pricing models.[5]

[3] Haliassos and Bertaut (1995), studying the U.S. Survey of Consumer Finances, conclude that "inertia and departures from expected-utility maximization" might explain nonparticipation. Vissing-Jørgensen (2003) finds that moderate fixed participation costs explain the nonparticipation of many U.S. households. However, Mankiw and Zeldes (1991) and Heaton and Lucas (2000) argue that such fixed costs do not explain the rate of nonparticipation among the wealthy. To explain the latter, researchers turn to lack of stock market awareness (Hong, Kubik, and Stein (2004), Guiso and Jappelli (2005), Brown et al. (2008)), nonstandard preferences like ambiguity aversion (Dow and Werlang (1992), Ang, Bekaert, and Liu (2005), Cao, Wang, and Zhang (2005), Epstein and Schneider (2007)), education deficits (Campbell (2006), Calvet, Campbell, and Sodini (2007), Christiansen, Joensen, and Rangvid (2008), van Rooij, Lusardi, and Alessie (2007)), and lack of trust (Guiso, Sapienza, and Zingales (2008)).

[4] For example, Benzoni, Collin-Dufresne, and Goldstein (2007) suggest that young individuals should take short positions in stocks because returns to their human capital significantly correlate with market returns.

[5] Stockholder data better match the salient features of asset prices because the consumption of stockholders is more volatile and more highly correlated with the excess market return than the consumption of nonparticipants. See Mankiw and Zeldes (1991), Brav, Constantinides, and Geczy (2002), Vissing-Jørgensen (2002), Vissing-Jørgensen and Attanasio (2003), and Malloy, Moskowitz, and Vissing-Jørgensen (2009).

Measurable traits that reflect a subject's skill at processing information are hard to come by and, if available, generally face a host of endogeneity issues. Christelis, Jappelli, and Padula (2010), using survey data from almost 20,000 European seniors, find that answers to the number of animals one can name in one minute, the number of nouns (out of 10) one recalls, and a series of up to four numeracy questions influence self-reported stock market participation. In related work, Benjamin, Brown, and Shapiro (2006) study how intelligence-related test scores from 1980 influence 2,088 sibling groups' answers to the question posed in 1998 and 2000: "Do you (or your spouse) have any common stock, preferred stock, stock options, corporate or government bonds, or mutual funds?" Their findings, from the National Longitudinal Survey of Youth, were later extended to additional dimensions of cognitive ability in Cole and Shastry's (2009) analysis of the same data set. Finally, Kezdi and Willis (2003) show that IQ influences the reported participation of more than 12,000 National Retirement Survey subjects.

We study Finnish stock market participation at the end of 2000 as a function of IQ measured early in adult life; we also study the relation between IQ and various contributors to portfolio risk and return. The IQ scores are comprehensive for Finnish males in a 20-year age range because they are obtained upon induction into Finland's mandatory military service. We have IQ data on all inductees entering service between 1982 and 2001, as well as stock registry and mutual fund ownership data that unambiguously assess inductees' stock or mutual fund ownership later in life. We also have the year 2000 tax returns of approximately 160,000 of these inductees. The tax returns contain subject-level controls for different types of wealth, income, marital status, children, age, home and foreign asset ownership, primary language, employment status, and occupation (including whether one is an entrepreneur, farmer, or finance professional). We control for education, using zip code–level data for each age grouping.

In contrast to other research on the topic, our study employs a larger sample and contains more controls. Furthermore, the paper's sophisticated econometric techniques—control function regression, Blinder-Oaxaca-Fairlie decompositions, and random effects probit—remedy pitfalls in this line of research. Address data facilitate standard error clustering at the zip code level, avoiding inferential biases from correlated residuals within neighborhoods. Finally, individual-level ownership data facilitate the study of IQ's link to various determinants of portfolio risk and return.

Most importantly, we do not rely on voluntary surveys. Kezdi and Willis (2009), for example, find that low-IQ respondents simply do not know how to answer many queries in the National Retirement Survey, leaving many of them blank. Low-IQ investors also are more likely to answer "no" to ownership queries that describe financial instruments in more complex terms than they are used to (e.g., "equity" rather than "stock," "fund" rather than "account"). For half of the aforementioned studies of participation, affirmative participation responses are supposed to arise from mutual fund ownership. Even if money market fund ownership is related to stock market participation, a survey designed in this fashion could generate a spurious IQ–participation relationship if high-IQ investors better understand that their money market account is a mutual fund.[6] Malloy, Moskowitz, and Vissing-Jørgensen (2009) express notable concern about the reliability of survey responses to participation questions. Some of their analyses throw out almost half of all survey responses because a probit predictor of participation is inconsistent with the survey response. By contrast, our stockholdings are drawn directly from ownership records, are comprehensive, and lack the response bias inherent in almost all surveys. Our mutual fund holdings, drawn from tax records, are reported to the tax authorities by the mutual funds themselves rather than being self-reported. The data set reports the aggregate value of mutual funds owned by each individual on December 31, 2000, but does not identify the specific funds held.

Probit regressions exhibit IQ stanine dummies with perfectly monotonic coefficients. The highest IQ subjects are most likely to participate; those with the second-highest scores participate more than those with the third-highest scores, etc. The economic size of the IQ effect is remarkably large—larger than income's participation effect. Moreover, all IQ subcomponents (logical, verbal, and especially mathematical scores) influence participation.

In part because of the early age at which our study's IQ variable is measured, one might plausibly believe that the observed correlation between IQ and the regression's control variables arises from IQ's effect on the controls rather than the reverse. In this case, IQ differences account for differences in participation, not only independent from controls like education, wealth, and income, but also by having an influence over these controls. We decompose IQ's effect on participation into various channels through which this secondary IQ effect operates. For example, subjects with the second-highest IQ stanine have a 42.5% participation rate. By contrast, those in the second-lowest IQ stanine have a 13.1% participation rate. About three-fifths of the 29.4% difference in participation rates can be explained by differences in the means of the control variables across the two stanines. The decomposition indicates that IQ-related wealth, education, and income differences are the channels of primary importance. This conclusion also applies to other pairings of IQ groups at opposite ends of the IQ spectrum.

Lack of cognitive skill is so fundamental as a driver of nonparticipation that it deters large amounts of wealth from entering the stock market. As verification of the latter conclusion, we also study the influence of IQ on the participation decisions of affluent individuals. These individuals face direct costs of participation that are relatively small in comparison to its benefits. If these market-based frictions fully accounted for nonparticipation, we would not expect IQ to influence the participation of the affluent to any great extent. However, we find that IQ's role in the participation decisions of the affluent is about the same as it is for the less affluent. The definition of affluence—net worth or income—does not affect this finding.

[6] For a more comprehensive critique of survey data, see Campbell (2003) and Lamont (2003).

The quality of our data offers other unique benefits that prior empirical research has not been able to take advantage of. Analysis of sibling data facilitates the use of several powerful econometric techniques. Based on these techniques, we conclude that omitted variables—such as risk aversion or more precise education categories—tied to one's own IQ or to the average IQ of one's family are unlikely to account for the effect of IQ on participation. A proper instrumental variables analysis of brothers employing the control function method indicates that IQ measured from a brother's IQ exam plays a significant role in the subject's participation decision. (The finding extends to sisters' participation.) Moreover, random effects probit analysis of brothers indicates that individual IQ differences, even within families, help to explain differences in participation.

IQ could influence participation if a subject's risk-return trade-off is positively related to his IQ. Motivated by this conjecture, we document that IQ correlates with participants' Sharpe ratios, controlling for the usual suspects, and we trace this correlation to IQ-related differences in diversification and systematic risk.[7] High-IQ participants are more likely to hold mutual funds, larger numbers of stocks, and have lower-beta portfolios than lower-IQ participants. High-IQ investors also have greater exposure to the risks of small and value stocks. These results lend credence to the story that high-IQ subjects participate because they face a superior risk-return trade-off and that low-IQ subjects shun participation because they make investment mistakes.

The paper is outlined as follows: Section I describes the data along with summary statistics. Section II's regressions analyze IQ and participation. Section III studies the risk-return trade-off faced by IQ-sorted participants. Section IV summarizes and draws conclusions.

I. Data and Summary Statistics

A. Six Data Sets That We Merge for Our Analysis

A.1. Finnish Central Securities Depository (FCSD) Registry

This data set contains the daily portfolios and trades of all Finnish household investors in FCSD-registered stocks (all traded Finnish stocks plus all foreign stocks traded on the Helsinki Exchanges) from January 1, 1995 through November 29, 2002.[8] The electronic FCSD data we use, which exclude ownership of mutual funds, are exact duplicates of the official records of ownership and trades, and hence are very reliable. We use the FCSD holdings on December 31, 2000, the report date for control variables obtained from other data sets described below, to assess whether an investor holds any stocks, which stocks the investor owns, and what his stock portfolio is worth.

[7] Because we lack data on which funds each individual holds, but know the total value of fund holdings at the investor level, the estimated Sharpe ratios rely on assumptions about fund composition.

[8] Grinblatt and Keloharju (2000) provide the relevant details about this data set.

A.2. Helsinki Exchanges (HEX) Stock Data

The HEX provide daily closing transaction prices and returns for all stocks traded on the HEX. Year 2001 daily returns are combined with the FCSD data to measure the return variance of each individual's stock portfolio.

A.3. Finnish Tax Administration (FTA) Data

The FTA provides entries from the year 2000 tax returns of all individuals domiciled in the provinces of Uusimaa and East Uusimaa, a region encompassing Greater Helsinki, as well as data from a population registry. Variables constructed from this source include ordinary (labor) income (referred to as "income"), taxable net worth from all sources (referred to as "wealth"), whether and to what extent one owns various assets (a home, forest, mutual fund, stock in a nonpublic company, or foreign assets), native language (Finnish or Swedish), marital status (single, married, or unmarried but cohabiting), whether one has dependents under age 18, occupation (including whether one is an entrepreneur, farmer, or finance professional), employment status, year of birth, and gender (used to produce a comprehensive sample of females from the two provinces with the same set of variables described above). We also use this data set, in conjunction with the FCSD data set, to assess participation—a dummy variable that takes on the value one for subjects who held any FCSD-registered stock or FTA-reported mutual fund on December 31, 2000.[9] Our robustness checks, reported in an Internet Appendix, analyze narrower definitions of participation, including participation arising from the holding of at least one individual stock at the end of 2000, and whether one purchased stock on or before November 29, 2002.[10]

A.4. Finnish Armed Forces (FAF) Intelligence Assessment

Around the time of induction into mandatory military duty in the FAF, typically at age 19 or 20 and thus generally prior to significant stock trading, males in Finland take a battery of psychological tests to assess which conscripts are most suited for officer training. One portion consists of 120 questions that score cognitive functioning in three areas: mathematical, verbal, and logical skill. The FAF aggregates these subscores to form a composite intelligence score, which we use and refer to as IQ. IQ is standardized to follow the stanine

[9] *Finnish Mutual Fund Report December 2000* reports that 94% of Finnish mutual fund accounts were in equity or balanced funds. A negligible fraction of fund investors use money market or bond funds exclusively. Because the FTA does not identify fund type, a few participants could be misclassified for this reason.

[10] Fifty-five percent of fund owners also own stock, while 22% of those who own individual stocks also own funds. The median number of stocks held is two. The median individual stock portfolio value is 3,440 euros. The end-of-2000 values of Finnish households' mutual fund and individual stock holdings were 5.2 billion and 23.7 billion euros, respectively. The Internet Appendix is available online at http://www.afajof.org/supplements.asp.

distribution (integers 1 to 9 with 9 being most intelligent).[11] We have test results for all exams scored between January 1, 1982 and December 31, 2001.

Variation in measured IQ is unlikely to reflect significant differences in culture or environmental factors like schooling that might be related to participation. Compared to other countries, the Finnish school system is remarkably homogeneous: all education, including university education, is free and the quality of education is uniformly high across the country.[12] The country is also racially homogeneous and, because of the FTA data set, most of the subjects studied live in the largest urban area within Finland. These factors make it more likely that differences in measured IQ reflect differences in innate intelligence.

A.5. Finnish Address Data Set

A supplementary section of the tax return data contains current and historical addresses for all individuals domiciled in the provinces of Uusimaa and East Uusimaa. We have every subject's residence on each day from 1998 to 2000, the move-in date for the first address in this three-year period, and the move-out date (up to late 2002) for the three-year period's last address. For example, if a person was born on February 7, 1963, moved to a new address on June 10, 1968, and resided there until 2003, the data show the latter address, the June 10 move date, and continual residence between June 10, 1968 and December 31, 2002. All addresses were converted to latitude and longitude coordinates. The coordinates were then translated and rotated with parameters that were destroyed to maintain anonymity.

The historical location data combined with gender data from the FTA determine brother–brother and brother–sister sibling pairs. Two individuals born within 15 years of one another are siblings if they can be classified as either: (1) both moving on the same date to the same location and both moving out of that location at a later date or (2) living in a single family dwelling at the same location at some date. If the latter, we also impose a parent criterion: that one other person, or exactly two opposite-gendered persons, live at the same address at the same date, with the younger of the two being at least 18 years older than the oldest member of the sibling pair. We also use transitivity to establish sibling pairs. For example, suppose A and B are siblings, based on the criteria above. If B and C can also be established as a sibling pair, then

[11] A "stanine" (standard 9) distribution discretely partitions the normal distribution into nine intervals, with stanine 5 being the mean. A 1-stanine score difference represents one-half of a standard deviation for the median subject within each stanine. Because value-9 subjects represent continuous scores rounded up from 8.5, stanine-9 subjects are all at least 1.75 standard deviations above the mean (approximately 4% of the population). Similarly, stanine-1 investors are at least 1.75 standard deviations below the mean, stanine 2 at least 1.25 standard deviations below the mean, etc.

[12] See, for example, "Puzzling new evidence on education: The race is not always to the richest" (*Economist Magazine*, December 6, 2007) and "What makes Finnish kids so smart?" (*Wall Street Journal*, February 29, 2008).

A and C is a sibling pair. As an additional criterion for siblings generated by transitivity, we require A and C to share a common adult.[13] These criteria, which also restrict siblings to be 18 or older as of December 31, 2000, may omit sibling pairs but are unlikely to misclassify a pair as siblings.

A.6. Finnish Census Data Set

We employ average education level of adults of similar age within the subject's end-of-2000 zip code to control for the subject's education. The census data set breaks educational attainment into four categories: basic education, which ends at 9th grade; vocational education; matriculation (a high school diploma earned by passing a college-prep examination at the end of 12th grade); and university degree. For each zip code and each of four age groups—18 to 24, 25 to 34, 35 to 44, and 45 to 54—the data set reports what fraction of the age group attained each of these education levels. We estimate the subject's education level as the average for the age group living within his residence zip code on December 31, 2000.[14]

B. Summary Statistics

Table I reports summary statistics for the 158,044 males who took the FAF intelligence test between 1982 and 2001 and for whom we have year 2000 tax returns and zip code–level education data for the subject's age group. (We later extend our analysis to 4,358 sisters of these subjects). The data window, combined with the requirement that military service commence prior to age 29, implies that our subjects were born between 1953 and 1982. Panel A lists the theoretical distribution and describes the distribution of IQ scores both for the subjects used in our regression and for the entire FAF data set. Panel B reports average values of variables used to develop control regressors (often as decile-based category dummies). This includes averages for all males in the study, as well as average values based on whether the males participate in the stock market. Panel C reports the means of these same variables as a function of IQ.

The third row of Panel A shows that the intelligence scores in our sample are slightly higher than both the theoretical stanine distribution and the scores of males throughout Finland. This is because the FTA (tax) data, from which we derive most of our controls, come from those who reside either in the largest and most urban province in Finland (Uusimaa) or its neighboring province (East Uusimaa). These provinces tend to attract affluent professionals. This mean

[13] We also know that these rules establish reliable sibling pairs because, when we apply the rules to identify brother–brother pairs, the IQ correlation is 0.40. This correlation is similar to those found in the literature on IQ and families. Bound, Griliches, and Hall (1986), for example, report a brother–brother correlation of 0.44 and brother–sister correlation of 0.48 in the U.S. National Longitudinal Surveys of Young Men and Young Women.

[14] We later use zip code–aggregated IQ scores to address errors-in-variables issues arising from lack of individual-level education data.

Table I

Descriptive Statistics

Panel A reports the distribution of IQ scores. Panels B and C report mean values for variables used in regression analyses. See the text for descriptions of the variables. Panel B reports means sorted by participation and Panel C reports means sorted by IQ score. Participation is a dummy variable that takes the value one for subjects who held mutual funds or individual stocks registered with the FCSD at the end of 2000. Income and wealth variables in Panel B are from the 2000 Finnish tax data set. Education variables are derived from the Finnish census data set using each individual's age and zip code. Other demographic and occupation information are from the tax data.

Panel A: Distribution of IQ Score

	IQ Score									
Sample	1	2	3	4	5	6	7	8	9	*N*
Theoretical stanine distribution	4.0%	7.0%	12.0%	17.0%	20.0%	17.0%	12.0%	7.0%	4.0%	
Full IQ score data set	5.2%	9.3%	9.5%	18.4%	21.0%	18.0%	9.1%	5.6%	3.8%	586,187
Uusimaa/East Uusimaa	3.5%	6.8%	7.6%	15.8%	21.0%	20.2%	11.4%	7.7%	6.0%	158,044

Panel B: Mean Socioeconomic Characteristics by Stock Market Participation

		Stock Market Participant	
	All	No	Yes
IQ	5.25	4.97	5.94
Education			
Basic	21.6%	22.4%	19.6%
Vocational	42.6%	43.4%	40.8%
Matricular	18.8%	18.6%	19.5%
University	16.9%	15.6%	20.2%
Ordinary income, EUR	22,642	19,901	29,604
Ordinary income, log-growth	11.8%	11.5%	12.6%
Wealth			
Taxable home wealth >0	37.7%	31.7%	52.8%
Taxable forest wealth >0	1.3%	1.0%	2.0%
Taxable foreign wealth >0	0.0%	0.0%	0.1%

(continued)

Table I—*Continued*

Panel B: Mean Socioeconomic Characteristics by Stock Market Participation

	All	Stock Market Participant: No	Stock Market Participant: Yes
Taxable private equity >0	2.6%	2.1%	3.8%
Taxable net worth, EUR	11,193	2,808	32,489
Other demographics			
Swedish	7.0%	6.3%	8.8%
Married	29.6%	27.7%	34.3%
Cohabiter	6.5%	6.9%	5.3%
Kids	29.8%	29.2%	31.5%
Occupation			
Entrepreneur	2.8%	2.9%	2.6%
Farmer	0.9%	0.8%	1.3%
Finance professional	0.7%	0.3%	1.7%
Unemployed	8.6%	10.7%	3.2%
Number of observations	158,044	113,393	44,651

Panel C: Mean Socioeconomic Characteristics by IQ Score

	IQ Score									
	1	2	3	4	5	6	7	8	9	All
Stock market participant	9.8%	13.1%	16.6%	20.4%	26.3%	32.8%	37.9%	42.5%	46.5%	28.3%
Education										
Basic	23.8%	23.6%	23.2%	22.9%	22.0%	21.2%	20.2%	19.5%	18.6%	21.6%
Vocational	47.5%	46.5%	45.9%	44.4%	43.1%	41.7%	40.3%	39.0%	37.2%	42.6%
Matricular	14.1%	15.1%	16.0%	17.3%	18.4%	19.6%	20.9%	22.1%	24.0%	18.8%
University	14.6%	14.8%	14.9%	15.3%	16.5%	17.5%	18.6%	19.5%	20.2%	16.9%
Ordinary income, EUR	16,062	17,666	18,427	19,640	21,413	23,874	26,171	28,191	31,707	22,642
Ordinary income, log-growth	7.1%	7.4%	8.3%	11.0%	11.5%	13.3%	13.4%	14.3%	16.1%	11.8%

(continued)

Table I–*Continued*

Panel C: Mean Socioeconomic Characteristics by IQ Score

	IQ Score									
	1	2	3	4	5	6	7	8	9	All
Wealth										
Taxable home wealth >0	27.9%	31.4%	34.0%	34.8%	37.6%	40.1%	40.8%	42.1%	42.8%	37.7%
Taxable forest wealth >0	1.2%	1.4%	1.2%	1.3%	1.3%	1.2%	1.2%	1.3%	1.4%	1.3%
Taxable foreign wealth >0	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.1%	0.0%
Taxable private equity >0	1.8%	2.1%	2.3%	2.4%	2.4%	2.8%	3.0%	3.0%	3.3%	2.6%
Taxable net worth, EUR	3,627	4,655	7,393	6,730	9,231	9,575	12,019	16,340	43,619	11,193
Other demographics										
Swedish	6.6%	7.4%	10.0%	5.9%	6.7%	6.9%	6.5%	6.9%	8.4%	7.0%
Married	22.5%	25.7%	25.8%	27.0%	29.3%	31.7%	32.0%	34.0%	33.2%	29.6%
Cohabiter	10.1%	10.0%	9.4%	8.0%	6.8%	5.3%	4.3%	3.7%	2.8%	6.5%
Kids	29.7%	32.0%	31.7%	30.5%	30.2%	29.8%	28.3%	28.5%	26.6%	29.8%
Occupation										
Entrepreneur	3.2%	3.6%	3.2%	2.9%	2.7%	2.6%	2.4%	2.5%	2.6%	2.8%
Farmer	1.1%	1.1%	1.2%	0.9%	1.0%	0.8%	0.7%	0.7%	0.7%	0.9%
Finance professional	0.0%	0.1%	0.0%	0.2%	0.6%	0.9%	1.2%	1.7%	1.6%	0.7%
Unemployed	22.4%	16.7%	13.8%	11.3%	8.3%	6.0%	4.2%	3.4%	2.2%	8.6%
Number of observations	5,552	10,749	12,002	25,040	33,124	31,943	17,958	12,145	9,531	158,044

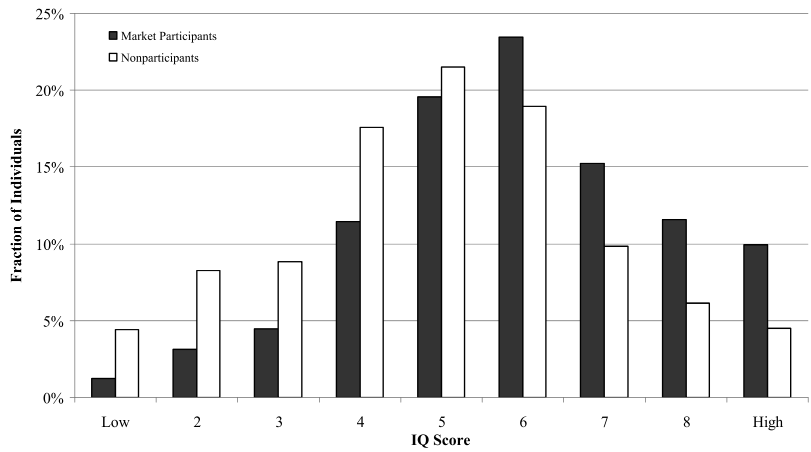

Figure 1. Distribution of IQ score conditional on market participation. Figure 1 plots IQ score distributions for stock market participants and nonparticipants. An individual is a stock market participant if he held mutual funds or individual stocks registered with the FCSD at the end of 2000.

effect is of little concern as there are sufficiently large sample sizes within each IQ stanine.

Panel B shows that the participant and nonparticipant groups markedly differ in many dimensions (all significant at the 1% level). Participants' average IQ stanine is almost a full point (about half a standard deviation) above the average for nonparticipants. Figure 1, which graphs IQ distribution for participants and nonparticipants, illustrates that the difference in the average IQ scores of participants and nonparticipants does not arise from a preponderance of IQ scores of any one stanine for either group. There are relatively fewer participants in every below-average IQ stanine and more in every above-average IQ stanine. Panel B also shows that for all variables used to construct regression controls, participants' average values differ from those of nonparticipants. Participants, with average annual wages of 29,604 euros per year, earn about 50% more labor income than nonparticipants' 19,901 euro average; are wealthier; and have a greater tendency to own homes, forests, and private equity (typically their business).

Using zip code–level education data for each age grouping, we find that nonparticipants are more likely to have only basic education (less than high school) or vocational education, while participants are more likely to have earned a university degree. Other demographic variables like employment and marital status also are related to market participation. Participants are 1.24 times more likely than nonparticipants to marry, 1.08 times more likely to have kids, five times more likely to work in the finance profession, and three times less likely to be unemployed.

Panel C, which presents averages for these same variables conditional on IQ stanine, shows that many variables are related to IQ. Income and wealth are almost perfectly monotonic in IQ. Average income increases from 16,062 euros per year for stanine 1 to 31,707 euros per year for stanine 9. Taxable net worth increases from just 3,627 euros for the lowest IQ category to 43,619 euros for the highest IQ category. Using zip code–level data, the proportion of individuals attaining only basic education monotonically decreases from 24% for the lowest IQ stanine to 19% for the highest. At the same time, the fraction of individuals with university-level education monotonically increases from 15% to 20% as the IQ stanine increases from 1 to 9. The IQ-related differences of other control variables are also notable. The unemployment rate of the lowest IQ stanine is about 10 times higher than the rate observed among those with the highest IQ stanine. The homeownership rate increases from 28% to 43%; the marriage rate goes from 22% to 33%; and the fraction of people working in the finance profession increases from 0% to about 2% as we move from the least to the most intelligent stanines. Most notable, however, is that the participation rate increases monotonically: from 10% for stanine 1 to 47% for stanine 9.

II. IQ and the Participation Decision

A. Probit Regressions of Participation Decisions on IQ and Controls

Bivariate relationships, like those documented in Table I, sometimes diminish or disappear when controls are introduced. Our primary analysis therefore uses regression to study IQ's marginal effect. Because the participation outcome is binary, Table II reports probit coefficients, test statistics (from zip code–clustered residuals), and marginal participation rate effects (at the average values of non-IQ regressors) for two regression specifications of a stock market participation dummy[15] against IQ and a host of control variables.

The "IQ dummy specification," observed in the first three columns, employs dummies for each IQ stanine. The dummy for the highest IQ score, stanine 9, serves as the omitted category. The 1,912.5 Wald statistic at the bottom of the first column tests whether the participation rate of the highest IQ stanine differs from the other eight stanines. The critical chi-squared value of the Wald statistic using the 0.001 significance level is 26.1. The effect of IQ on participation also is perfectly monotonic. Those in the lowest IQ stanine are less likely to own stock than individuals with the second-lowest IQ stanine, etc. The economic significance is equally impressive. The marginal effects column indicates that the lowest IQ individuals have a participation rate that is 20.5 percentage points less than that of the highest IQ individuals.

The "linear-IQ specification," reported in the three rightmost columns of Table II, explores IQ stanine as a single variable. Not surprisingly, the results and their interpretation are similar to those for the IQ dummy specification. The IQ coefficient of 0.090 for this specification mirrors the average difference in coefficients for the IQ dummy specification.

[15] Recall that the participation dummy is one only if a subject holds FCSD stocks or mutual funds at the end of 2000.

Table II

IQ Scores and Stock Market Participation

Table II reports summary data from probit regressions of stock market participation on IQ stanine dummies (or IQ score) and a host of control variables (described in the body of the paper) derived from the Finnish tax data and the Finnish census data set. Participation is a dummy variable that takes the value one for subjects who held mutual funds or individual stocks registered with the FCSD at the end of 2000. Pseudo R^2 and sample sizes are reported at the bottom of the table. Standard errors are clustered by zip code. For each of two specifications, the columns report coefficients from the probit regression, associated z-values, and marginal effects on participation probability (evaluated at the average value of the other regressors, except for IQ stanine dummies, which are evaluated at zero). The marginal effects for indicator variables indicate the shift in the participation probability when the indicator variable changes from zero to one. The dummy variable associated with the highest category—IQ stanine 9, university-level education, highest ordinary income, and taxable net worth in the highest decile—are omitted and serve as a benchmark. Taxable net worth deciles are computed after removing individuals with no taxable net worth; a dummy variable for no net worth identifies the latter individuals. The regressions also contain 30 (unreported) cohort fixed effects for birth years 1953 through 1982.

	IQ Dummy Specification			Linear-IQ Specification		
Independent Variables	Coefficients	z-values	Marginal Effects	Coefficients	z-values	Marginal Effects
IQ stanine				0.090	41.84	0.028
Lowest	−0.706	−24.71	−0.205			
2	−0.580	−27.17	−0.177			
3	−0.477	−21.49	−0.151			
4	−0.369	−21.72	−0.121			
5	−0.263	−15.64	−0.089			
6	−0.149	−8.88	−0.052			
7	−0.075	−4.35	−0.027			
8	−0.023	−1.24	−0.008			
Education						
Basic	−0.006	−5.66	−0.002	−0.006	−5.72	−0.002
Vocational	−0.015	−14.27	−0.006	−0.015	−14.16	−0.005
Matricular	0.000	−0.04	0.000	0.000	−0.17	0.000

(continued)

Table II—*Continued*

	IQ Dummy Specification			Linear-IQ Specification		
Independent Variables	Coefficients	z-values	Marginal Effects	Coefficients	z-values	Marginal Effects
Ordinary income decile						
No income	−0.359	−10.86	−0.119	−0.359	−10.86	−0.099
Lowest	−0.494	−24.73	−0.160	−0.494	−24.70	−0.133
2	−0.561	−27.97	−0.179	−0.561	−27.94	−0.147
3	−0.555	−27.72	−0.177	−0.556	−27.75	−0.146
4	−0.595	−35.23	−0.188	−0.596	−35.09	−0.155
5	−0.601	−33.72	−0.189	−0.602	−33.78	−0.156
6	−0.523	−28.51	−0.169	−0.523	−28.52	−0.139
7	−0.427	−25.46	−0.141	−0.425	−25.32	−0.117
8	−0.324	−19.03	−0.110	−0.321	−18.96	−0.092
9	−0.167	−10.38	−0.059	−0.164	−10.19	−0.049
Income log-growth rate	0.027	3.65	0.010	0.027	3.64	0.009
Wealth dummies by wealth type						
Housing	0.149	13.61	0.054	0.149	13.69	0.048
Forest	−0.085	−1.85	−0.030	−0.085	−1.86	−0.026
Private equity	−0.173	−7.54	−0.060	−0.174	−7.56	−0.052
Foreign assets excluding equity	0.319	1.34	0.122	0.321	1.36	0.111
Net worth decile						
No net worth	−1.640	−49.53	−0.588	−1.638	−49.30	−0.570
Lowest	−0.215	−5.42	−0.074	−0.212	−5.33	−0.062
2	−0.405	−10.99	−0.132	−0.404	−10.91	−0.109
3	−0.588	−16.95	−0.181	−0.587	−16.88	−0.147
4	−0.698	−19.47	−0.206	−0.698	−19.44	−0.166
5	−0.738	−21.98	−0.215	−0.736	−21.86	−0.172
6	−0.712	−20.70	−0.209	−0.711	−20.55	−0.168
7	−0.677	−18.87	−0.201	−0.676	−18.80	−0.162

(continued)

Table II—*Continued*

	IQ Dummy Specification			Linear-IQ Specification		
Independent Variables	Coefficients	z-values	Marginal Effects	Coefficients	z-values	Marginal Effects
8	−0.574	−16.61	−0.177	−0.574	−16.60	−0.144
9	−0.394	−12.21	−0.129	−0.393	−12.13	−0.107
Other demographics						
Swedish speaker	0.151	7.83	0.056	0.148	7.72	0.049
Married	0.023	1.45	0.008	0.023	1.44	0.007
Cohabiter	0.029	1.22	0.011	0.027	1.14	0.009
Kids	−0.138	−8.23	−0.049	−0.137	−8.18	−0.042
Occupation						
Entrepreneur	−0.230	−8.77	−0.079	−0.232	−8.84	−0.067
Farmer	−0.182	−3.20	−0.063	−0.183	−3.21	−0.054
Finance professional	0.439	9.29	0.170	0.439	9.27	0.156
Unemployed	−0.334	−20.68	−0.113	−0.336	−20.79	−0.095
Cohort fixed effects	Yes			Yes		
Baseline probability			0.332			0.246
Wald-χ^2 (IQ1 = ... = IQ8 = 0)	1,912.5					
Pseudo R^2	0.211			0.210		
N	158,044			158,044		

The 67 regression control variables, described in the prior section, include educational attainment proxies; cohort fixed effects (i.e., birth-year dummies)[16]; as well as dummy variables for income decile, wealth decile, certain types of wealth ownership and occupations, native language, marital status, and employment status. A few of these variables have been used in prior participation literature. Many of their coefficients are highly significant. For example, individuals in income deciles 1 to 9 are significantly less likely to be participants than the highest income subjects in decile 10. Moreover, the coefficients are impressive. For example, the marginal effects column for the IQ dummy (left) specification indicates that the highest income decile (omitted) has a participation rate that is 5.9 percentage points greater than that of any other decile, keeping other observables, including wealth, fixed. Unemployed individuals have a participation rate that is 11.3 percentage points lower than that of employed individuals. Finance professionals' participation rate is 17.0 percentage points greater than that of other professions. Consistent with Heaton and Lucas (2000), entrepreneurs' participation rate is 7.9 percentage points lower than that of others. With the linear-IQ specification, individuals in the highest income category have a 13.3 percentage point greater participation rate than those in the lowest income decile; the marginal effects of being employed, having a career as a finance professional, or working as an entrepreneur are similar to those from the IQ dummy specification.

The most striking coefficients belong to IQ rather than to the controls. In the IQ dummy specification, the marginal effects and probit coefficients of the two lowest stanines (about 10% of the sample) are 20% to 30% larger than the corresponding impact from being in the lowest income decile. This is remarkable considering that the IQ test consists of just 120 questions and, for most subjects, is assessed many years before measuring participation. By contrast, income is measured contemporaneously with participation and deemed to be highly reliable because of criminal penalties for false reporting. Wealth, controlling for all other variables (including birth-year dummies), seems relatively more important, but this could be due to participation causing wealth: the 1990s were a good decade for owning Finnish stocks.

Neoclassical participation theories (e.g., Vissing-Jørgensen (2002, 2003)) argue that even modest direct costs of participation deter participation for less wealthy individuals: benefits from participation are small when there is little at stake in the markets. With no measurement error, misspecification, or endogeneity biases, these theories predict a wealth effect on participation only at the lower wealth levels. This prediction is inconsistent with the observation that subjects in the highest net worth decile are, by far, most likely to participate.[17]

Our findings are consistent with prior studies of IQ and participation in suggesting that quantitative skill components of IQ are prominent determinants

[16] Korniotis and Kumar (2011) relate age to investment skill.

[17] Vissing-Jørgensen (2003, pp. 179–180) would counter that this could follow from participation costs that are decreasing in IQ and measured wealth correlating with differences between true and measured IQ.

of participation. The composite IQ score we use is computed from three subscores, one of which is mathematical ability. Each of the three subscores is highly correlated with the composite score: correlation coefficients range from 0.83 to 0.89. Separate analyses of Table II's linear specification with each of the three subcomponents of IQ indicate that each influences participation (with the lowest t-statistic exceeding 32). The mathematical ability coefficient, 0.088, is virtually identical to Table II's composite score coefficient (0.090); the other two subscores have coefficients of 0.070 (verbal ability) and 0.065 (logical ability). The verbal and logical components significantly influence participation in a linear specification that includes all three components in the same regression.

Irrespective of whether composite IQ or its subcomponents are used, our measure of cognitive ability remains a salient determinant of participation when compared to the control variables. The importance of IQ lends credence to a theory of participation that is at least partly based on cognitive segmentation. One way to quantify IQ's importance in relation to the controls is a specification that replaces the linear-IQ specification's wealth decile dummies with wealth. In this specification, the IQ coefficient is 0.096 and the coefficient on wealth is 9.05×10^{-6}, generating a ratio of 10,608. Thus, each one-stanine drop in IQ, which corresponds to a one-half standard deviation drop in ability, is equivalent to a 10,608 euro decline in taxable net worth.

All results are robust to measuring participation in alternative years, omitting various blocks of control regressors, using age-filtered subsamples, and excluding Nokia holdings.[18] However, two issues remain. First, as a condition for use of the highly sensitive and private IQ data, we had to omit individual education controls from this study. To assess whether noisy education controls (due to aggregation) affect our main finding, we reran Table II's analysis, replacing an individual's IQ with the corresponding average from the age cohort within his zip code. Aggregating IQ in the same manner as education yields coefficients and test statistics that are similar to Table II's coefficients and test statistics.[19] Similar results obtain when replacing all regressors with their age-stratified zip code averages. We later address this issue further with two statistical techniques designed to address errors-in-variables and omitted variables biases.

The second issue is that we lack data on place of employment. At the end of 2000, approximately 40% of FCSD-registered companies had issued stock

[18] When various blocks of control regressors are dropped, the linear-IQ coefficient becomes 0.107 (education dropped), 0.102 (wealth dropped), and 0.109 (income dropped). Splitting the sample by subject age, the linear-IQ coefficient is 0.078 in the 1953 to 1969 birth-year sample and 0.098 in the 1970 to 1982 sample, suggesting that the IQ effect weakens slightly with age. We also reran the linear specification for the sample of (generally older) male investors who lack an IQ score. These analyses (detailed in the Internet Appendix) indicate that our sample is representative.

[19] For example, with the zip code–aggregated IQ dummy specification, the coefficients on IQ dummies 1, 2, and 3, are, respectively, −1.010, −0.779, and −0.738 (all highly significant) whereas in Table II they are −0.706, −0.580, and −0.477. The Wald statistic for joint significance of the zip code–aggregated IQ dummies, 80.1, is still highly significant. For the linear specification, the noisy IQ measure's coefficient, 0.131 (with a probit z-value of 6.91), exceeds the 0.090 coefficient in Table II (with a probit z-value of 41.84).

or options to their executives or employees. The average (median) number of investors in a plan is 544 (86). If smarter individuals are more likely to be awarded stock or options by their employer, the IQ–participation relationship may reflect employment-based awards rather than any active decision by high-IQ subjects to hold stock. However, replacing Table II's dependent variable with various participation dummies designed to limit the influence of compensation on participation yields similar results to Table II. These dummies include participation defined as holding a mutual fund (but not stock), holding at least two different individual stocks, or the purchase of stock with cash.[20] Results from all three analyses are consistent with Table II's conclusion that IQ is significantly positively related to stock market participation.

B. Participation Decisions of Affluent Individuals

The benefits of participation have been quantified for neoclassical preferences. These benefits increase in wealth and appear to exceed the direct costs of participation for all but the poorest individuals. Hence, if participation costs deter participation, only the poor would rationally avoid stockholdings.[21] Cochrane (2007) concludes from this that participation costs have little effect on asset pricing; these costs deter only negligible amounts of wealth from the stock market. Related to this, Curcuru et al. (2009) and Campbell (2006) observe that the degree of nonparticipation among wealthy individuals is puzzling. They reason that direct participation costs cannot plausibly explain such nonparticipation. However, other mechanisms that might account for this phenomenon have not been verified empirically.

Table II's IQ coefficients point to other frictions that hinder stock market participation. In contrast to the fixed costs of participation, nonparticipation that arises from limited cognitive skill could deter participation by the affluent. The credibility of this hypothesis is best assessed by empirical study of IQ's influence on the participation of the most affluent subjects in our sample—those in the top decile of the wealth and income distribution. These affluent individuals are not constrained by any fixed cost of market entry but could be deterred by limited cognitive skill. Another motivation for studying the affluent is that one cannot explain their IQ-related nonparticipation as a spurious consequence of noisy measurement of income or wealth controls. It would take an implausibly large amount of measurement error to misclassify those too poor to rationally bear participation costs as belonging to the 10% of most affluent subjects.[22]

[20] The third definition excludes purchases of stock with employer-issued warrants or convertible bonds, purchases of shares before a company is publicly listed, and purchases of employee tranches of offerings or private placements. We are grateful to an anonymous referee for suggesting many of these analyses, detailed in the Internet Appendix.

[21] See, for example, Vissing-Jørgensen (2002, 2003).

[22] Moreover, rare misclassifications are unlikely to account for the magnitude of Table II's IQ coefficients.

Table III employs the probit regression methodology of Table II to estimate the participation regressions for affluent individuals. Panel A restricts the sample to subjects with ordinary income in the top decile; Panel B restricts it to those with taxable net worth in the top decile. For obvious reasons, the former regression omits income decile controls and the latter omits wealth decile controls (in contrast to Table II's regressions). With both affluence metrics, IQ significantly predicts participation. For the IQ dummy specification, the IQ coefficient pattern remains almost perfectly monotonic. The economic significance column indicates that the participation rate for the lowest IQ stanine is 15.7% lower than the rate of the highest IQ stanine for the income-affluent specification; it is 22.5% lower for the wealth-affluent specification. Although the sample is smaller, which tends to increase estimation error, the coefficients for the low-IQ stanine dummies in Table III are similar to those for the full sample in Table II.

These results speak to IQ's important role in the participation decisions of the most affluent individuals—negating criticism of Table II's link between IQ and participation based on noisy measurement of wealth or income. Table III also refutes the argument that IQ affects participation because it might be positively correlated with risk tolerance. If frictions, like entry costs, deter the most risk averse, the effect should be prominent only for the least affluent.

C. Secondary Channels for IQ

Table II's regressions demonstrate that IQ's influence over stock market participation does not arise from its correlation with measured income, wealth, education, and a host of other control variables. However, IQ could drive many of these variables. Hence, there are secondary channels through which IQ may influence participation. For example, our data indicate that a high-IQ individual is more likely to be married, have a high income, be wealthy, and have children. He also is more likely to be in certain professions, such as financial services. These secondary channels may lead to stock market investment. High-income subjects tend to save more; for them, a comfortable risk-free nest egg can coexist with stockholdings. A parent may hold risky assets to provide for a child's future. To assess IQ's influence on participation via secondary channels, Table IV presents results from a decomposition developed in Blinder (1973), Oaxaca (1973), and Fairlie (1999, 2005). Panel A presents results for control variables that partially account for the 36.7% difference in participation rates between IQ stanines 1 and 9; Panel B presents results on control variables that partially account for the 29.4% difference in participation between IQ stanines 2 and 8. While any pairing of stanines can be analyzed with this approach, we study only two extremes—the stanine 1, 9 and 2, 8 pairings—for brevity.

To derive the decomposition, we first repeat Table II's regression, but omit the IQ regressor(s), generating control variable coefficients and predicted z-scores for each stanine group. Predicted z-scores, the summed product of the regression coefficients and the control variables' group means, are then translated into predicted participation rates. The technique additionally

Table III

IQ Scores and Stock Market Participation of Affluent Individuals

Table III reports summary data from probit regressions of stock market participation on IQ stanine dummies (or IQ score) and a host of control variables (described in the body of the paper) derived from the Finnish tax data and the Finnish census data set. The sample is restricted to the 10% of most affluent individuals in the data set. Panel A restricts the sample to the 10% of individuals with the largest ordinary income for 2000 as reported on their tax returns. Panel B restricts the sample to the 10% of individuals with the largest taxable net worth as reported on their year 2000 tax returns. Participation is a dummy variable that takes the value one for subjects who held mutual funds or individual stocks registered with the FCSD at the end of 2000. Pseudo R^2 and sample sizes are reported at the bottom of the table. Standard errors are clustered by zip code. For each of two specifications, the columns report coefficients from the probit regression, associated z-values, and marginal effects on participation probability (evaluated at the average value of the other regressors, except for IQ stanine dummies, which are evaluated at zero). The marginal effects for indicator variables indicate the shift in the participation probability when the indicator variable changes from zero to one. The dummy variable associated with the highest category—IQ stanine 9, university-level education, highest ordinary income, and taxable net worth in the highest decile—are omitted and serve as a benchmark. Taxable net worth deciles are computed after removing individuals with no taxable net worth; a dummy variable for no net worth identifies the latter individuals. The regressions also contain 30 (unreported) cohort fixed effects for birth years 1953 through 1982.

Panel A: Ordinary Income in Top 10% of the Distribution						
	IQ Dummy Specification			Linear-IQ Specification		
Independent Variables	Coefficients	z-values	Marginal Effects	Coefficients	z-values	Marginal Effects
IQ stanine				0.059	8.00	0.023
Lowest	−0.396	−2.45	−0.157			
2	−0.708	−6.48	−0.275			
3	−0.372	−4.58	−0.147			
4	−0.273	−5.11	−0.108			

(continued)

Table III—*Continued*

Panel A: Ordinary Income in Top 10% of the Distribution						
	IQ Dummy Specification			Linear-IQ Specification		
Independent Variables	Coefficients	z-values	Marginal Effects	Coefficients	z-values	Marginal Effects
5	−0.164	−4.11	−0.064			
6	−0.046	−1.16	−0.018			
7	−0.066	−1.71	−0.026			
8	−0.008	−0.19	−0.003			
Education						
Basic	−0.004	−1.37	−0.001	−0.004	−1.35	−0.002
Vocational	−0.015	−6.26	−0.006	−0.015	−6.22	−0.006
Matricular	−0.001	−0.25	0.000	−0.001	−0.19	0.000
Income log-growth rate	0.060	1.44	0.023	0.053	1.27	0.021
Wealth dummies by wealth type						
Housing	0.188	7.45	0.073	0.188	7.47	0.075
Forest	−0.024	−0.23	−0.009	−0.025	−0.24	−0.010
Private equity	−0.045	−0.82	−0.018	−0.049	−0.90	−0.020
Foreign assets excluding equity	0.901	1.70	0.280	0.915	1.75	0.299
Net worth decile						
No net worth	−1.311	−24.58	−0.467	−1.304	−24.43	−0.475
Lowest	−0.779	−8.84	−0.300	−0.772	−8.78	−0.293
2	−0.692	−7.45	−0.269	−0.696	−7.45	−0.267
3	−0.729	−8.21	−0.283	−0.724	−8.16	−0.277
4	−0.823	−9.03	−0.316	−0.812	−8.95	−0.307
5	−0.798	−11.67	−0.307	−0.791	−11.57	−0.300
6	−0.710	−9.15	−0.276	−0.704	−9.04	−0.271
7	−0.680	−8.69	−0.265	−0.672	−8.58	−0.260
8	−0.542	−7.97	−0.214	−0.537	−7.89	−0.211
9	−0.379	−5.95	−0.150	−0.374	−5.83	−0.148

(continued)

Table III—*Continued*

Panel A: Ordinary Income in Top 10% of the Distribution						
	IQ Dummy Specification			Linear-IQ Specification		
Independent Variables	Coefficients	z-values	Marginal Effects	Coefficients	z-values	Marginal Effects
Other demographics						
Swedish speaker	0.138	3.00	0.053	0.131	2.84	0.051
Married	−0.010	−0.28	−0.004	−0.008	−0.23	−0.003
Cohabiter	0.080	1.39	0.031	0.074	1.28	0.029
Kids	−0.154	−4.27	−0.059	−0.152	−4.23	−0.060
Occupation						
Entrepreneur	−0.202	−3.79	−0.080	−0.221	−4.23	−0.088
Farmer	−0.092	−0.66	−0.036	−0.099	−0.71	−0.039
Finance professional	0.347	5.94	0.128	0.350	5.99	0.133
Unemployed	−0.116	−0.52	−0.046	−0.116	−0.52	−0.046
Cohort fixed effects	Yes			Yes		
Baseline probability			0.591			0.555
Wald-χ^2 (IQ1 = ... = IQ8 = 0)	93.0					
Pseudo R^2	0.111			0.109		
N	15,413			15,413		

Panel B: Net Worth in Top 10% of the Distribution						
	IQ Dummy Specification			Linear-IQ Specification		
Independent Variables	Coefficients	z-values	Marginal Effects	Coefficients	z-values	Marginal Effects
IQ stanine				0.094	6.70	0.023
Lowest	−0.826	−4.27	−0.225			
2	−0.628	−4.30	−0.157			
3	−0.496	−3.74	−0.117			
4	−0.595	−4.97	−0.147			

(continued)

Table III—*Continued*

Panel B: Net Worth in Top 10% of the Distribution						
	IQ Dummy Specification			Linear-IQ Specification		
Independent Variables	Coefficients	z-values	Marginal Effects	Coefficients	z-values	Marginal Effects
5	−0.305	−2.96	−0.065			
6	−0.250	−2.47	−0.051			
7	−0.248	−2.33	−0.051			
8	−0.088	−0.67	−0.016			
Education						
Basic	−0.003	−0.55	0.000	−0.003	−0.60	−0.001
Vocational	−0.025	−5.81	−0.004	−0.025	−5.79	−0.006
Matricular	0.003	0.37	0.001	0.003	0.40	0.001
Ordinary income decile						
No income	−0.013	−0.08	−0.002	−0.014	−0.09	−0.003
Lowest	0.131	0.97	0.021	0.120	0.89	0.028
2	−0.189	−1.48	−0.037	−0.188	−1.47	−0.049
3	−0.246	−2.10	−0.050	−0.245	−2.10	−0.066
4	−0.221	−2.02	−0.044	−0.217	−1.97	−0.058
5	−0.261	−2.34	−0.053	−0.271	−2.44	−0.073
6	−0.291	−2.54	−0.060	−0.290	−2.54	−0.079
7	−0.241	−2.14	−0.048	−0.246	−2.21	−0.066
8	−0.132	−1.35	−0.025	−0.130	−1.35	−0.033
9	−0.091	−1.09	−0.017	−0.096	−1.15	−0.024
Income log-growth rate	0.009	0.23	0.002	0.010	0.25	0.002
Wealth dummies by wealth type						
Housing	−0.109	−1.04	−0.018	−0.110	−1.06	−0.026
Forest	0.130	1.03	0.022	0.131	1.04	0.030
Private equity	−0.070	−0.85	−0.013	−0.070	−0.85	−0.017

(continued)

Table III—*Continued*

Panel B: Net Worth in Top 10% of the Distribution						
	IQ Dummy Specification			Linear-IQ Specification		
Independent Variables	Coefficients	z-values	Marginal Effects	Coefficients	z-values	Marginal Effects
Foreign assets excluding equity	−0.291	−0.79	−0.061	−0.274	−0.74	−0.075
Other demographics						
Swedish speaker	0.153	2.22	0.025	0.160	2.34	0.037
Married	0.080	0.87	0.014	0.080	0.88	0.019
Cohabiter	0.160	1.16	0.026	0.167	1.21	0.037
Kids	−0.286	−3.05	−0.051	−0.287	−3.08	−0.070
Occupation						
Entrepreneur	−0.137	−1.16	−0.026	−0.138	−1.18	−0.035
Farmer	−0.420	−3.13	−0.090	−0.419	−3.14	−0.117
Finance professional	0.781	2.95	0.084	0.778	2.93	0.124
Unemployed	0.091	0.52	0.015	0.087	0.50	0.020
Cohort fixed effects	Yes			Yes		
Baseline probability			0.899			0.842
Wald-χ^2 (IQ1 = … = IQ8 = 0)	49.6					
Pseudo R^2	0.144			0.142		
N	3,857			3,857		

Table IV

Fairlie-Blinder-Oaxaca Decomposition of the Secondary Effects of IQ on Stock Market Participation

Table IV reports on a Fairlie-Blinder-Oaxaca decomposition. This analysis measures how much of the difference in high- and low-IQ individuals' stock market participation rates at the end of 2000 can be explained by differences in control variables such as education, income, and wealth. We first estimate a probit regression of a stock market participation dummy against all control variables, omitting the IQ regressor(s). We save the z-scores from this regression and translate them into predicted participation rates for different IQ groups. The decomposition technique computes the marginal effect of group mean differences for seven natural collections of the control variables. For a given stanine pairing, marginal effects are the sequence of changes in predicted participation rates obtained by sequentially changing each control variable's value from its group mean at the lower stanine to its mean at the higher stanine. Sequencing of the changes in the control variables are randomized, repeated, and averaged, and members are paired across the two stanines, to obtain marginal changes in participation rates and test statistics. Panel A reports on an analysis of participation rate differences between stanines 1 and 9. Panel B reports on stanines 2 and 8.

Panel A: Decomposition Estimates for IQ 1 versus IQ 9 Individuals		
	Decomposition Estimate, %	z-value
Education	6.03	48.1
Income	5.70	52.1
Asset class ownership	0.58	14.0
Wealth	8.29	131.2
Demographics	0.29	7.0
Profession and unemployment	1.83	28.5
Cohort	0.61	7.8
IQ=1 participation rate	9.80	
IQ=9 participation rate	46.52	
Explained difference in participation rates	23.33	
Unexplained difference in participation rates	13.39	
Panel B: Decomposition Estimates for IQ 2 versus IQ 8 Individuals		
	Decomposition Estimate, %	z-value
Education	4.57	47.6
Income	4.92	51.0
Asset class ownership	0.42	14.4
Wealth	5.99	135.4
Demographics	0.20	6.0
Profession and unemployment	1.32	29.6
Cohort	0.44	7.7
IQ=2 participation rate	13.07	
IQ=8 participation rate	42.52	
Explained difference in participation rates	17.88	
Unexplained difference in participation rates	11.57	

computes the marginal effect of group mean differences for seven natural collections of the control variables. For a given stanine pairing, marginal effects are the sequence of changes in predicted participation rates, obtained by sequentially changing each control variable collection's value (a vector) from its group mean at the lower stanine to its mean at the higher stanine. Sequencing of the changes in the seven collections of control variables must be randomized, repeated, and averaged, and members must be paired across the two stanines, to obtain marginal changes in participation rates and test statistics. For details, see Fairlie (2005).

Table IV, Panel A, indicates that group mean differences in the control variables account for almost two-thirds (0.635) of the 36.7% difference in participation rates between stanines 1 and 9. An 8% difference in participation is explained by differences in wealth between the stanines (holding other control variables fixed), a 6% difference is explained by education differences alone, a 6% difference is explained by income alone, and a 2% difference is explained by profession and employment status dummies. The remaining control variables have far less effect either because the group means scarcely differ between stanines 1 and 9 or because group mean differences have little influence on participation.

Panel B of Table IV leads to similar findings. Approximately three-fifths of the 29.4% difference in participation between stanines 2 and 8 can be explained by group mean differences in the control variables. This 18% difference in predicted participation rates is largely accounted for by group differences in wealth (6%), education (5%), and income (5%), with the remainder (2%) explained by group mean differences in all the other control variables.

The decomposition has relevance for studies that lack the rich IQ data we have. Our findings raise doubts about conclusions in such studies about the effect of wealth, income, or education on participation; their effects cannot easily be disentangled from an omitted IQ variable. By contrast, studies suggesting that age, marital status, or parental status influence participation are less likely to have alternative interpretations related to IQ.

D. IQ's Influence on the Participation of Females

The geographic location data, described earlier, identify 4,358 sisters of the males from Table II's regression. Lacking data on female IQ because they do not serve in the FAF, we substitute for the missing data. The regression specifications are identical to those in Table II, except that a brother's IQ stanine dummy or IQ score replaces the female's missing IQ stanine dummy or score. The IQ coefficients, reported in the Internet Appendix, are of slightly smaller magnitude than the comparable coefficients in Table II, but remain statistically significant. For example, in the linear specification, the IQ coefficient has a z-statistic of 4.75. This suggests that the component of IQ that sisters share with brothers is a potent predictor of participation.

Substitution of a sibling's IQ for one's own generates a biased estimate of the coefficient on own IQ. This bias can over- or understate the effect of IQ on participation for the sisters, even assuming that gender does not influence the relationship between the shared family component of IQ and participation. The direction of the bias depends on the degree to which the family component of IQ influences participation in comparison to the degree to which family IQ is a noisy predictor of own IQ. We can assess the magnitude of this bias directly by repeating the sibling analysis using 1,996 brother pairs. This alternative analysis yields a negligible difference (detailed in the Internet Appendix) between the participation regression's coefficient on the IQ of one's brother and that on own IQ.

E. Addressing Endogeneity Biases: Evidence from Sibling Control Function Regressions

The ability to match brothers offers a unique opportunity to address potential endogeneity bias in Table II's results. In a setting with endogeneity, IQ's effect on participation can be viewed as estimation of a stylized pair of structural equations

$$\begin{aligned} \mathit{participation}(j) &= \beta_0 + \beta_1 * \boldsymbol{IQ}(j) + \beta_2 * \mathit{observed\ controls}(j) \\ &\quad + \beta_3 * \mathit{unobservable\ controls}(j) + e(j), \\ \mathit{unobservable\ controls}(j) &= c_0 + c_1 * \boldsymbol{IQ}(j) + c_2 * \mathit{observed\ controls}(j) + z(j). \end{aligned}$$

Inconsistent estimates of the vector β_1 arise from the correlation between one's actual IQ and the unobservable controls. Following Heckman (1978, 1979), Rivers and Vuong (1988), and Petrin and Train (2010), one can correct for the inconsistency by adding the control function residual *s(j)*, obtained from an OLS regression of own IQ on the IQ of one's brother and own controls, that is,

$$\boldsymbol{IQ}(j) = d_0 + d_1 * \boldsymbol{IQ}\mathit{brother}(j) + d_2 * \mathit{observed\ controls}(j) + s(j), \qquad (1)$$

to the first (probit-estimated) regression above. That is, estimation of

$$\begin{aligned} \mathit{participation}(j) &= b_0 + b_1 * \boldsymbol{IQ}(j) + b_2 * \mathit{observed\ controls}(j) \\ &\quad + b_3 * s(j) + b_4 * \mathit{unobservable\ controls}(j) + e(j) \end{aligned}$$

leads to consistent estimates of β_1 and β_2 given by the transformation

$$\beta_i = b_i / sqrt(1 + b_i^2 * \mathrm{var}(s)),$$

if the unobservable controls of subject j are uncorrelated with his brother's IQ. (Here, var(s) denotes the variance of the residual from equation (1).)

Table V reports these estimated βs. We use jackknife estimated test statistics to account for the first-stage estimation error in *s(j)*. The table also reports marginal effects, which are based on the transformed coefficients. Table V's IQ coefficient for the linear specification,[23] 0.253, is statistically significant, even though it is based on a far smaller sample than Table II.

The key assumption of the control function method, that the residual is orthogonal to the regressors, does not rule out inconsistent IQ coefficient estimates from all omitted variables. However, if both the shared family IQ and

[23] This method can be used only with the linear-IQ specification; its first-stage residual comes from linear projection.

Table V

Stock Market Participation Decisions Using a Control Function Approach to Estimation

Table V reports on a probit regression of stock market participation on a person's own IQ score, a host of control variables (described in the body of the paper) derived from the Finnish tax data and the Finnish census data set, and a residual from a first-stage OLS regression of one's own IQ score against his brother's IQ score and the control variables. The inclusion of the residual controls for an endogeneity problem that would arise if some unobservable controls were correlated with one's own IQ score. We identify 1,996 pairs of brothers using historical addresses and move-in and move-out dates for each subject in the Finnish tax data. Two males are identified as brothers if they lived together as children at the same address at the same time or moved at the same time. We also use transitivity to establish a sibling pair as described in the body of the paper. Participation is a dummy variable that takes on the value one for subjects who held mutual funds or individual stocks registered with the FCSD at the end of 2000. Pseudo R^2 and sample sizes are reported at the bottom of the table. Columns report coefficients from the probit regression, associated jackknife-estimated z-values, and marginal effects on participation probability (evaluated at the average value of the regressors). The dummy variable associated with the highest category—university-level education, highest ordinary income, and taxable net worth in the highest decile—are omitted and serve as a benchmark. Taxable net worth deciles are computed after removing individuals with no taxable net worth; a dummy variable for no net worth identifies the latter individuals. The regressions also contain 30 (unreported) cohort fixed effects for birth years 1953 through 1982.

Independent Variables	Coefficients	z-values	Marginal Effects
IQ stanine	0.253	5.21	0.048
Education			
Basic	0.000	0.00	0.001
Vocational	−0.019	−2.45	−0.004
Matricular	0.002	0.22	0.000
Ordinary income decile			
No income	0.092	0.49	0.036
Lowest	0.370	1.58	0.115
2	−0.247	−1.20	−0.021
3	−0.241	−1.34	−0.004
4	−0.238	−1.43	−0.005
5	−0.284	−2.08	−0.045
6	−0.106	−0.81	0.006
7	−0.233	−2.09	−0.028
8	−0.234	−2.17	−0.030
9	−0.222	−2.17	−0.024
Income log-growth rate	0.037	0.86	0.002
Wealth dummies by wealth type			
Housing	−0.282	−2.18	−0.017
Forest	−1.344	−2.37	−0.200
Private equity	−0.706	−2.66	−0.032
Foreign assets excluding equity			
Net worth decile			
No net worth	−2.238	−10.73	−0.352
Lowest	0.506	0.73	−0.213
2	0.891	3.45	−0.162
3	0.062	0.19	−0.178
4	0.288	0.81	−0.186
5	0.146	0.49	−0.185

(continued)

Table V—*Continued*

Independent Variables	Coefficients	z-values	Marginal Effects
6	−0.243	−0.90	−0.167
7	−0.197	−0.82	−0.129
8	−0.367	−1.49	−0.089
9	−0.550	−2.50	−0.079
Other demographics			
Swedish speaker	0.407	4.04	0.034
Married	−0.087	−0.32	−0.017
Cohabiter	0.280	0.44	0.015
Kids	−0.430	−0.77	−0.050
Occupation			
Entrepreneur	−0.553	−1.49	−0.023
Farmer	0.279	0.43	0.063
Finance professional	0.870	1.05	0.033
Unemployed	−0.412	−2.72	−0.082
1^{st}-stage control variable	−0.176	−3.39	−0.033
Cohort fixed effects	Yes		
Baseline probability			0.110
Pseudo R^2	0.269		
N	3,992		

idiosyncratic (nonfamily) IQ components have no influence on participation, one would need a unique type of omitted variable to account for the results in Table V. Because the IQ of one's brother influences Table V's IQ coefficient, idiosyncratic differences in propensities to cheat on exams, risk tolerance, financial literacy, or education could not explain our results. There are differences between families in these dimensions, but any component of these differences that is not accounted for by the other control variables in the regression is likely to be small. Moreover, such a strange control variable could not explain IQ-related differences between the participation decisions of brothers (which we now investigate).

F. Addressing Omitted Family Background Biases: Random Effects Regressions

Table V effectively substitutes the IQ of one's brother for own IQ to address endogeneity issues arising from omitted idiosyncratic controls. The table's significant IQ effect suggests that IQ components that are shared within a family significantly influence participation. To control for family effects, Table VI uses a random effects probit model to estimate participation within families having at least one brother pair in our IQ subject sample. Such estimation eliminates "within family" omitted variables, like shared knowledge about investments, as potential explanations for IQ's effect on participation. Both Table VI specifications demonstrate that, after controlling for family effects, IQ is a significant

Table VI

Random Effects Probit Analysis of Brothers' Stock Market Participation Decisions

Table VI reports summary data from probit regressions of stock market participation on IQ scores and a host of control variables (described in the body of the paper) derived from the Finnish tax data and the Finnish census data set. Participation is a dummy variable that takes on the value one for subjects who held mutual funds or individual stocks registered with the FCSD at the end of 2000. The regressions are estimated using data on 1,996 brother pairs for whom we have both IQ scores and all control variables. Two males are identified as brothers if they lived together as children at the same address at the same time or moved at the same time. We also use transitivity to establish a sibling pair as described in the body of the paper. The regression controls for unobserved family background variables with family random effects. Pseudo R^2 and sample sizes are reported at the bottom of the table. For each of two specifications, the columns report coefficients from the probit regression and associated z-values. The dummy variable associated with the highest category—IQ stanine 9, university-level education, highest ordinary income, and taxable net worth in the highest decile—are omitted and serve as a benchmark. Taxable net worth deciles are computed after removing individuals with no taxable net worth; a dummy variable for no net worth identifies the latter individuals. The regressions also contain 30 (unreported) cohort fixed effects for birth years 1953 through 1982.

	IQ Dummy Specification		Linear-IQ Specification	
Independent Variables	Coefficients	z-values	Coefficients	z-values
IQ stanine			0.130	4.54
Lowest	−1.041	−2.62		
2	−0.599	−1.89		
3	−0.501	−1.77		
4	−0.530	−2.27		
5	−0.121	−0.56		
6	0.123	0.58		
7	−0.101	−0.44		
8	0.278	1.12		
Education				
Basic	−0.011	−0.80	−0.010	−0.73
Vocational	−0.047	−3.53	−0.045	−3.51
Matricular	−0.003	−0.25	−0.003	−0.24
Ordinary income decile				
No income	0.449	1.28	0.471	1.37
Lowest	0.669	1.69	0.645	1.65
2	−0.217	−0.61	−0.221	−0.63
3	−0.214	−0.72	−0.178	−0.61
4	−0.277	−1.05	−0.254	−0.98
5	−0.091	−0.40	−0.069	−0.31
6	0.048	0.22	0.038	0.18
7	−0.148	−0.78	−0.137	−0.74
8	−0.313	−1.78	−0.305	−1.75
9	−0.249	−1.51	−0.243	−1.50
Income log-growth rate	0.108	1.38	0.108	1.40
Wealth dummies by wealth type				
Housing	−1.866	−2.00	−1.885	−2.05

(continued)

Table VI—*Continued*

	IQ Dummy Specification		Linear-IQ Specification	
Independent Variables	Coefficients	z-values	Coefficients	z-values
Forest	−1.381	−2.99	−1.352	−2.98
Private equity				
Foreign assets excluding equity	−3.790	−10.62	−3.709	−10.67
Net worth decile				
No net worth	0.963	1.43	0.941	1.41
Lowest	1.854	1.94	1.877	1.98
2	0.245	0.42	0.288	0.50
3	0.992	1.63	0.975	1.65
4	0.558	1.03	0.613	1.15
5	−0.061	−0.13	−0.100	−0.22
6	−0.102	−0.25	−0.088	−0.22
7	−0.454	−1.09	−0.428	−1.04
8	−0.722	−1.88	−0.748	−1.98
9	0.642	3.33	0.630	3.32
Other demographics				
Swedish speaker				
Married	0.138	0.32	0.090	0.21
Cohabiter	0.977	1.04	0.821	0.89
Kids	−0.793	−0.99	−0.703	−0.90
Occupation				
Entrepreneur	−1.165	−2.31	−1.107	−2.24
Farmer	0.207	0.25	0.348	0.42
Finance professional	1.973	1.73	1.855	1.66
Unemployed	−0.748	−2.75	−0.746	−2.79
Cohort fixed effects	Yes		Yes	
Wald-χ^2 (IQ1 = ... = IQ8 = 0)	30.5			
N	3,766		3,766	

predictor of participation. This is a powerful result. Education's influence on participation does not survive this kind of test.[24]

III. The Effect of IQ on Sharpe Ratios and Risk

To study whether low-IQ subjects' reluctance to participate stems from a more adverse risk-return trade-off, Table VII, Panel A, regresses Sharpe ratios, estimated from participants' risky portfolios of individual stocks and mutual funds, on IQ and controls. The Sharpe ratios we compute employ investor-level data on the aggregate value of funds held. However, lacking data on the specific funds held, we are forced into an assumption about fund composition—here, that every fund is identical to the euro-denominated HEX portfolio index. From this assumption, it is possible to derive each participant's year 2001

[24] See Calvet and Sodini (2010).

Table VII

Sharpe Ratios, Portfolio Variance, Diversification, and Factor Exposures

Table VII reports coefficients and test statistics from regressions of portfolio attributes on IQ scores and a host of control variables (described in the body of the paper). The dependent variables for Panel A, estimated with OLS, are three parameterizations of the estimated Sharpe ratio for the portfolio the subject held at the end of 2000 (described in the body of the paper). The dependent variables for Panel B, estimated with OLS, are the standard deviation denominator of Panel A as well as the logged return variance and variance of the stock portfolio, computed using year 2001 daily data. The dependent variables for Panel C, estimated with OLS, negative binomial, and probit, are the one-factor dollar MSCI World Index market model residual variance, the number of stocks the subject held at the end of 2000, and a dummy variable that takes the value one for subjects who held mutual funds at the end of 2000, respectively. Finally, the dependent variables for Panel D, estimated with OLS, are the one-factor dollar MSCI World Index market model systematic variance as well as the Scholes–Williams MSCI beta (from year 2001 daily data), end-of-2000 size percentile divided by 100, and book-to-market percentile divided by 100. All regressions use data on individuals who held mutual funds or stocks registered with the FCSD at the end of 2000. R^2 and sample size are reported at the bottom of each panel. Standard errors are clustered by zip code. Panel C's marginal effects are evaluated at the average value of other regressors, except for IQ stanine dummies, which are evaluated at zero. The marginal effects for indicator variables indicate the shift in the participation probability when the indicator variable changes from zero to one. The dummy variable associated with the highest category—IQ stanine 9, university-level education, highest ordinary income decile, and taxable net worth in the highest decile—are omitted and serve as a benchmark. Taxable net worth deciles are computed after removing individuals with no taxable net worth; a dummy variable for no net worth identifies the latter individuals. The regressions also contain 30 (unreported) cohort fixed effects for birth years 1953 through 1982.

Panel A: Sharpe Ratios

	Coefficients			*t*-values		
	Stock Risk Premium/Fund Risk Premium			Stock Risk Premium/Fund Risk Premium		
Independent Variables	80%	100%	120%	80%	100%	120%
IQ stanine						
Lowest	−0.007	−0.009	−0.011	−2.42	−3.13	−3.76
2	−0.005	−0.007	−0.010	−2.45	−3.71	−4.96
3	−0.011	−0.013	−0.014	−6.54	−7.47	−8.14
4	−0.005	−0.006	−0.008	−3.51	−4.63	−5.63
5	−0.005	−0.006	−0.007	−4.24	−5.01	−5.62
6	−0.004	−0.005	−0.006	−3.51	−4.10	−4.56
7	−0.002	−0.003	−0.003	−1.94	−2.18	−2.34
8	−0.002	−0.002	−0.003	−1.81	−2.03	−2.16
Education						
Basic	0.000	0.000	0.000	−2.03	−2.53	−2.94
Vocational	0.000	0.000	0.000	2.78	2.01	1.22
Matricular	0.000	0.000	0.000	−3.92	−4.40	−4.37
Ordinary income decile						
No income	0.004	0.008	0.012	1.72	3.24	4.60
Lowest	−0.004	0.000	0.004	−2.41	0.11	2.45
2	−0.002	0.001	0.005	−0.97	0.89	2.70
3	−0.002	0.000	0.003	−1.21	0.20	1.57
4	−0.001	0.001	0.002	−0.37	0.56	1.46
5	0.001	0.001	0.002	0.38	0.92	1.46
6	0.001	0.002	0.003	1.14	1.67	2.15

(continued)

Table VII—*Continued*

Panel A: Sharpe Ratios						
	Coefficients			*t*-values		
	Stock Risk Premium/Fund Risk Premium			Stock Risk Premium/Fund Risk Premium		
Independent Variables	80%	100%	120%	80%	100%	120%
7	0.001	0.002	0.003	1.15	1.79	2.38
8	0.000	0.000	0.001	−0.36	0.10	0.54
9	−0.001	−0.001	0.000	−1.18	−0.82	−0.45
Income log-growth rate	0.002	0.002	0.003	3.14	3.73	4.12
Wealth dummies by wealth type						
Housing	−0.005	−0.004	−0.004	−6.73	−6.08	−5.16
Forest	0.005	0.006	0.007	1.54	1.88	2.14
Private equity	−0.001	0.000	0.001	−0.72	0.06	0.76
Foreign assets excluding equity	0.000	0.006	0.011	−0.01	0.46	0.79
Net worth decile						
No net worth	−0.019	−0.022	−0.025	−13.21	−14.03	−14.39
Lowest	0.024	0.014	0.004	11.21	6.65	1.97
2	0.002	−0.005	−0.011	1.13	−2.42	−5.73
3	0.002	−0.003	−0.008	1.28	−1.46	−4.04
4	−0.003	−0.006	−0.010	−1.50	−3.62	−5.55
5	−0.004	−0.007	−0.010	−1.91	−3.50	−4.87
6	−0.009	−0.011	−0.014	−4.58	−5.72	−6.57
7	−0.011	−0.013	−0.015	−6.15	−6.92	−7.39
8	−0.008	−0.010	−0.012	−4.71	−5.62	−6.22
9	−0.005	−0.006	−0.008	−2.76	−3.44	−3.95
Other demographics						
Swedish speaker	0.016	0.015	0.013	11.04	10.71	10.09
Married	0.001	0.001	0.001	1.22	1.10	0.95
Cohabiter	0.000	0.000	−0.001	0.02	−0.19	−0.40
Kids	−0.004	−0.003	−0.002	−3.13	−2.42	−1.65
Occupation						
Entrepreneur	−0.024	−0.020	−0.016	−21.09	−15.51	−10.92
Farmer	−0.015	−0.014	−0.012	−4.35	−3.64	−2.92
Finance professional	0.005	0.005	0.005	1.91	1.96	1.95
Unemployed	0.002	0.002	0.001	1.36	1.11	0.83
Cohort fixed effects	Yes	Yes	Yes			
Wald-χ^2 (IQ1 = ... = IQ8 = 0)	6.7	9.4	12.0			
Adjusted R^2	0.074	0.064	0.055			
N	44,592	44,592	44,592			

Panel B: Portfolio Variance						
	Coefficients			*t*-values		
		Stock Portfolio Variance			Stock Portfolio Variance	
Independent Variables	Total Portfolio Volatility	$\log(\sigma^2)$	σ^2	Total Portfolio Volatility	$\log(\sigma^2)$	σ^2
IQ stanine						
Lowest	0.032	0.255	0.052	3.17	6.51	4.32
2	0.025	0.227	0.046	3.54	8.89	5.30
3	0.044	0.241	0.053	6.74	10.25	6.62

(continued)

Table VII—*Continued*

Panel B: Portfolio Variance

Independent Variables	Coefficients: Total Portfolio Volatility	Coefficients: Stock Portfolio Variance $\log(\sigma^2)$	Coefficients: Stock Portfolio Variance σ^2	t-values: Total Portfolio Volatility	t-values: Stock Portfolio Variance $\log(\sigma^2)$	t-values: Stock Portfolio Variance σ^2
4	0.024	0.170	0.041	4.72	9.28	6.34
5	0.024	0.146	0.036	4.87	8.02	5.64
6	0.015	0.102	0.022	3.55	6.28	4.11
7	0.009	0.052	0.010	1.91	2.94	1.56
8	0.005	0.043	0.004	1.13	2.51	0.65
Education						
Basic	0.001	0.003	0.001	2.36	3.22	2.19
Vocational	0.000	0.001	0.001	−1.44	1.40	1.55
Matricular	0.001	0.004	0.001	4.26	3.04	2.31
Ordinary income decile						
No income	−0.042	−0.206	−0.062	−4.55	−5.60	−4.79
Lowest	−0.019	−0.139	−0.056	−2.81	−4.96	−5.66
2	−0.020	−0.119	−0.050	−3.01	−4.69	−5.02
3	−0.013	−0.064	−0.031	−2.05	−2.74	−3.80
4	−0.013	−0.030	−0.025	−2.50	−1.43	−3.42
5	−0.012	0.004	−0.016	−2.55	0.24	−2.61
6	−0.014	−0.008	−0.018	−3.10	−0.48	−3.07
7	−0.016	−0.020	−0.022	−3.84	−1.19	−3.66
8	−0.005	−0.001	−0.011	−1.28	−0.09	−1.82
9	0.000	0.017	−0.002	−0.05	1.15	−0.37
Income log-growth rate	−0.008	−0.042	−0.009	−3.59	−4.61	−3.05
Wealth dummies by wealth type						
Housing	0.014	0.038	0.010	5.05	4.13	2.79
Forest	−0.015	−0.070	−0.012	−1.27	−1.63	−0.86
Private equity	0.001	−0.047	−0.009	0.25	−2.25	−1.36
Foreign assets excluding equity	−0.031	−0.167	−0.060	−0.93	−1.08	−1.91
Net worth decile						
No net worth	0.083	0.433	0.112	16.38	20.34	18.48
Lowest	−0.028	0.320	0.079	−4.06	9.42	7.58
2	0.025	0.369	0.086	3.78	13.97	10.63
3	0.007	0.216	0.036	1.19	8.76	4.83
4	0.022	0.213	0.046	3.75	8.34	6.17
5	0.023	0.208	0.042	3.76	7.80	5.57
6	0.035	0.223	0.047	4.96	8.15	5.34
7	0.041	0.244	0.049	6.37	8.98	6.24
8	0.029	0.176	0.031	4.92	6.92	4.54
9	0.018	0.110	0.020	2.87	4.24	2.73
Other demographics						
Swedish speaker	−0.051	−0.118	−0.037	−11.85	−6.79	−6.83
Married	−0.005	−0.021	−0.007	−1.24	−1.25	−1.37
Cohabiter	0.003	0.010	0.003	0.41	0.39	0.40
Kids	0.009	0.018	0.005	2.03	1.03	0.82
Occupation						
Entrepreneur	0.063	0.099	0.025	10.81	4.87	3.38
Farmer	0.037	0.096	0.018	2.68	1.75	1.10
Finance professional	−0.018	−0.081	−0.019	−1.97	−1.95	−1.56
Unemployed	0.002	0.041	0.019	0.28	1.57	2.15

(continued)

Table VII—*Continued*

Panel B: Portfolio Variance

Independent Variables	Coefficients: Total Portfolio Volatility	Coefficients: Stock Portfolio Variance $\log(\sigma^2)$	Coefficients: Stock Portfolio Variance σ^2
Cohort fixed effects	Yes	Yes	Yes
Wald-χ^2 (IQ1 = … = IQ8 = 0)	9.5	26.7	14.3
Adjusted R^2	0.052	0.058	0.036
N	44,592	36,359	36,559

Panel C: Portfolio Diversification

Independent Variables	$\log(\sigma_e^2)$ Coeffs.	$\log(\sigma_e^2)$ z-values	Number of Stocks Held Coeffs.	Number of Stocks Held z-values	Number of Stocks Held Marginal Effects	Decision to Own Mutual Funds Coeffs.	Decision to Own Mutual Funds z-values	Decision to Own Mutual Funds Marginal Effects
IQ stanine								
Lowest	0.274	6.86	−0.321	−5.98	−0.630	−0.138	−2.28	−0.049
2	0.245	9.37	−0.338	−9.06	−0.659	−0.115	−2.45	−0.041
3	0.258	10.73	−0.287	−9.38	−0.573	−0.209	−5.01	−0.074
4	0.181	9.62	−0.191	−9.15	−0.399	−0.080	−2.66	−0.029
5	0.155	8.22	−0.138	−7.47	−0.296	−0.102	−4.00	−0.037
6	0.106	6.34	−0.061	−3.35	−0.136	−0.070	−2.93	−0.026
7	0.053	2.94	−0.063	−2.82	−0.139	−0.057	−2.15	−0.021
8	0.044	2.52	−0.024	−1.21	−0.055	−0.031	−1.22	−0.012
Education								
Basic	0.004	3.31	−0.004	−3.20	−0.009	0.001	0.57	0.000
Vocational	0.002	1.81	−0.008	−6.80	−0.019	0.003	2.57	0.001
Matricular	0.004	3.00	−0.001	−0.38	−0.002	−0.001	−0.73	0.000
Ordinary income decile								
No income	−0.192	−5.07	0.000	0.00	0.000	−0.226	−3.93	−0.080
Lowest	−0.122	−4.25	−0.063	−2.51	−0.142	−0.430	−11.60	−0.145
2	−0.101	−3.73	−0.145	−6.06	−0.313	−0.358	−9.53	−0.123
3	−0.046	−1.91	−0.181	−6.86	−0.386	−0.291	−8.22	−0.101
4	−0.007	−0.32	−0.255	−11.20	−0.525	−0.265	−8.15	−0.093
5	0.025	1.37	−0.270	−10.23	−0.553	−0.181	−5.70	−0.065
6	0.013	0.75	−0.281	−11.62	−0.574	−0.140	−4.74	−0.051
7	−0.002	−0.14	−0.217	−9.15	−0.456	−0.127	−4.48	−0.046
8	0.014	0.85	−0.138	−6.85	−0.301	−0.109	−4.23	−0.040
9	0.029	1.98	−0.108	−6.74	−0.240	−0.091	−3.94	−0.033
Income log-growth rate	−0.042	−4.57	0.014	1.22	0.032	0.012	0.89	0.005
Wealth dummies by wealth type								
Housing	0.048	5.06	−0.007	−0.56	−0.017	−0.106	−6.29	−0.039
Forest	−0.058	−1.32	−0.027	−0.53	−0.061	−0.068	−0.87	−0.025
Private equity	−0.044	−2.08	0.091	2.86	0.218	−0.084	−2.57	−0.031
Foreign assets excluding equity	−0.159	−1.06	0.136	0.92	0.335	−0.167	−0.59	−0.059

(continued)

Table VII—*Continued*

Panel C: Portfolio Diversification

Independent Variables	$\log(\sigma_e^2)$ Coeffs.	$\log(\sigma_e^2)$ *z*-values	Number of Stocks Held Coeffs.	Number of Stocks Held *z*-values	Number of Stocks Held Marginal Effects	Decision to Own Mutual Funds Coeffs.	Decision to Own Mutual Funds *z*-values	Decision to Own Mutual Funds Marginal Effects
Net worth decile								
No net worth	0.511	22.97	−1.092	−49.83	−2.540	−0.636	−21.57	−0.230
Lowest	0.384	11.00	−1.560	−44.87	−1.990	0.489	11.98	0.190
2	0.429	15.67	−1.237	−42.07	−1.743	0.004	0.12	0.002
3	0.258	10.26	−0.987	−35.31	−1.512	0.013	0.36	0.005
4	0.252	9.31	−0.825	−25.88	−1.340	−0.109	−2.78	−0.040
5	0.252	9.16	−0.793	−25.59	−1.304	−0.172	−4.47	−0.061
6	0.266	9.49	−0.683	−25.92	−1.172	−0.245	−6.27	−0.086
7	0.288	10.37	−0.680	−21.76	−1.171	−0.321	−8.36	−0.110
8	0.209	7.93	−0.546	−19.15	−0.994	−0.236	−5.66	−0.083
9	0.129	4.79	−0.419	−15.78	−0.805	−0.176	−5.05	−0.063
Other demographics								
Swedish speaker	−0.125	−7.14	−0.031	−1.41	−0.071	0.320	12.19	0.123
Married	−0.021	−1.26	−0.054	−2.95	−0.122	0.029	1.22	0.011
Cohabiter	0.008	0.31	0.015	0.53	0.035	0.044	1.11	0.017
Kids	0.027	1.54	−0.065	−3.46	−0.147	−0.173	−6.34	−0.063
Occupation								
Entrepreneur	0.120	5.91	0.082	3.02	0.194	−1.612	−19.07	−0.338
Farmer	0.132	2.37	−0.008	−0.12	−0.019	−0.590	−6.01	−0.185
Finance professional	−0.099	−2.38	0.233	6.66	0.601	0.250	5.44	0.096
Unemployed	0.043	1.65	−0.014	−0.43	−0.033	0.006	0.17	0.002
Cohort fixed effects	Yes		Yes			Yes		
Baseline no. of stocks/prob.					2.295			0.347
$F(8, 670)$/Wald-χ^2 (IQ1 = … = IQ8 = 0)	29.6		227.6			41.2		
R^2	0.069					0.082		
N	36,359		44,592			44,592		

Panel D: Systematic Risk

Independent Variables	Coefficients $\log(\sigma_m^2)$	Coefficients Beta	Coefficients Size Rank	Coefficients B/M Rank	*t*-values $\log(\sigma_m^2)$	*t*-values Beta	*t*-values Size Rank	*t*-values B/M Rank
IQ stanine								
Lowest	0.233	0.080	0.038	−0.042	5.09	4.66	6.09	−4.18
2	0.181	0.062	0.026	−0.034	5.16	5.12	4.56	−4.70
3	0.183	0.065	0.025	−0.037	5.55	5.60	5.26	−5.73
4	0.145	0.051	0.018	−0.020	6.10	5.56	4.21	−4.40
5	0.122	0.046	0.014	−0.015	5.70	5.42	3.86	−3.73
6	0.099	0.034	0.010	−0.012	4.99	4.66	2.98	−2.98
7	0.070	0.021	0.012	−0.004	3.10	2.55	3.18	−1.06
8	0.058	0.016	0.005	−0.001	2.39	1.70	1.13	−0.26
Education								
Basic	0.003	0.001	0.000	−0.001	2.49	2.27	2.44	−1.63
Vocational	−0.002	0.000	0.000	0.001	−1.46	−0.96	−1.72	3.10
Matricular	0.003	0.001	0.000	−0.001	2.55	1.89	0.42	−3.86

(continued)

Table VII—*Continued*

Panel D: Systematic Risk								
	Coefficients				t-values			
Independent Variables	$\log(\sigma^2_{\mathrm{m}})$	Beta	Size Rank	B/M Rank	$\log(\sigma^2_{\mathrm{m}})$	Beta	Size Rank	B/M Rank
Ordinary income decile								
No income	−0.326	−0.119	0.011	0.063	−6.58	−6.73	1.71	6.50
Lowest	−0.257	−0.098	0.024	0.054	−7.25	−8.00	5.95	7.85
2	−0.216	−0.088	0.024	0.052	−7.41	−8.50	5.74	7.73
3	−0.149	−0.064	0.024	0.043	−5.03	−5.97	5.40	6.83
4	−0.152	−0.069	0.020	0.035	−5.11	−6.36	4.69	5.95
5	−0.080	−0.041	0.025	0.021	−3.25	−4.56	6.24	4.05
6	−0.097	−0.048	0.020	0.025	−4.20	−5.67	4.64	5.11
7	−0.094	−0.043	0.020	0.022	−4.47	−5.65	6.18	4.90
8	−0.068	−0.030	0.012	0.013	−3.38	−4.08	3.73	3.09
9	−0.041	−0.015	0.007	0.006	−2.04	−1.99	2.04	1.68
Income log-growth rate	−0.055	−0.017	−0.003	0.008	−4.23	−4.03	−1.69	3.00
Wealth dummies by wealth type								
Housing	−0.005	−0.001	0.001	−0.001	−0.40	−0.26	0.28	−0.40
Forest	−0.134	−0.037	−0.009	0.038	−2.43	−1.96	−1.14	3.52
Private equity	−0.082	−0.020	−0.017	0.016	−2.71	−2.19	−3.38	2.85
Foreign assets excluding equity	−0.148	−0.043	−0.019	0.030	−0.72	−0.71	−0.62	0.81
Net worth decile								
No net worth	0.106	0.068	0.000	0.016	4.11	8.18	−0.07	3.46
Lowest	0.067	0.047	−0.010	0.035	1.56	3.26	−1.76	4.14
2	0.167	0.079	0.012	−0.017	5.06	6.96	2.68	−2.54
3	0.107	0.048	0.012	0.006	3.27	4.41	2.64	0.95
4	0.104	0.054	0.010	0.004	3.64	5.64	2.19	0.54
5	0.055	0.042	0.007	0.008	1.53	3.54	1.51	1.25
6	0.085	0.053	0.008	0.002	2.48	4.59	1.79	0.33
7	0.085	0.049	0.011	0.009	2.48	4.37	2.64	1.32
8	0.091	0.044	0.014	0.002	2.87	4.12	3.11	0.42
9	0.061	0.029	0.004	0.005	1.94	2.85	1.07	0.86
Other demographics								
Swedish speaker	−0.097	−0.045	0.006	0.017	−3.88	−5.60	1.73	2.95
Married	−0.023	−0.013	0.004	0.005	−0.99	−1.53	1.11	0.95
Cohabiter	0.012	0.004	−0.006	−0.002	0.34	0.27	−1.18	−0.25
Kids	−0.034	−0.009	0.002	0.008	−1.42	−1.03	0.53	1.61
Occupation								
Entrepreneur	−0.040	−0.007	0.002	0.006	−1.27	−0.64	0.43	0.99
Farmer	−0.212	−0.051	−0.057	0.049	−2.36	−1.69	−4.30	2.95
Finance professional	−0.017	0.004	−0.021	−0.004	−0.30	0.21	−3.38	−0.34
Unemployed	0.038	0.021	−0.002	−0.002	1.08	1.79	−0.38	−0.25
Cohort fixed effects	Yes	Yes	Yes	Yes				
$F(8, 670)$ (IQ1 = … = IQ8 = 0)	9.1	8.8	7.7	9.3				
Adjusted R^2	0.017	0.019	0.025	0.036				
N	36,359	36,359	36,359	36,359				

time series of daily euro-denominated risky asset portfolio returns used to compute his Sharpe ratio denominator.[25] Moreover, because estimating the risk premia of stocks and funds is notoriously difficult, we require assumptions to compute a participant's Sharpe ratio numerator—here, that an individual

[25] These are the end-of-2000 unrebalanced portfolio-weighted daily returns of funds and every individual stock. To adjust for thin trading, we compute portfolio variance as the sum of twice the serial covariance of this time series and its average squared demeaned return.

stock's risk premium differs from the HEX index (and fund) premium, but not from other stocks.[26] The risk premium of the euro-denominated HEX index (and thus mutual funds) is assumed to be 1.02 times Calvet, Campbell, and Sodini's (2007) 5.52% estimate for the dollar-denominated MSCI World Index risk premium.[27] Panel A studies IQ's Sharpe ratio effect for a range of assumed risk premia for individual stocks. Depending on the column, stocks' risk premia can be 80%, 100%, or 120% of the HEX premium. Note that the risk premium of the HEX proportionately scales up the risk premium of all risky assets and thus has no effect on test statistics.

Panel A indicates that Sharpe ratios increase with IQ. The coefficients, monotonically increasing for the most part, significantly differ from zero.[28] For example, if stocks and funds share identical risk premia, the difference in Sharpe ratios between the lowest and highest stanine participants is -0.009 ($t = -3.13$). Panel A's IQ coefficients also are similar to those obtained from imputed Sharpe ratios using both the methodology and numbers suggested in Calvet, Campbell, and Sodini (2009), which generate a stanine 1 coefficient of -0.011 ($t = -2.77$),[29] a figure that matches the 120% column's corresponding coefficient in Panel A. The Panel A coefficients also exhibit remarkable similarity across specifications of the risk premium; linear interpolation gives fairly accurate coefficient estimates for any other stock risk premium assumption one might wish to impose. High-IQ investors' superior Sharpe ratios thus arise mostly from lower portfolio volatility. Table VII, Panel B's first column, which regresses Panel A's Sharpe ratio denominator against IQ and the usual controls, confirms this result.

To further analyze this Sharpe ratio component, the second and third columns of Table VII, Panel B, report coefficients from OLS regressions of logged and nonlogged stock component variance on IQ and the usual controls. Panel B shows that logged total variance and total variance of participants' portfolios of stocks decrease sharply and significantly in IQ stanine. With the (Internet Appendix's) linear-IQ specification for logged variance, a one-stanine increase in IQ decreases variance by a highly significant 3.5% ($t = 13.5$).

If systematic risk is fully rewarded with higher average returns, Sharpe ratios are primarily increased by reductions in diversifiable risk. To investigate whether IQ influences the diversifiable risk of the stock component, Table VII, Panel C's first column reports coefficients from an OLS regression of the residual variance of each participant's stock portfolio component against IQ and

[26] We later offer indirect evidence that heterogeneous stock risk premia, from factor exposure differences, strengthen our results.

[27] The HEX's Scholes–Williams beta on the MSCI World Index is 1.02.

[28] The Internet Appendix indicates that this significance, as well as all other results in Table VII, extends to the linear-IQ specification and to the 10% most affluent.

[29] The number of stocks held and the fraction of risky assets invested in mutual funds entirely account for their imputed Sharpe ratios. See http://kuznets.fas.harvard.edu/~campbell/papers/swedishinvestorsappendix20070905.pdf. The full results for our regression using their imputation methodology are in our Internet Appendix.

the usual controls.[30] Panel C's lower residual variance for high-IQ investors' portfolios suggests that high-IQ investors may also be more diversified. To directly investigate diversification, Table VII, Panel C, also studies the number of individual stocks in participants' portfolios and whether participants own any mutual funds. Negative binomial regressions with the IQ dummy specification show that cognitive skill increases the number of stocks held. Table VII, Panel C's probit regression, analogous to Table II, suggests that high IQ makes participants more likely to hold mutual funds. Both findings are monotonic in IQ and significant.

Table VII, Panel D, studies the systematic variance of investors' stock portfolios. It indicates that high-IQ investors' one-factor systematic risk is lower.[31] Panel D also reports coefficients from regressions of portfolio beta (estimated against the dollar MSCI World Index), book-to-market rank, and size rank of the stocks in each investor's portfolio against the usual regressors. IQ is significantly positively related to book-to-market exposure and negatively related to both beta (explaining the lower systematic risk of high-IQ investors' portfolio) and size.

Panel D's systematic variance results have no influence on Panel A's Sharpe ratio numerators, which do not depend on the factor exposures of participants' portfolios of individual stocks. However, a large literature establishes that selecting high-beta stocks with low exposure to the SMB and HML factors reduces ex post Sharpe ratios. Table VII shows that low-IQ investors bear more risk, partly due to inferior diversification, and choose large growth stocks with high betas—all of which arguably reduce the true Sharpe ratios of low-IQ participants' portfolios.

In short, Table VII documents that low-IQ participants are likely to experience a more adverse risk-return trade-off than high-IQ participants. For equity portfolios with 30% annual volatility, the stanine 1 coefficients from Panel A's Sharpe ratio regressions, ranging from −0.007 to −0.011, amount to the lowest IQ investors earning 21 to 33 basis points less per year than the highest IQ stanine. However, these figures probably underestimate the typical low-IQ investor's risk-return disadvantage. Because assessments measure IQ imprecisely, and thus generate an errors-in-variables bias, Panel A's IQ coefficients understate the impact of the IQ regressors. Low-IQ investors, unlike their high-IQ counterparts, also shun Sharpe ratio–enhancing factor exposures; Panel A's Sharpe ratio estimates do not account for differences in exposures to factors such as size and book-to-market. Finally, nonparticipants probably perceive an even worse risk-return trade-off than the participants that Table VII studies. These considerations lend credence to the conjecture that some nonparticipants

[30] Residual variance is variance from Table VII, Panel B, less systematic variance. Systematic variance is the product of total variance from Table VII, Panel B, times the R^2 from regressions of 2001 daily stock portfolio returns on contemporaneous, lead, and lagged dollar MCSI World Index returns.

[31] See the prior footnote for details. Similar results for IQ's influence on three-factor systematic (Panel C) and unsystematic risk (Panel D) using the HEX index benchmark are detailed in the Internet Appendix.

opt out of the market because of a justifiable conviction that the market's risk-reward trade-off is unappealing.[32] Table VII suggests that this belief should be more prevalent among low-IQ subjects.

IV. Conclusion

One's IQ stanine, measured early in adult life, is monotonically related to participation and diversification later in life. The high correlation between IQ and participation, which exists even among the 10% most affluent individuals, controls for wealth, income, age, and other demographic and occupational information. The economic size of the IQ effect is remarkably large: controlling for each subject's observable characteristics, the participation rate for individuals in the lowest IQ stanine is 20.5% lower than that for individuals at the other end of the IQ spectrum. IQ's effect on participation is monotonic, far larger than the effect of income on participation, and it generalizes to females. The importance of 120 questions from an IQ test taken years before one decides whether to participate is remarkable, indeed.

Control function instrumentation of IQ with brothers' scores does not alter our conclusions about IQ and participation, suggesting that omitted variables bias does not account for the IQ–participation relationship—at least for any omitted variable that is caused by own IQ. Random effects probit regressions for brother pairs also suggest that there is an own-IQ effect on participation that is separate from a family effect. Moreover, if the IQ–participation relationship arises from an omitted variables bias (or related specification errors), IQ coefficient magnitudes from Table II's probit regressions should be far larger than the IQ coefficients from these two bias-mitigating econometric techniques—but are not.

Cognitive skill's correlation with participation has implications for the distribution of wealth and policies that affect it. Because low-IQ investors participate less frequently in the stock market, their savings tend to earn lower returns. Compounded over many years, this return difference could contribute to the wealth gap between low- and high-IQ individuals to a greater extent than wage differences. Moreover, governments often use privatization offerings with incentives that encourage retail investors to subscribe.[33] Because high-IQ investors disproportionately reap the benefits of these incentives, privatization offerings may transfer wealth from low-IQ to high-IQ individuals. Our findings also have relevance for what financial economists have learned about markets. Because participants have higher IQ than the average citizen, and thus are less likely to be noise traders, markets could be more efficient than what experimental studies of the average citizen suggest.

Our paper makes some effort to understand IQ-related mechanisms that encourage or deter participation. A statistical decomposition suggests that

[32] This idea is consistent with Campbell's (2006, p. 1590) view that "Nonparticipating households may be aware of their limited investment skill and may react by withdrawing from risky markets altogether."

[33] See Keloharju, Knüpfer, and Torstila (2008).

wealth, income, and education, all influenced by IQ, are key contributors to participation. These results are consistent with IQ's correlation with indirect participation costs. Despite the promising start, the precise mechanism by which IQ influences participation remains elusive. We document an IQ–participation effect that is separate from the three major IQ channels found in the decomposition, as well as the more minor effects of occupation that proxy for financial literacy. Finding additional variables that might explain the separate IQ effect will be difficult. The paper's control function analysis implies that no unshared omitted variable could account for shared IQ's effect on participation. Random effects probit regressions indicate that analyses of shared omitted variables cannot explain own IQ's effect on participation. This success in ruling out so many of the usual suspects makes it challenging to identify the mechanism behind IQ's influence on participation.

While we have not fully resolved the participation puzzle, our results suggest the intriguing possibility that the odds are stacked against low-IQ investors when they do participate in the financial markets. Calvet et al. (2009) show that investors who make some investment mistakes tend to make many of them. Grinblatt, Keloharju, and Linnainmaa (2011) document that high-IQ investors' stock purchases earn larger risk-adjusted returns, that their purchases and sales experience lower trading costs, and that their trades are less subject to profit-eroding behavioral biases like the disposition effect. Grinblatt, Ikäheimo, Keloharju, and Knüpfer (2011) observe that high-IQ investors pay lower effective mutual fund fees by constructing "home-made balanced funds," that is, portfolios of equity and bond funds. A companion explanation comes from our last set of results. High-IQ investors are more likely to have larger Sharpe ratios because of increased diversification (from holding mutual funds and greater numbers of stocks). They also prefer Sharpe ratio–enhancing factor exposures (from low beta, high book-to-market, and small stocks). If low-IQ participants are likely to experience excess volatility because of poor diversification or poor choice of factor exposures, low-IQ individuals may view participation's risk-return trade-off as being less favorable than the trade-off faced by high-IQ individuals.

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