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IQ and Stock Market Participation

Mark Grinblatt
UCLA Anderson School of Management

Matti Keloharju
Helsinki School of Economics and CEPR

Juhani Linnainmaa
University of Chicago Booth School of Business

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Mark Grinblatt
UCLA Anderson School of Management

Matti Keloharju
Aalto University and CEPR

Juhani Linnainmaa
University of Chicago Booth School of Business

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ABSTRACT

An individual's IQ stanine, measured early in adult life, is monotonically related to his stock market participation later in life. The high correlation between IQ and participation, which exists even among the 10% most affluent individuals, controls for wealth, income, and other demographic and occupational information. Supplemental data from siblings are used with both an instrumental variables approach and regression procedures that control for family effects. These supplemental data show that our results apply to both females and males, and that omitted familial and non-familial variables are unlikely to account for our findings. IQ also is related to diversification: high IQ investors are more likely to hold mutual funds and larger numbers of stocks, other things equal.

Keywords: Intelligence, household finance, stock market participation

JEL classification: G11, D14

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In the U.S., approximately 50% of households invest in the stock market, either directly or indirectly (via mutual funds in retirement and non-retirement accounts).[1] Participation tends to be even lower in Europe.[2] When investors do participate, they often under-diversify.[3] Low participation rates have long puzzled economists because non-participation is inconsistent with neoclassical models of portfolio choice. In these models, everyone, irrespective of risk tolerance, invests something in risky stocks because the equity premium is positive and investor preferences are locally risk-neutral at zero risky investment.[4] The lack of diversification exhibited by some investors is also puzzling. These same models tell us that under-diversification unnecessarily increases risk without adding any benefit.

Why some investors fail to participate is an unresolved mystery despite a vast and rapidly growing literature.[5] 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. Non-neoclassical preferences have been proposed, but these alternative approaches to financial decision making lack wide acceptance in the literature.

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[1] See Bucks, Kennickell, and Moore (2009).

[2] See Guiso, Sapienza, and Zingales (2008).

[3] See Campbell (2006) and Calvet, Campbell, and Sodini (2007).

[4] See Arrow (1965).

[5] Haliassos and Bertaut (1995), using data from the U.S. Survey of Consumer Finances, conclude that "inertia and departures from expected-utility maximization" are more promising explanations for non-participation. Vissing-Jørgensen (2003) finds that moderate fixed participation costs can explain the non-participation of many U.S. households. However, Mankiw and Zeldes (1991) and Heaton and Lucas (2000) conclude that fixed participation costs do not explain the significant rate of non-participation among the wealthy. To explain the latter, researchers have turned to lack of awareness about the stock market (Hong, Kubik, and Stein 2004; Guiso and Jappelli 2005; Brown, Ivković, Smith, and Weisbenner 2008), non-standard preferences with agents exhibiting ambiguity aversion (Dow and Werlang 1992; Ang, Bekaert, and Liu 2005; Cao, Wang, and Zhang 2005; Epstein and Schneider 2006), lack of education (Campbell 2006; Calvet, Campbell, and Sodini 2007; Christiansen, Joensen, and Rangvid 2008; Rooij, Lusardi, and Alessie 2007), and lack of trust (Guiso, Sapienza, and Zingales 2008).

Limited ability to process information, an indirect participation cost, is perhaps the most widely advanced explanation for non-participation, but testing this has been problematic. To date, measurable traits that reflect a subject's skill at processing information are hard to come by and, if available, generally plagued with a host of endogeneity issues.

Christelis, Jappelli, and Padula (2009), the largest study to date, uses survey data from almost 20,000 seniors in Europe. They find that answers to a series of up to four numeracy questions, the number of animals one can name in one minute, and the number of nouns (out of 10) one recalls, influence self-reported stock market participation. Their probit regressions control for wealth, income, college attendance, and a host of other variables. In related work, Benjamin, Brown, and Shapiro (2006) study how intelligence-related test scores from 1980 influence 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?" The OLS-estimated regressions, which make use of 2088 sibling groups from the National Longitudinal Survey of Youth initiated in 1979, control for income, age, gender, survey year, and sibling fixed effects. Their findings, later extended by Cole and Shastry (2009) to additional dimensions of cognitive ability using the same dataset, suggest that IQ influences participation. Finally, Kezdi and Willis (2003) use OLS regressions to demonstrate that IQ influences the participation of more than 12,000 subjects in the National Retirement Survey.

We contribute to the understanding of the participation issue by studying Finnish stock market participation at the end of 2000 as a function of IQ measured early in adult life. We also study the issue of whether IQ relates to diversification, which has not been studied before. The IQ scores are comprehensive for Finnish males in a 20-year age range because they are obtained on induction into Finland's mandatory military service. We have IQ data on all inductees who took the IQ test between 1982 and 2001, as well as stock registry data that can unambiguously assess whether they own or acquire stock between January 1, 1995 and November 29, 2002. We also have access to data from the year 2000 tax returns of approximately 160,000 of these inductees. These tax returns contain subject-level controls for 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, and use asset allocation choices to show that our measure of IQ does not proxy for risk tolerance. In contrast to other work on the topic, our study makes use of a larger sample, contains more controls, and uses sophisticated econometric techniques to address pitfalls in this line of research. Because we have address data, we can even cluster our standard errors at the zip code level to control for correlations in residuals within neighborhoods. Ownership data also allows us to link our findings to other critical investment issues like diversification.

Most importantly, in contrast to all other work on participation, our results are not based on voluntary surveys. Kezdi and Willis (2009), for example, found that low IQ respondents simply did not know how to answer many of the queries in the National Retirement Survey, leaving many of them blank. Low IQ investors also seem more likely to answer "no" to ownership queries that describe financial instruments in more complicated terms than they understand (e.g., "equity" rather than "stock," "fund" rather than "account"). For example, in 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 relationship between IQ and participation if high IQ investors are more likely to understand that their money market account is a mutual fund.[6] Malloy et al. (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. There is no ambiguity in our study about what stock market participation means. Our measures of participation are drawn directly from ownership records, are comprehensive, and lack the response bias inherent in almost all surveys.

Our study finds that with all controls, probit regression coefficients on IQ stanine dummies exhibit a perfectly monotonic pattern: Individuals with the highest IQ scores are most likely to participate; those with the second highest scores participate more than those with the third highest scores, and so forth. IQ also remains a statistically and economically significant predictor of the participation decision even among the most affluent 10% of individuals. The economic size of the IQ effect is remarkably large—larger than the effect of income on participation. We also find that while all subcomponents of the IQ score influence participation, the most important component of IQ is the subcomponent related to mathematical ability.

In part because of the early age at which IQ is measured in our study, 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 independently from controls like education, wealth, and income, but also by having an influence over these controls. A Fairlie-Blinder-Oaxaca decomposition analyzes the channels through which this secondary IQ effect operates. For example, subjects with the second highest IQ stanine have a 36.6% participation rate. By

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

contrast, those in the second lowest IQ stanine have a 10.5% participation rate. About three fifths of the 26.1% 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 the opposite ends of the IQ spectrum.

A sufficient degree of non-participation driven by cognitive failures to rationally process the costs and benefits of stock investment could resolve the equity premium puzzle of Mehra and Prescott (1985) and the low risk-free rate puzzle of Weil (1989). If many individuals stay out of the market for reasons unrelated to asset prices, then an econometrician can ignore the consumption of the non-participants and estimate asset pricing models by using stockholder consumption data. 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 non-participants.[7]

In our analysis, cognitive skill emerges as a key driver of participation. Lack of cognitive skill can deter large amounts of wealth from entering the stock market. As verification of the latter conclusion, we 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 their benefits. If these market-based frictions fully accounted for non-participation, 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

[7] See Mankiw and Zeldes (1991), Basak and Cuoco (1998), Brav, Constantinides, and Geczy (2002), Vissing-Jørgensen (2002), Vissing-Jørgensen and Attanasio (2003), and Malloy, Moskowitz, and Vissing-Jørgensen (2009).

same as it is for the less affluent. The definition of affluence—net worth or income—does not affect this finding.

The quality of our data offers other unique benefits that prior empirical research has not been able to take advantage of. Analysis of siblings, identified from historical residential address data, facilitates the use of two powerful econometric techniques. From these, we conclude that omitted variables—such as risk aversion or more precise education categories—tied to one's own IQ or to one's family's average IQ, are unlikely to account for the effect of IQ on participation. For both brothers and sisters, we find that IQ measured from a brother's IQ exam plays a significant role in the subject's stock market participation decision. A proper instrumental variables analysis of brothers employing the control function method also supports the latter hypothesis. Moreover, probit analysis of brothers using Chamberlain's (1980) random effects approach indicates that individual IQ differences, even within families, help to explain differences in participation.

As a final test of IQ's importance, we assess the degree to which IQ influences diversification. IQ's role in diversification parallels its role in the participation decision: Controlling for other factors, probit regressions, analogous to those used to analyze participation, indicate that high IQ stock market participants are more likely to hold mutual funds. Related analysis, employing negative binomial regressions that control for the same factors, shows that high IQ investors' portfolios hold greater numbers of individual stocks. To our best knowledge, this finding is new to the literature. To the extent that diversification is tied to lower risk, it may offer an important clue about why high IQ investors are more likely to participate.

I. Data and Summary Statistics

A. Data Sources

We merge five data sets for our analysis.

Finnish Central Securities Depository (FCSD) Registry. This contains the daily portfolios and trades of all Finnish household investors in FCSD-registered stocks (all traded Finnish stocks and all foreign stocks traded on the Helsinki Exchanges) from January 1, 1995 through November 29, 2002. The electronic records we use are exact duplicates of the official certificates of ownership and trades, and hence are very reliable.[8] We analyze the FCSD holdings at the end of 2000, the date that coincides with the report date for control variables from our tax data. Participation is a dummy variable that takes on the value one for subjects who held any FCSD-registered stock on December 31, 2000. Our robustness checks analyze broader definitions of participation, including participation arising from the holding of stock or a mutual fund as of the end of 2000, and whether one purchased stock on or before November 29, 2002. We also use the dataset to determine the number of stocks owned on December 31, 2000 for our analysis of diversification.

Finnish Armed Forces (FAF) Intelligence Assessment. Around the time of induction into mandatory military duty in the Finnish Armed Forces, 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 measure cognitive functioning in three areas: mathematical ability, verbal ability,

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

and logical reasoning, which the FAF aggregates into a composite intelligence score. The FAF composite intelligence score, which we use and refer to as IQ, is standardized to follow the stanine distribution (integers 1 through 9 with 9 being most intelligent). We have test results for all exams that were scored between January 1, 1982 and December 31, 2001.

Compared to other countries, IQ variation in Finland is less likely to reflect differences in culture or environmental factors like schooling that might be related to successful stock market participation. For example, 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.[9] The country is also racially homogeneous. These factors make it more likely that differences in measured IQ in Finland reflect genuine differences in innate intelligence.

Finnish Tax Administration (FTA) Data. The Finnish Tax Administration 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 one owns various assets (a home, a forest, a mutual fund, stock in a non-public company, or foreign assets), native language (Finnish or Swedish), marital status (single, married, or unmarried but cohabiting), whether one has any dependents under 18 years old, 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).

[9] See, for example, a recent article in the Economist (December 6, 2007) and Garmerman (2008).

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. These data contain every subject's residence on each day from 1998-2000, the move-in date for the first address in this three-year period, and the move-out date for the last address after this three-year period (up to late 2002). For example, if a person was born on February 7, 1950, 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.

We use the historical location data along with gender data from the FTA to 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 (i) both moving on the same date to the same location and both moving out of that same location at a later date or (ii) living in a single family dwelling at the same location at some date. If the latter, we also impose a parent criterion: that either one other person, or exactly two opposite-gendered persons live at the same address at the same date, with the younger of the two persons 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 to be a sibling pair, then 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.[10] Our sample restricts siblings to be 18 or older as of December 31, 2000.

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 as determined by passing a college-prep examination at the end of 12th grade), and university degree. For each zip code and each of five age groups—18-24, 25-34, 35-44, 45-54, and 55 or older—the data set reports what fraction of the age group attained each of these education levels. We estimate the education attained by each individual as the average for their age group living within their zip code of residence as of December 31, 2000.

B. Summary Statistics

Table 1 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 commences prior to age 29, implies that our subjects were born between 1953 and 1982. Thus, we lack IQ data on older individuals. Panel A describes the distribution of IQ scores for the subjects used in

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[10] We know 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. Herrnstein and Murray (1994), for example, survey the literature and adopt a 60-percent estimate for the heritability of IQ. Bound, Griliches, and Hall (1984) 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.

our regression, for the entire Finnish Armed Forces data set, and the theoretical distribution. Panel B provides the average values of the variables used to develop regression variables (often as decile-based categorical dummies). In addition to reporting the averages for all males in the study, it reports 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 effect is of little concern as there are sufficiently large sample sizes within each IQ stanine.

Panel B shows that the participant and non-participant groups markedly differ in their IQ scores. Participants' average IQ stanine is almost a full point (about half a standard deviation) above the average for non-participants. Figure 1, which graphs IQ distribution for participants and non-participants, illustrates that the difference in the average IQ scores of participants and non-participants 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 stock market participants differ from non-participants for all of the variables used to construct regressor controls. Participants have significantly higher labor income. The average stock market participant collects annual wages of 30,341 Euros per year; this is about 50% more than non-participants' average of 20,214 Euros. Similarly, participants are wealthier and have a greater tendency to own homes, forests, and private equity (typically one's own business).

Using zip-code level education data broken down by age groupings, we find that non-participants are more likely to have attained only basic education (less than high school) or vocational education while participants are more likely to have earned a university degree. The other demographic variables, such as employment and marital status, also are related to market participation. Market participants are 1.29 times more likely than non-participants to marry and 1.14 times more likely to have kids. Market participants are five times more likely to work in the finance profession and three times less likely to be unemployed than non-participants.

Panel C, which presents averages for these same variables conditional on IQ stanine, shows that many of these same variables are related to IQ. Income and wealth are almost perfectly monotonic in IQ score. For example, 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 a basic education monotonically decreases from 24% for the lowest IQ score category to 19% for the highest IQ score category. 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 differences across IQ stanines 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 intelligent category to the most intelligent. Most notable, however, is that the stock market participation rate increases perfectly monotonically: from 8% for stanine 1 to 41% for stanine 9. Figure 2 illustrates that this finding is robust even when we control for wealth. It plots the participation rate against IQ stanine and net worth. Participation is largely monotonic in both variables.

II. Regression Results

A. Probit Regressions of Participation Decisions on IQ and Controls

Some of the relationships documented in Table 1 diminish or disappear when controlled for in a full multivariate setting. For this reason, our primary analysis makes use of regression to address the issue of the marginal effects of IQ. Because the participation outcome is binary, we use probit methodology to estimate the regression coefficients and compute their test statistics.

Table 2 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 against IQ and a host of control variables. As described earlier, the participation variable is one if an individual holds FCSD stocks at the end of 2000 and zero otherwise. 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 1,522.9 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. Note that the effect of IQ on participation is perfectly monotonic. Individuals with the lowest IQ score are less likely to own stock than individuals with the second lowest IQ scores, who in turn are less likely to own stock than individuals with the third lowest IQ scores, and so forth. The economic significance is equally impressive. The marginal effects column indicates that the lowest IQ individuals have a participation rate that is 17.6 percentage points less than that of the highest IQ individuals. The "linear IQ specification," reported in the three rightmost columns of Table 2, explores the alternative specification with IQ stanine as a single variable. Not surprisingly, the results and their interpretation are highly similar to those for the IQ dummy specification in the first three columns. The IQ coefficient of 0.086 for this specification mirrors the average difference in coefficients for the IQ dummy specification.

The 67 regression control variables are described in the prior data section. They include educational attainment proxies, cohort fixed effects,[11] 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 previously been used in the participation literature. Many of the explanatory variables are highly significant. For example, individuals in income deciles 1-9 are significantly less likely to be stock market 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 4.7 percentage points greater than any other decile, keeping other observables, including wealth, fixed. Unemployed individuals have a participation rate that is 10.5 percentage points lower than employed individuals. Finance professionals' participation rate is 14.1 percentage points greater than those employed in other professions. Consistent with Heaton and Lucas (2000), entrepreneurs' participation rate is 1.8

[11] Korniotis and Kumar (2009) relate age to investment skill.

percentage points lower than others. With the linear IQ specification, individuals in the highest income category have a 9.0 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.

As impressive as the coefficients on many of the controls are, the most striking coefficients largely belong to IQ. In the IQ dummy specification, the marginal effects and probit coefficients of the two lowest stanines (about 10% of the sample) are about 50% larger, on average, than the corresponding impact from being in the lowest income decile. This is all the more remarkable when one considers that the IQ test is just 120 questions and, for most subjects, the test is taken many years before participation is analyzed. Income, by contrast, is measured contemporaneously with participation and is deemed to be highly reliable because there are civil and criminal penalties associated with false reporting. Wealth seems to be relatively more important, but this might be accounted for by participation causing wealth: the 1990s were a good decade for holding Finnish stocks.

Neoclassical theories of participation, such as those in Vissing-Jørgensen (2002, 2003), argue that even modest direct costs of participation can deter participation for less wealthy individuals. This is because the dollar benefits of participation are small when there is little at stake in the markets. If we take these theories literally, and assume no measurement error, misspecification, or endogeneity biases, we would expect to see a wealth effect on participation only at the lower wealth levels. The fact that net worth deciles eight, nine, and ten are far more likely to participate than others is inconsistent with a participation cost theory. Of course, we do not live in such a perfect econometric world. As just one example, Vissing-Jørgensen (2003, pp. 179-180) hypothesizes that participation costs may be decreasing in cognitive ability. To the extent that measured wealth is correlated with deviations of true IQ from measured IQ, we might expect to see a more positive wealth effect on participation, even at higher wealth levels.

Our measure of cognitive ability remains a salient determinant of participation in comparison to the control variables—lending credence to a theory of participation and asset pricing based on cognitive segmentation. Punctuating the importance of IQ in relation to the controls are results from a third unreported specification that replaces the linear IQ specification's wealth decile dummies with wealth. In the third specification, the coefficient on IQ is 0.028 and the coefficient on wealth is 2.4×10^{-6}, generating a ratio of 11,491. Thus, each one stanine drop in IQ, which corresponds to half a standard deviation drop in ability, is equivalent to an 11,491 Euro decline in taxable net worth.

These results are highly robust. First, omitting regressors, including wealth, income, finance professional dummy, and education, does not lower the influence of IQ on participation. Second, the results are similar when we split the sample in half by age. For younger individuals, the linear specification's IQ coefficient is 0.076, while for the older individuals it is 0.092. Third, we analyzed the same regressions for participation based on end-of-1998 and 1999 holdings, the only other years for which we have tax data. Despite the different stock market environments, the results are largely the same. Fourth, designating those who invest only in Nokia as non-participants does not alter our results. For example, with the linear IQ specification, the IQ coefficient of 0.084 for the non-Nokia only sample is virtually identical to the overall sample's coefficient of 0.086. This should allay concerns that a large employer could influence our results by inducing participation, perhaps by compensating its most intelligent employees with stock or by incentivizing them to hold stock in the company. A fifth robustness check addresses whether

IQ's separate effect arises from the way in which education is measured.[12] IQ coefficients are of similar magnitude and sign as those in Table 2 if Table 2's regressions replace IQ with their corresponding average from one's age cohort within one's zip code. For example, with the IQ dummy specification, the coefficients on IQ dummies 1, 2, and 3, are respectively −1.032, −0.784, and −0.782 (all highly significant) whereas in Table 2 they are −0.683, −0.572, and −0.439. The Wald statistic for joint significance of the IQ dummies, 84.12, is still highly significant, although smaller than in Table 2. For the linear specification, the noisy IQ measure's coefficient, 0.137 (with a probit z-value of 6.59), exceeds the 0.086 coefficient in Table 2 (with a probit z-value of 37.48). Similar results obtain when all right hand side variables are replaced with their age-stratified zip-code averages.

Some of the prior studies on IQ and participation, discussed earlier, suggest that numeracy or other quantitative skill components of IQ are prominent in determining participation. This is true for our study as well. The composite IQ score we use is derived from three sub scores, one of which is mathematical ability. Each of the three sub scores is highly correlated with the composite score with correlation coefficients ranging from 0.83 to 0.89. Separate analyses of Table 2's linear specification with each of the three subcomponents of IQ indicate that each of the components influences participation (with the lowest t-statistic exceeding 28). The mathematical ability coefficient is virtually identical to the composite ability score coefficient of 0.086 from Table 2 and the other two subcomponents have coefficients of 0.063 (verbal ability) and 0.065 (logical ability). The verbal and logical components have a

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[12] Social and policy implications complicate any attempt to address nature vs. nurture issues. As a condition for the use of the highly sensitive and private IQ data, we are obliged to omit individual education from this study.

highly significant influence on participation in a linear specification that includes all three components in the same regression.

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 choose to avoid stockholdings.[13] Cochrane (2007) concludes from this that participation costs can have little effect on asset pricing because they prevent only a negligible amount of wealth from participating in the stock market. Related to this point, Curcuru, Heaton, Lucas, and Moore (2004) and Campbell (2006) observe that the degree of non-participation among wealthy individuals is puzzling. They reason that direct participation costs cannot plausibly explain such non-participation. Other mechanisms that might account for this phenomenon have not been verified empirically.

The influence of IQ on participation, documented in Table 2, suggests that there may be other frictions that hinder stock market participation. In contrast to the fixed costs of participation discussed above, non-participation that arises from limited cognitive skill could deter participation by the affluent. Whether there is any credence to this hypothesis is an empirical question best assessed by studying the influence of IQ on the most affluent subjects in our sample—those in the top decile of the wealth and income distribution. These affluent

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

individuals should not be constrained by any fixed cost of entry to the market but they could be deterred by limited cognitive skill. Another motivation is that one cannot explain IQ-related non-participation of the affluent 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% most affluent class. Even if such misclassification occurs in rare instances, one would not expect errors-in-variables or related estimation biases to account for IQ coefficients of the magnitude observed in Table 2. Finally, if IQ predicts the participation of the affluent, IQ's ability to predict participation does not arise from any hypothesized correlation between IQ and risk tolerance. If frictions, like entry costs, deter the most risk averse, the effect should be prominent only for the least affluent.

Table 3 employs the probit regression methodology of Table 2 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 2's regressions).

Both definitions of affluence lead to the same conclusion: IQ significantly predicts participation, even among these most affluent individuals. 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 14.3% lower than the rate of the highest IQ stanine for the income-affluent specification; it is 23.2% 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 3 are similar to those for the full sample in Table 2. These results speak to IQ's important role in the participation decisions of the most affluent individuals. They also rule out any argument that IQ proxies for risk tolerance or any other variable that, in combination with direct participation costs, deters participation.

C. Secondary Channels for IQ

Table 2's regressions demonstrate that IQ's influence over stock market participation does not arise from any correlation it has with our measures of income, wealth, education, and a host of other control variables. However, IQ clearly influences most 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, like the financial services industry. By virtue of these secondary channels, the individual may choose to invest in the stock market. Those with high income may desire to save and feel more comfortable about allocating some portion of their savings to stock. Those with children might want to provide for their future. To assess the degree to which IQ influences participation via secondary channels, Table 4 presents results from a Fairlie-Blinder-Oaxaca decomposition.[14] Panel A presents results on control variables that partially account for the 32.7% difference in participation rates between IQ stanines 1 and 9 while Panel B presents results on control variables that partially account for the 26.1% 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.

[14] See Blinder (1973), Oaxaca (1973), and Fairlie (1999, 2005).

The decomposition is derived in the following manner: First, we repeat Table 2's regression, but omit the IQ regressor(s). This regression yields control variable coefficients and predicted *z*-scores for each stanine group. Predicted *z*-scores, the summed product of the regression coefficients and the group means for the control variables, are then translated into predicted participation rates. The technique additionally 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 4 Panel A indicates that group-mean differences in the control variables account for almost two thirds (0.630) of the 32.7% difference in participation rates between stanines 1 and 9. There is a 7% difference in participation that is explained by differences in wealth between the stanines (holding other control variables fixed), a 6% difference explained by education differences alone, a 5% difference explained by income alone, and a 2% difference 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 4 leads to similar findings. Approximately three fifths of the 27% difference in participation between stanines 2 and 8 can be explained by group mean differences in the control variables. This 16% difference in predicted participation rates is largely accounted for by group differences in wealth (5%), education (4%), and income (4%), 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. Conclusions in such studies about the importance of wealth, income, or education on participation 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 and move-in/move-out dates in the Finnish tax data, described earlier, identify 4,358 sisters of the males from Table 2's regression. Table 5 reports results on participation and IQ for these females. Although we lack data on female IQ because they do not serve in the FAF, we can substitute for the missing data. The regression specifications are identical to those in Table 2, except that in place of the female's IQ stanine dummy or IQ score, we employ brother's IQ stanine dummy or IQ score. The IQ coefficients in Table 5 are of slightly smaller magnitude than the comparable coefficients in Table 2, but are still statistically significant. For example, in the linear specification on the right, the IQ coefficient has a *z*-statistic of 4.18. This suggests that the component of IQ that sisters share with brothers is a potent predictor of participation.

Substitution of 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. One cannot assess the bias by comparing Table 5's coefficients with Table 2's because the samples in these two tables differ so much. Gender differences alone may account for differences in IQ coefficient(s) and the Table 5 sample is younger because of the method used to identify siblings.

A more appropriate assessment of the bias in Table 5's coefficients can be found from a comparison of Panels A and B in Table 6. Table 6 repeats Table 5 for the subsample of data consisting of 1,996 brother pairs. Panel A reports results for brother pairs where, in place of own IQ, we use brother's IQ, while Panel B repeats the Table 2 regression on the subsample, using own IQ as the key regressor. Each brother in the pair appears as a data point, doubling the sample size to 3,992 subjects. Because of the nature of the historical address data set and the requirement that siblings be at least 18 years of age, the sibling sample is far smaller than the sample of 158,044 subjects from our prior analysis.

The coefficients in Table 6 Panel A are very similar to those in Panel B. For example, the coefficient on IQ in the linear specification is 0.08258 when we use one's brother's IQ as the regressor, and 0.08260 when own IQ is the regressor. This negligible difference suggests that any bias in Table 5's sister estimation of the IQ effect is probably small. The negligible difference also reinforces our earlier conclusion that there is a strong shared IQ component within families that influences participation.

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 2's results. In a setting with endogeneity, IQ's effect on participation can be viewed as estimation of a stylized pair of structural equations

$$participation(j) = \beta_0 + \beta_1 * IQ(j) + \beta_2 * observed\ controls(j) + \beta_3 * unobservable\ controls(j) + e(j),$$

$$unobservable\ controls(j) = c_0 + c_1 * IQ(j) + c_2 * observed\ controls(j) + z(j).$$

Inconsistent estimates of the coefficient vector β_1 arise from the correlation between the unobservable controls and one's actual IQ. Following Heckman (1978, 1979), and developed further by Rivers and Vuong (1988) and Petrin and Train (2009), one corrects for the inconsistency by adding the control function residual *s(j)* to the first regression, obtained from an OLS regression of own IQ on brother's IQ and own controls. That is, inserting *s(j)* from the OLS regression

$$IQ(j) = d_0 + d_1 * IQ\ brother\ (j) + d_2 * \ observed\ controls\ (j) + s(j) \qquad (1)$$

into the first (probit-estimated) regression,

$$participation(j) = b_0 + b_1 * IQ(j) + b_2 * observed\ controls(j) + b_3 * \ s(j) \qquad (2)$$

$$+ \ b_4 * unobservable\ controls(j) + e(j),$$

leads to consistent estimates of β_1 and β_2 if the unobservable controls of subject *j* are uncorrelated with his brother's IQ. The consistent estimates of β_1 and β_2 are transformations of b_1 and b_2 from the second regression (equation (2)) given by

$\beta_i = b_i/sqrt(1+b_i^2 * var(s)),$ where *var(s)* = variance of the residual from the first stage regression (equation (1)).

These estimated βs are the coefficients reported in Table 7. 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 7's coefficient estimate on IQ for the linear specification,[15] 0.256, is statistically significant, and about three times larger than the comparable coefficients in Tables 2 and 6 (Panel B). The marginal effect of IQ, 0.048, also is about twice as large as its counterparts in Table 2 and 6 (Panel B). The significant and economically large IQ coefficient here suggests that IQ score does not spuriously predict stock market participation because of a large class of omitted variables.

The key assumption of the control function method, that the residual be orthogonal to the regressors, does not rule out inconsistent IQ coefficient estimates from all omitted variables. However, if both the shared family IQ and idiosyncratic (non-family) IQ components have no influence on participation, one would need a unique type of omitted variable to account for the results in Table 7. Because brother's IQ influences Table 7'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).

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[15] There are no control function results for the IQ dummy specification. The control function approach can only be used for the linear IQ specification because the first stage control function residual needs to come from a linear projection.

F. Addressing Omitted Family Background Biases Using Chamberlain's Family Effects

Tables 5, 6, and 7, which proxy for IQ with sibling IQ, suggest that IQ components that are shared within a family are significant predictors of participation. It therefore seems plausible family effects, separate from a family IQ component, could influence participation. Prior work indicates that family background is correlated with all or some of the observables in the participation regression. For example, Chiteji and Stafford (1999) find that parental stock market participation alters the likelihood of child participation.[16] Charles and Hurst (2003) document a significant intergenerational correlation in wealth and suggest that family members share similar savings preferences. This raises an important issue. To what extent is participation determined by the component of IQ that is not shared within a family? Shared IQ components within a family may also proxy for inheritances or family environment, casting doubt on the role that native IQ may play in the participation decision. Table 8 tackles this issue with Chamberlain's (1980) random effects method to control for family effects.

Table 8's participation regression is estimated from the subsample used to construct the 1,996 brother pairs used in Tables 6 and 7. The Chamberlain random effects probit model differs from standard random effects models in that it allows the family effect to depend on family members' values for the independent variables. Chamberlain's method assumes that the family component of participation is a sum of a linear function of all the regressors, evaluated at their family averages, and the usual random effects residual.

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[16] Vissing-Jørgensen (2003) observes that within-family education about stock market "matters" may underlie this finding.

The Chamberlain approach used in Table 8 eliminates all "within family" omitted variables, including shared family knowledge about investment opportunities, as potential explanations for IQ's effect on participation. Table 8 demonstrates that after controlling for family effects, IQ is a significant predictor of participation with both specifications. For the lower IQ stanines and for the linear IQ specification, the IQ coefficients are of the same sign and larger magnitude than the corresponding coefficients from Tables 2 and Table 6 Panel B. For example, with the linear specification, Table 8 reports an IQ coefficient of 0.114. By contrast, the corresponding coefficient for Table 6 Panel B has an IQ coefficient 0.083 (for the same sample) and Table 2 has an IQ coefficient of 0.086 for the larger sample. Because of the far smaller sample size, the Table 8's test statistics are far lower than those for Table 2, but generally highly significant and of larger magnitude than those in Table 6 Panel B. Thus, even if the relationship between IQ and participation has a family component, the component of IQ that is orthogonal to that family component also determines participation.

G. Robustness: Alternative Definitions of Participation

There is no obvious way to best measure whether a subject invests in the stock market. For the sake of brevity, we selected one primary definition of participation, which is reflected in our tables. We summarize results with other definitions below.

The Table 2 results for both regression specifications are largely the same if we broaden the definition of participation. When we define the stock market participation variable to be one if a subject holds a mutual fund or individual stocks or both, the probit coefficients are again monotonic in IQ and of similar magnitude to those reported in Table 2. Unfortunately, the tax data from the FTA contain information about whether an individual held any mutual fund at the end of 2000, but do not identify which mutual fund an investor holds. Some of the funds held are money market and bond funds. However, given the preponderance of mutual fund accounts in equity mutual funds,[17] we are reassured about the robustness of our findings with the results from this broader definition of participation.

Some of the participation observed in the data arises from bequests. We partly know this because a few sibling pairs have identical stockholdings. If we redefine participation as a dummy that is one if the subject purchased stock between 1995 and 2002, and rerun Table 2's regression on the entire sample, we obtain even stronger results than in Table 2.

By contrast, the degree of participation seems to be unrelated to IQ. Controlling for wealth, income, age, and the other regressors in Table 2, there is no significant predictive power of IQ for the fraction of wealth (i.e., net worth) that participants invest in stocks. For example, with the linear specification, the coefficient on IQ is 0.0031, which has an insignificant z-statistic of 0.08 (p=0.94). We obtain similar results for the IQ dummy specification, as the Wald statistic for the eight IQ dummies being zero is insignificant and the coefficient pattern on the IQ dummies is not even close to being monotonic. Recall from Table 2 that when IQ was predicting participation (rather than the wealth fraction invested in risky stocks), the z-statistic for the linear specification was 37.48, IQ dummy coefficients were highly monotonic, and the Wald statistic for the joint significance of the eight IQ stanine dummies was an incredible 1522.9. IQ also is an insignificant predictor of the degree of participation when the dependent variable is the

[17] According to *Finnish Mutual Fund Report December 2000*, 94% of the mutual fund accounts in Finland were in equity mutual funds or balanced funds.

percentage of gross wealth[18] invested in stock and when significance for both specifications is judged from bootstrapped coefficient distributions.[19] These findings stand in marked contrast to those in McArdle, Smith, and Willis (2009), who find that numeracy ability is related to the degree of participation.

H. The Effect of IQ on Diversification

The evidence presented so far indicates that lack of sufficient cognitive skill prevents some individuals from holding stock. If this is the case, cognitive ability may play a role in other financial decisions. Table 9 investigates whether IQ plays a role in diversification. We employ two measures of diversification using the subsample of subjects that hold at least one individual stock. Panel A focuses on whether a subject holds a mutual fund. Panel B analyzes negative binomial regressions that explain the number of stocks held.

The analysis of whether a mutual fund is held is a binary decision. The specification and methodology used to study this issue is identical to Table 2, but the dependent variable is determined by whether the subject holds a mutual fund, as reported on his year 2000 tax return. Panel A of Table 9 suggests that IQ significantly predicts whether a subject holds a mutual fund, controlling for other factors. The effect is monotonic in IQ as evidenced by the coefficients for the IQ dummy specification and highly significant.

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[18] This alternative measure of the degree of stock investment is also popular in the literature. See, for example, Heaton and Lucas (2000).

[19] Because of the large number of observations, the distribution of the IQ coefficient in the bootstrap, which is drawn from 1000 simulations, is close to the asymptotic normality predicted by theory.

Panel B of Table 9 focuses on the issue of diversification, as measured by the number of stocks held. Negative binomial regression, an extension of Poisson regression, is employed here using the same regressors as Panel A. It, too, shows that diversification, as defined by the number of stocks held, is influenced by cognitive skill. In both specifications, those with lower IQ hold fewer stocks, controlling for income, wealth, education, and the other controls discussed earlier. The IQ coefficients in the IQ dummy specification on the left of Table 9 Panel B are almost perfectly monotonic and generally highly significant. The significance and magnitude of the IQ coefficient in the linear IQ specification is equally impressive. All of this leads to a conclusion that even among those who hold stock, low IQ investors are likely to hold more poorly diversified portfolios.

III. Conclusion

An individual's IQ stanine, measured early in adult life, is monotonically related to his 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, 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 17.6% lower than what it is for individuals at the other end of the IQ spectrum. This IQ effect on participation is monotonic, far larger than the effect of income on participation and it generalizes to females. The fact that 120 questions from an IQ test taken years before we measure participation explains as much if not more than contemporaneous controls like income in so many contexts is truly remarkable.

Instrumenting for IQ with brother's scores does not alter our conclusions about IQ and participation, suggesting that omitted variables bias is not relevant here—at least for any omitted variable that is caused by own IQ. Chamberlain (1980) random effects regressions for brother pairs also suggest that there is an own-IQ effect on participation that is separate from a family effect. These findings rule out omitted variables bias if IQ's effect on participation is entirely driven by shared family or entirely by idiosyncratic omitted variables that are correlated with IQ. However, if both shared family and idiosyncratic omitted variables drive participation, both sets of variables correlate with IQ, and if these variables are not spanned by observed controls, our estimation procedures could simply be identifying a spurious IQ coefficient. However, it is difficult to believe that the usual suspects could overturn our major findings. If omitted variables bias of this sort were so important, it is hard to explain why our measure of IQ does not appear to influence related outcomes like the fraction of wealth invested to stocks. Moreover, it seems unlikely that a strong omitted variables bias would generate IQ coefficient magnitudes that are similar or larger when we employ statistical techniques designed to mitigate the bias, like the control function and Chamberlain random effects approaches.

In addition to the robustness tests reported in the body of the paper, we have verified that IQ's influence on participation is similar across stratifications of the sample based on predictions of participation that are not tied to IQ. This "propensity score approach" involves a two-step regression procedure.[20] First, for the entire sample, we estimate Table 2's regression without IQ regressors and sort the sample into quintiles based on the regression's predicted participation, which derive entirely from the controls and age fixed effects. Second, for each of the five

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[20] See, for example, Rosenbaum and Rubin (1983).

quintile subsamples of subjects, we then run a regression of participation against IQ (or IQ dummies). For both the IQ-dummy and linear IQ specifications, the IQ slope estimates across the quintiles are very close to one another. This suggests that IQ's influence on participation is unlikely to be altered by the levels of the control variables employed in the first step.

In addition to the probit analyses reported, we have repeated the major analysis of the paper using a linear probability model. The OLS estimates of the coefficients differ from the probit coefficients due to their differing scale but the OLS test statistics are of similar significance to those reported in the paper. We have also reanalyzed our major results using gross wealth rather than net worth as a control. Using the substitute wealth control does not change any of our findings. For brevity's sake, we have omitted further details about these analyses, although they serve to confirm how robust the relationship between IQ and participation truly is.

Why low IQ investors do not participate remains an unresolved question. There is the intriguing possibility that the odds are stacked against these investors when they do participate in the financial markets. Grinblatt, Linnainmaa, and Keloharju (2009, 2010) have documented that smart 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. Another possible explanation comes from our diversification results. IQ is almost perfectly monotonically related to decisions to hold diversified mutual funds and portfolios with larger numbers of stocks. To our best knowledge, this finding is unique. If our diversification results imply that higher IQ investors bear less risk, this makes stock market participation more attractive. This ties in with the possibility that indirect participation costs (e.g., how intellectually taxing it is to learn about the stock market or how much extra risk one perceives about something one knows little about) may play a role. Our paper has also made efforts to understand IQ-related mechanisms that encourage participation. A Fairlie-Blinder-Oaxaca decomposition suggests wealth, income, and education, all of which are influenced by IQ, are key contributors to participation.

Despite this promising start, the precise mechanism by which IQ influences participation remains unresolved. We have documented an IQ effect on participation that is separate from the three major channels found in the Oaxaca decomposition, as well as the more minor effects of occupation dummies that proxy for financial literacy. Finding additional variables that might explain the separate IQ effect will be difficult. The paper's control function approach indicates that no unshared omitted variable could spuriously account for shared IQ's effect on participation. Chamberlain's (1980) random effects probit regressions for brothers also suggest that an analysis of shared omitted variables cannot explain the own IQ effect on participation. Thus, our success here in ruling out so many of the usual suspects implies that addressing the question of how IQ influences participation will be quite a challenge for future research.

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Figure 1: Distribution of IQ Score Conditional on Market Participation

Figure 1 plots IQ score distributions for stock market participants and non-participants. An individual is a stock market participant if he held individual stocks registered with the FCSD at the end of 2000.

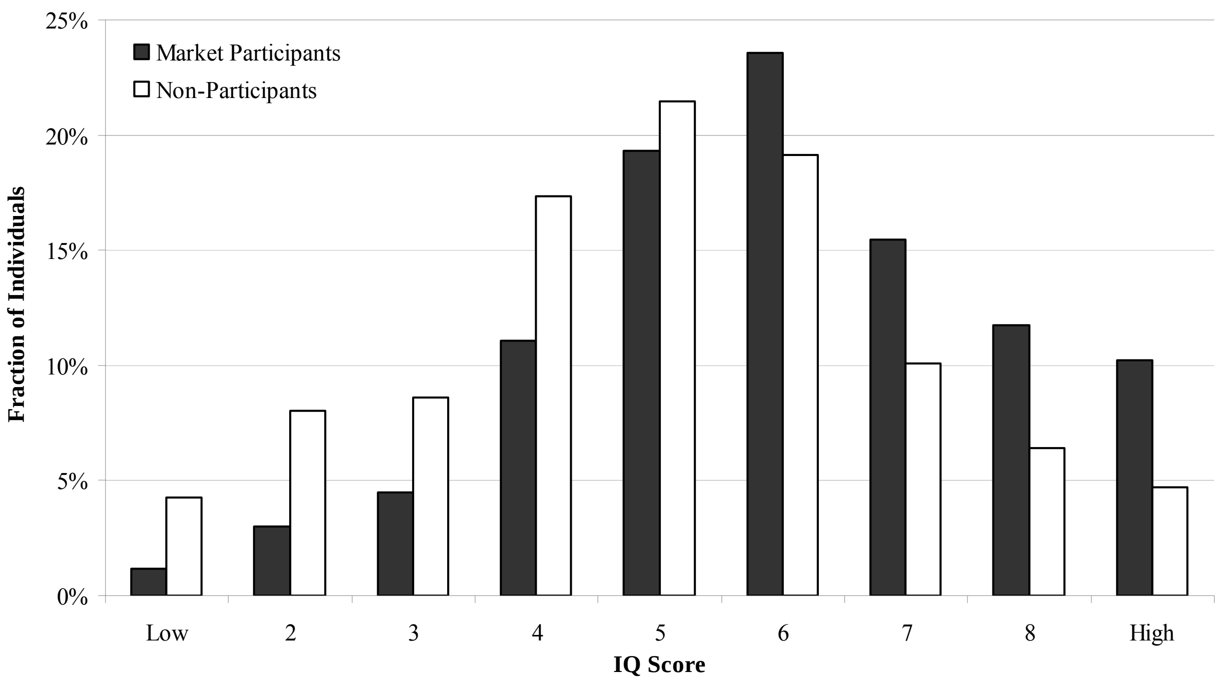

Figure 2: Average Participation Rate Conditional on IQ Score and Net Worth Decile

Figure 2 plots stock market participation rates as function of IQ stanine and net worth decile for all subjects with positive net worth. An individual is a stock market participant if he held individual stocks registered with the FCSD at the end of 2000. Net worth is from the 2000 Finnish tax dataset.

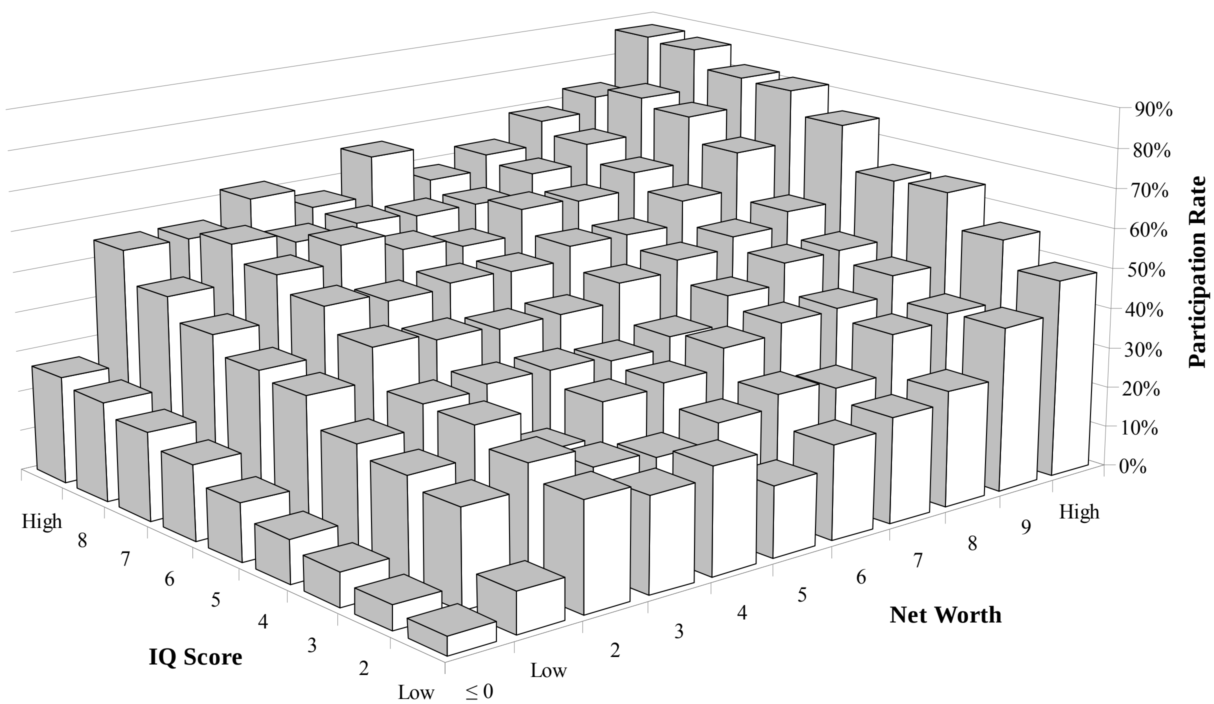

Table 1

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 on the value one for subjects who held individual stocks registered with the FCSD at the end of 2000. Income and wealth variables in Panel B are from the 2000 Finnish tax dataset. 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	5.02	5.97
Education			
Basic	21.6%	22.4%	19.3%
Vocational	42.6%	43.2%	40.9%
Matricular	18.8%	18.8%	19.0%
University	16.9%	15.7%	20.8%
Ordinary Income, EUR	22,642	20,214	30,341
Ordinary Income, Log-Growth	11.8%	11.8%	12.0%
Wealth			
Taxable home wealth > 0	37.7%	32.0%	55.5%
Taxable forest wealth > 0	1.3%	1.0%	2.2%
Taxable foreign wealth > 0	0.0%	0.0%	0.1%
Taxable private equity > 0	2.6%	2.1%	4.1%
Taxable net worth, EUR	11,193	3,036	37,051
Other Demographics			
Swedish	7.0%	6.7%	8.1%
Married	29.6%	27.6%	35.7%
Cohabiter	6.5%	6.8%	5.4%
Kids	29.8%	28.8%	33.0%
Occupation			
Entrepreneur	2.8%	2.7%	3.0%
Farmer	0.9%	0.7%	1.4%
Finance professional	0.7%	0.4%	1.8%
Unemployed	8.6%	10.3%	3.1%
Number of observations	158,044	120,143	37,901

Panel C: Mean socioeconomic characteristics by IQ score

	IQ score									
	1	2	3	4	5	6	7	8	9	All
Stock Market Participant	8.0%	10.5%	14.1%	16.8%	22.1%	28.0%	32.6%	36.6%	40.7%	24.0%
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%
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

Table 2

IQ Scores and Stock Market Participation

Table 2 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 on the value one for subjects who held individual stocks registered with the FCSD at the end of 2000. Pseudo *R*-squared 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 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, 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				0.086	37.48	0.024
Lowest	-0.683	-23.00	-0.176			
2	-0.572	-23.86	-0.155			
3	-0.439	-19.28	-0.126			
4	-0.360	-19.92	-0.107			
5	-0.251	-14.64	-0.077			
6	-0.139	-8.17	-0.045			
7	-0.072	-4.06	-0.024			
8	-0.028	-1.44	-0.009			
Education						
Basic	-0.006	-5.02	-0.002	-0.006	-5.08	-0.002
Vocational	-0.016	-13.42	-0.005	-0.016	-13.28	-0.005
Matricular	0.000	-0.06	0.000	0.000	-0.18	0.000
Ordinary income decile						
No Income	-0.285	-8.61	-0.087	-0.286	-8.62	-0.071
Lowest	-0.365	-17.38	-0.111	-0.366	-17.36	-0.090
2	-0.450	-20.58	-0.133	-0.450	-20.58	-0.108
3	-0.458	-21.72	-0.135	-0.459	-21.72	-0.109
4	-0.522	-29.54	-0.151	-0.524	-29.44	-0.122
5	-0.541	-28.99	-0.155	-0.543	-29.11	-0.125
6	-0.476	-24.68	-0.139	-0.476	-24.73	-0.113
7	-0.389	-23.76	-0.117	-0.387	-23.63	-0.095
8	-0.285	-16.38	-0.089	-0.283	-16.30	-0.072
9	-0.147	-9.04	-0.047	-0.144	-8.88	-0.039
Income Log-Growth Rate	0.023	2.94	0.008	0.023	2.93	0.007
Wealth dummies by wealth type						
Housing	0.193	17.27	0.065	0.193	17.36	0.056
Forest	-0.068	-1.46	-0.022	-0.068	-1.47	-0.019
Private equity	-0.070	-3.05	-0.023	-0.070	-3.06	-0.019
Foreign assets excluding equity	0.378	1.72	0.138	0.379	1.73	0.123
Net Worth decile						
No Net Worth	-1.548	-52.65	-0.552	-1.546	-52.34	-0.518
Lowest	-0.865	-24.09	-0.209	-0.861	-23.85	-0.162
2	-0.683	-19.66	-0.179	-0.681	-19.49	-0.140
3	-0.735	-23.02	-0.188	-0.734	-22.90	-0.147
4	-0.768	-22.48	-0.194	-0.766	-22.38	-0.151
5	-0.785	-24.28	-0.197	-0.784	-24.14	-0.153
6	-0.717	-22.60	-0.185	-0.716	-22.42	-0.145
7	-0.676	-20.25	-0.178	-0.675	-20.14	-0.139
8	-0.568	-17.69	-0.156	-0.568	-17.63	-0.124
9	-0.394	-12.53	-0.116	-0.392	-12.43	-0.093
Other demographics						
Swedish speaker	0.028	1.30	0.010	0.027	1.24	0.008
Married	0.010	0.65	0.003	0.010	0.64	0.003
Cohabitor	0.017	0.73	0.006	0.015	0.65	0.004
Kids	-0.099	-6.36	-0.033	-0.098	-6.29	-0.027
Occupation						
Entrepreneur	-0.053	-2.20	-0.018	-0.056	-2.29	-0.015
Farmer	-0.110	-1.89	-0.036	-0.111	-1.90	-0.030
Finance professional	0.386	9.25	0.141	0.386	9.23	0.125
Unemployed	-0.344	-19.23	-0.105	-0.347	-19.38	-0.086
Cohort Fixed Effects	Yes			Yes		
Baseline probability			0.278			0.203
Wald-χ^2 (IQ1 = … = IQ8 = 0)	1,522.9					
Pseudo R-squared	0.1848			0.1843		
N	158,044			158,044		

Table 3

IQ Scores and Stock Market Participation of Affluent Individuals

Table 3 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% 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 on the value one for subjects who held individual stocks registered with the FCSD at the end of 2000. Pseudo R-squared 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 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, 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				0.051	7.31	0.020
Lowest	-0.364	-2.32	-0.143			
2	-0.646	-6.25	-0.245			
3	-0.338	-4.13	-0.133			
4	-0.238	-4.76	-0.094			
5	-0.132	-3.30	-0.053			
6	-0.031	-0.77	-0.012			
7	-0.046	-1.15	-0.018			
8	-0.010	-0.26	-0.004			
Education						
Basic	-0.004	-1.40	-0.001	-0.004	-1.39	-0.001
Vocational	-0.014	-5.53	-0.005	-0.014	-5.50	-0.005
Matricular	0.001	0.23	0.000	0.001	0.28	0.001
Income Log-Growth Rate	0.036	0.90	0.014	0.030	0.74	0.012
Wealth dummies by wealth type						
Housing	0.220	9.04	0.088	0.220	9.03	0.088
Forest	0.006	0.06	0.002	0.006	0.06	0.002
Private equity	-0.012	-0.24	-0.005	-0.016	-0.32	-0.006
Foreign assets excluding equity	0.507	1.53	0.191	0.515	1.49	0.197
Net Worth decile						
No Net Worth	-1.225	-26.53	-0.456	-1.218	-26.49	-0.457
Lowest	-0.880	-10.67	-0.319	-0.873	-10.56	-0.308
2	-0.687	-8.44	-0.260	-0.690	-8.43	-0.255
3	-0.733	-9.92	-0.275	-0.729	-9.87	-0.268
4	-0.806	-10.39	-0.299	-0.796	-10.28	-0.288
5	-0.761	-10.89	-0.285	-0.755	-10.85	-0.276
6	-0.662	-9.31	-0.252	-0.656	-9.23	-0.245
7	-0.609	-8.06	-0.234	-0.602	-7.95	-0.227
8	-0.503	-8.17	-0.196	-0.498	-8.08	-0.191
9	-0.352	-6.25	-0.139	-0.347	-6.15	-0.136
Other demographics						
Swedish speaker	0.060	1.34	0.024	0.054	1.18	0.021
Married	-0.033	-0.86	-0.013	-0.031	-0.81	-0.012
Cohabitor	0.047	0.75	0.019	0.041	0.66	0.017
Kids	-0.106	-3.01	-0.042	-0.105	-2.98	-0.042
Occupation						
Entrepreneur	-0.058	-1.13	-0.023	-0.077	-1.54	-0.031
Farmer	-0.086	-0.61	-0.034	-0.093	-0.65	-0.037
Finance professional	0.288	5.37	0.112	0.291	5.46	0.115
Unemployed	-0.240	-0.95	-0.095	-0.243	-0.97	-0.096
Cohort Fixed Effects	Yes			Yes		
Baseline probability			0.524			0.494
Wald-χ^2 (IQ1 = … = IQ8 = 0)	82.3					
Pseudo R-squared	0.0991			0.0977		
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				0.090	6.78	0.025
Lowest	-0.741	-3.94	-0.232			
2	-0.606	-4.31	-0.182			
3	-0.445	-3.81	-0.126			
4	-0.488	-4.70	-0.140			
5	-0.238	-2.54	-0.062			
6	-0.143	-1.56	-0.036			
7	-0.158	-1.71	-0.039			
8	-0.007	-0.06	-0.002			
Education						
Basic	-0.002	-0.35	0.000	-0.002	-0.41	-0.001
Vocational	-0.023	-5.29	-0.005	-0.023	-5.27	-0.006
Matricular	0.002	0.29	0.001	0.002	0.30	0.001
Ordinary income decile						
No Income	0.004	0.03	0.001	0.004	0.03	0.001
Lowest	0.156	1.24	0.033	0.150	1.19	0.040
2	-0.186	-1.52	-0.047	-0.185	-1.51	-0.055
3	-0.124	-1.16	-0.030	-0.122	-1.14	-0.036
4	-0.176	-1.65	-0.044	-0.172	-1.61	-0.051
5	-0.198	-1.94	-0.050	-0.205	-2.02	-0.062
6	-0.212	-2.01	-0.054	-0.211	-2.00	-0.063
7	-0.146	-1.39	-0.036	-0.150	-1.44	-0.044
8	-0.049	-0.53	-0.012	-0.045	-0.49	-0.013
9	-0.004	-0.06	-0.001	-0.002	-0.02	-0.001
Income Log-Growth Rate	-0.042	-1.05	-0.010	-0.040	-1.01	-0.011
Wealth dummies by wealth type						
Housing	-0.037	-0.40	-0.008	-0.039	-0.42	-0.011
Forest	0.102	0.90	0.023	0.098	0.87	0.027
Private equity	-0.056	-0.69	-0.013	-0.055	-0.68	-0.016
Foreign assets excluding equity	-0.377	-1.01	-0.104	-0.352	-0.93	-0.112
Other demographics						
Swedish speaker	0.104	1.58	0.023	0.109	1.65	0.029
Married	0.044	0.52	0.010	0.048	0.56	0.013
Cohabitor	0.123	0.94	0.027	0.129	0.98	0.034
Kids	-0.238	-2.77	-0.056	-0.243	-2.81	-0.068
Occupation						
Entrepreneur	-0.013	-0.11	-0.003	-0.010	-0.09	-0.003
Farmer	-0.352	-2.79	-0.093	-0.351	-2.78	-0.109
Finance professional	0.442	2.40	0.081	0.450	2.44	0.103
Unemployed	0.037	0.21	0.008	0.036	0.21	0.010
Cohort Fixed Effects	Yes			Yes		
Baseline probability			0.852			0.801
Wald-χ^2 (IQ1 = … = IQ8 = 0)	51.0					
Pseudo R-squared	0.1123			0.1107		
N	3,857			3,857		

Table 4

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

Table 4 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	5.86	45.8
Income	4.92	45.4
Asset Class Ownership	0.77	18.9
Wealth	6.85	107.5
Demographics	0.18	4.5
Profession and Unemployment	1.66	27.2
Cohort	0.36	4.2
IQ=1 Participation Rate	7.98	
IQ=9 Participation Rate	40.68	
Explained Difference in Participation Rates	20.60	
Unexplained Difference in Participation Rates	12.10	

Panel B: Decomposition Estimates for IQ 2 versus IQ 8 Individuals

	Decomposition Estimate, %	z-value
Education	4.41	44.2
Income	4.32	45.1
Asset Class Ownership	0.53	18.8
Wealth	4.79	108.4
Demographics	0.16	4.9
Profession and Unemployment	1.17	27.2
Cohort	0.31	4.6
IQ=2 Participation Rate	10.55	
IQ=8 Participation Rate	36.62	
Explained Difference in Participation Rates	15.69	
Unexplained Difference in Participation Rates	10.38	

Table 5

Stock Market Participation Decisions of Women using Brothers' IQ Scores as Proxies

Table 5 reports summary data from probit regressions of women's stock market participation on their brother's IQ stanine dummies (or IQ score), used as a proxy for person's own IQ, 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. We identify 4,358 brother-sister pairs using historical addresses and move-in and move-out dates for each subject in the Finnish tax data. Two opposite-gendered individuals are identified as a brother-sister pair 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 individual stocks registered with the FCSD at the end of 2000. Pseudo R-squared 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 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, 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
Brother's IQ stanine				0.065	4.18	0.011
Lowest	-0.742	-2.79	-0.114			
2	-0.353	-2.22	-0.068			
3	-0.515	-3.65	-0.091			
4	-0.328	-2.66	-0.065			
5	-0.324	-2.71	-0.064			
6	-0.240	-2.17	-0.050			
7	-0.039	-0.32	-0.009			
8	-0.263	-2.23	-0.054			
Education						
Basic	-0.017	-1.85	-0.004	-0.016	-1.80	-0.003
Vocational	-0.029	-3.40	-0.007	-0.029	-3.37	-0.005
Matricular	-0.009	-0.98	-0.002	-0.009	-0.94	-0.002
Ordinary income decile						
No Income	0.062	0.32	0.015	0.060	0.31	0.011
Lowest	-0.161	-0.61	-0.035	-0.164	-0.62	-0.026
2	-0.084	-0.49	-0.019	-0.069	-0.40	-0.011
3	0.068	0.40	0.017	0.074	0.43	0.013
4	0.052	0.35	0.013	0.064	0.43	0.011
5	-0.060	-0.41	-0.014	-0.045	-0.31	-0.008
6	-0.006	-0.04	-0.001	0.005	0.03	0.001
7	0.009	0.07	0.002	0.008	0.06	0.001
8	-0.078	-0.66	-0.018	-0.070	-0.58	-0.012
9	-0.112	-0.88	-0.025	-0.105	-0.82	-0.017
Income Log-Growth Rate	0.011	0.25	0.003	0.010	0.23	0.002
Wealth dummies by wealth type						
Housing	-0.081	-0.66	-0.018	-0.076	-0.63	-0.013
Forest						
Private equity	-0.154	-0.62	-0.033	-0.145	-0.59	-0.023
Foreign assets excluding equity						
Net Worth decile						
No Net Worth	-1.790	-10.29	-0.594	-1.781	-10.24	-0.531
Lowest	-0.918	-3.07	-0.128	-0.909	-3.05	-0.085
2	-1.029	-3.41	-0.134	-1.041	-3.45	-0.089
3	-0.768	-2.68	-0.117	-0.753	-2.63	-0.078
4	-0.556	-1.98	-0.096	-0.545	-1.95	-0.065
5	-1.008	-4.62	-0.134	-1.004	-4.62	-0.089
6	-0.630	-3.02	-0.105	-0.627	-3.03	-0.072
7	-0.658	-2.98	-0.107	-0.659	-2.97	-0.073
8	-0.387	-1.99	-0.074	-0.395	-2.02	-0.053
9	-0.433	-2.34	-0.081	-0.435	-2.34	-0.057
Other demographics						
Swedish speaker	-0.112	-1.06	-0.025	-0.105	-0.99	-0.017
Married	-0.242	-1.25	-0.050	-0.233	-1.21	-0.035
Cohabitor	0.073	0.21	0.018	0.058	0.17	0.010
Kids	-0.066	-0.39	-0.015	-0.067	-0.40	-0.011
Occupation						
Entrepreneur						
Farmer						
Finance professional	1.533	1.84	0.541	1.591	1.90	0.518
Unemployed	-0.285	-2.48	-0.059	-0.288	-2.51	-0.042
Cohort Fixed Effects	Yes			Yes		
Baseline probability			0.152			0.098
Wald-χ^2 (IQ1 = … = IQ8 = 0)	29.3					
Pseudo R-squared	0.2023			0.1995		
N	4,358			4,358		

Table 6

Stock Market Participation Decisions of Brothers using IQ Score Proxies

Table 6 reports summary data from probit regressions of stock market participation on IQ score proxies 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. Panel A reports on regressions in which IQ stanine dummies (or IQ score) are the IQ stanine dummies (or IQ score) of one's brother. Panel B reports on regressions which use the person's own IQ stanine dummies (or IQ score) as the IQ regressor(s). 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 individual stocks registered with the FCSD at the end of 2000. Pseudo R-squared 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 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, no net worth, identifies the latter individuals. The regressions also contain 30 (unreported) cohort fixed effects for birth years 1953 through 1982.

Panel A: Stock Market Participation as a Function of Brother's IQ

	IQ Dummy Specification			Linear IQ Specification		
Independent variables	Coefficients	*z*-values	Marginal Effects	Coefficients	z-values	Marginal Effects
Brother's IQ stanine				0.083	5.30	0.016
Lowest	-0.464	-2.00	-0.072			
2	-0.540	-3.15	-0.080			
3	-0.187	-1.21	-0.035			
4	-0.310	-2.46	-0.053			
5	-0.039	-0.33	-0.008			
6	0.048	0.40	0.010			
7	0.246	2.10	0.058			
8	0.071	0.56	0.015			
Education						
Basic	-0.005	-0.71	-0.001	-0.005	-0.68	-0.001
Vocational	-0.027	-4.01	-0.006	-0.027	-4.08	-0.005
Matricular	0.000	0.01	0.000	0.000	-0.03	0.000
Ordinary income decile						
No Income	0.457	2.42	0.117	0.417	2.16	0.098
Lowest	0.686	3.05	0.195	0.689	3.02	0.185
2	0.104	0.58	0.023	0.076	0.42	0.015
3	0.183	1.19	0.042	0.171	1.11	0.036
4	0.179	1.12	0.040	0.179	1.12	0.037
5	-0.001	-0.01	0.000	-0.007	-0.06	-0.001
6	0.174	1.36	0.039	0.178	1.40	0.037
7	0.004	0.03	0.001	0.008	0.07	0.001
8	-0.032	-0.28	-0.006	-0.024	-0.21	-0.004
9	-0.049	-0.47	-0.010	-0.056	-0.54	-0.010
Income Log-Growth Rate	0.047	1.10	0.010	0.040	0.93	0.008
Wealth dummies by wealth type						
Housing	-0.166	-1.37	-0.032	-0.174	-1.45	-0.030
Forest						
Private equity	-0.266	-1.07	-0.047	-0.278	-1.15	-0.045
Foreign assets excluding equity						
Net Worth decile						
No Net Worth	-1.963	-11.10	-0.615	-1.956	-11.23	-0.596
Lowest	-1.141	-4.05	-0.116	-1.128	-4.07	-0.104
2	-0.775	-2.69	-0.099	-0.798	-2.78	-0.091
3	-0.970	-3.66	-0.110	-0.963	-3.75	-0.099
4	-0.981	-3.57	-0.111	-0.980	-3.61	-0.099
5	-0.975	-3.87	-0.111	-0.954	-3.86	-0.099
6	-0.907	-3.69	-0.108	-0.879	-3.56	-0.096
7	-0.770	-3.48	-0.100	-0.750	-3.43	-0.089
8	-0.453	-2.02	-0.072	-0.436	-1.98	-0.063
9	-0.435	-1.98	-0.070	-0.437	-1.98	-0.064
Other demographics						
Swedish speaker	0.114	0.97	0.025	0.118	1.01	0.024
Married	0.018	0.07	0.004	0.034	0.14	0.007
Cohabitor	0.130	0.29	0.029	0.146	0.33	0.030
Kids	-0.257	-0.64	-0.046	-0.269	-0.67	-0.043
Occupation						
Entrepreneur						
Farmer						
Finance professional	0.319	0.54	0.078	0.370	0.63	0.087
Unemployed	-0.686	-4.20	-0.099	-0.671	-4.15	-0.089
Cohort Fixed Effects	Yes			Yes		
Baseline probability			0.125			0.112
Wald-χ^2 (IQ1 = … = IQ8 = 0)	48.5					
Pseudo R-squared	0.2674			0.2620		
N	3,992			3,992		

Panel B: Stock Market Participation as a Function of Own IQ in the Sample of Pairs of Brothers

	IQ Dummy Specification			Linear IQ Specification		
Independent variables	Coefficients	*z*-values	Marginal Effects	Coefficients	z-values	Marginal Effects
Brother's IQ stanine				0.083	5.01	0.016
Lowest	-0.573	-2.31	-0.087			
2	-0.547	-3.00	-0.084			
3	-0.192	-1.20	-0.037			
4	-0.321	-2.39	-0.057			
5	-0.131	-1.06	-0.026			
6	0.104	0.90	0.024			
7	0.072	0.58	0.016			
8	0.114	0.94	0.026			
Education						
Basic	-0.005	-0.60	-0.001	-0.004	-0.59	-0.001
Vocational	-0.027	-4.03	-0.006	-0.028	-4.15	-0.005
Matricular	0.000	0.02	0.000	0.000	-0.06	0.000
Ordinary income decile						
No Income	0.409	2.12	0.106	0.416	2.17	0.098
Lowest	0.729	3.08	0.215	0.711	3.10	0.193
2	0.101	0.56	0.023	0.081	0.45	0.016
3	0.163	1.02	0.038	0.159	1.00	0.033
4	0.135	0.87	0.031	0.143	0.90	0.029
5	-0.043	-0.32	-0.009	-0.046	-0.34	-0.009
6	0.152	1.19	0.035	0.157	1.24	0.032
7	-0.010	-0.09	-0.002	-0.011	-0.10	-0.002
8	-0.052	-0.45	-0.011	-0.050	-0.43	-0.009
9	-0.066	-0.63	-0.014	-0.068	-0.65	-0.013
Income Log-Growth Rate	0.038	0.87	0.008	0.040	0.93	0.008
Wealth dummies by wealth type						
Housing	-0.168	-1.40	-0.033	-0.158	-1.33	-0.028
Forest						
Private equity	-0.236	-0.96	-0.044	-0.256	-1.06	-0.042
Foreign assets excluding equity						
Net Worth decile						
No Net Worth	-1.936	-11.13	-0.614	-1.925	-11.06	-0.587
Lowest	-1.120	-3.98	-0.122	-1.118	-3.98	-0.104
2	-0.770	-2.70	-0.104	-0.737	-2.59	-0.087
3	-0.935	-3.55	-0.114	-0.932	-3.60	-0.098
4	-0.941	-3.51	-0.114	-0.952	-3.49	-0.099
5	-0.987	-3.99	-0.117	-0.958	-3.88	-0.099
6	-0.833	-3.42	-0.109	-0.837	-3.43	-0.094
7	-0.695	-3.17	-0.099	-0.705	-3.20	-0.087
8	-0.422	-1.91	-0.071	-0.423	-1.94	-0.062
9	-0.368	-1.64	-0.064	-0.405	-1.83	-0.060
Other demographics						
Swedish speaker	0.114	0.97	0.026	0.121	1.03	0.024
Married	0.038	0.15	0.008	0.000	0.00	0.000
Cohabitor	0.208	0.46	0.050	0.089	0.19	0.018
Kids	-0.334	-0.84	-0.059	-0.260	-0.65	-0.042
Occupation						
Entrepreneur						
Farmer						
Finance professional	0.329	0.56	0.084	0.325	0.54	0.074
Unemployed	-0.597	-3.69	-0.095	-0.605	-3.71	-0.083
Cohort Fixed Effects	Yes			Yes		
Baseline probability			0.132			0.112
Wald-χ^2 (IQ1 = … = IQ8 = 0)	37.1					
Pseudo R-squared	0.2658			0.2614		
N	3,992			3,992		

Table 7

Stock Market Participation Decisions using a Control Function Approach to Estimation

Table 7 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 individual stocks registered with the FCSD at the end of 2000. Pseudo R-squared and sample sizes are reported at the bottom of the table. t-values are estimated using the jackknife estimators. The columns report coefficients from the probit regression, associated 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, 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	0.256	5.51	0.048
Education			
Basic	0.003	0.39	0.001
Vocational	-0.021	-2.69	-0.004
Matricular	0.003	0.33	0.000
Ordinary income decile			
No Income	0.191	1.01	0.036
Lowest	0.613	2.75	0.115
2	-0.110	-0.54	-0.021
3	-0.019	-0.11	-0.004
4	-0.027	-0.17	-0.005
5	-0.240	-1.67	-0.045
6	0.030	0.22	0.006
7	-0.150	-1.33	-0.028
8	-0.162	-1.49	-0.030
9	-0.128	-1.24	-0.024
Income Log-Growth Rate	0.013	0.30	0.002
Wealth dummies by wealth type			
Housing	-0.093	-0.84	-0.017
Forest	-1.066	-1.82	-0.200
Private equity	-0.170	-0.71	-0.032
Foreign assets excluding equity			
Net Worth decile			
No Net Worth	-1.873	-10.37	-0.352
Lowest	-1.135	-3.63	-0.213
2	-0.860	-2.74	-0.162
3	-0.945	-3.52	-0.178
4	-0.990	-3.66	-0.186
5	-0.987	-3.87	-0.185
6	-0.891	-3.65	-0.167
7	-0.688	-3.17	-0.129
8	-0.475	-2.19	-0.089
9	-0.422	-2.08	-0.079
Other demographics			
Swedish speaker	0.182	1.78	0.034
Married	-0.093	-0.34	-0.017
Cohabitor	0.079	0.13	0.015
Kids	-0.264	-0.52	-0.050
Occupation			
Entrepreneur	-0.124	-0.42	-0.023
Farmer	0.336	0.57	0.063
Finance professional	0.177	0.23	0.033
Unemployed	-0.436	-2.35	-0.082
1st Stage Control Variable	-0.195	-3.88	0.229
Cohort Fixed Effects	Yes		
Baseline probability			0.110
Pseudo R-squared	0.2689		
N	3,992		

Table 8

Chamberlain Random Effects Analysis of Brothers' Stock Market Participation Decisions

Table 8 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 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 data control for unobserved family background variables with Chamberlain's (1980) random effects model. Pseudo R-squared 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 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, 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			0.114	3.87
Lowest	-0.860	-2.09		
2	-0.803	-2.34		
3	-0.255	-0.91		
4	-0.481	-2.06		
5	-0.302	-1.40		
6	0.097	0.47		
7	-0.111	-0.51		
8	0.148	0.61		
Education				
Basic	-0.007	-0.52	-0.007	-0.50
Vocational	-0.049	-3.73	-0.049	-3.77
Matricular	0.000	-0.01	-0.001	-0.06
Ordinary income decile				
No Income	0.765	2.23	0.752	2.22
Lowest	1.257	3.31	1.208	3.20
2	0.006	0.02	-0.025	-0.07
3	0.333	1.17	0.317	1.13
4	0.244	0.96	0.244	0.96
5	0.109	0.48	0.109	0.48
6	0.330	1.51	0.321	1.48
7	0.019	0.10	0.006	0.03
8	-0.085	-0.48	-0.088	-0.49
9	-0.028	-0.17	-0.038	-0.23
Income Log-Growth Rate	0.101	1.32	0.099	1.30
Wealth dummies by wealth type				
Housing	-1.309	-1.28	-1.380	-1.37
Forest	-0.298	-0.65	-0.323	-0.71
Private equity	-3.181	-9.89	-3.152	-9.88
Foreign assets excluding equity				
Net Worth decile				
No Net Worth	-2.010	-4.07	-2.036	-4.13
Lowest	-1.324	-2.84	-1.283	-2.76
2	-1.682	-3.46	-1.671	-3.44
3	-1.214	-2.68	-1.217	-2.71
4	-1.646	-3.92	-1.618	-3.87
5	-1.359	-3.33	-1.365	-3.37
6	-1.158	-3.07	-1.161	-3.09
7	-0.769	-1.96	-0.764	-1.96
8	-0.508	-1.37	-0.524	-1.42
9	0.229	1.16	0.240	1.23
Other demographics				
Swedish speaker				
Married	0.406	0.96	0.322	0.77
Cohabitor	1.230	1.30	1.024	1.10
Kids	-1.033	-1.28	-0.903	-1.14
Occupation				
Entrepreneur	-0.570	-1.15	-0.511	-1.05
Farmer	0.203	0.23	0.311	0.36
Finance professional	0.431	0.41	0.442	0.43
Unemployed	-0.810	-2.82	-0.806	-2.83
Cohort Fixed Effects	Yes		Yes	
Wald-χ^2 (IQ1 = … = IQ8 = 0)	24.4			
N	3,766		3,766	

Table 9

IQ Scores and Diversification

Table 9 reports summary data from probit regressions (Panel A) and negative binomial regressions (Panel B) of portfolio diversification 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. The dependent variable in Panel A's probit regression is a dummy variable that takes on the value one for subjects who held mutual funds at the end of 2000. The dependent variable in Panel B's negative binomial regression is the number of individual stocks the subject held at the end of 2000 in the FCSD data. All regressions are estimated using data on individuals who held at least one individual stock registered with the FCSD at the end of 2000. Pseudo *R*-squared (in Panel A) 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 regression, associated *z*-values, and marginal effects on mutual fund participation probability (Panel A) or number of stocks held (Panel B), 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 mutual fund participation probability (Panel A) or number of stocks held (Panel B) 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, no net worth, identifies the latter individuals. The regressions also contain 30 (unreported) cohort fixed effects for birth years 1953 through 1982.

Panel A: Probit Regression of the Decision to Own Mutual Funds

	IQ Dummy Specification			Linear IQ Specification		
Independent variables	Coefficients	*z*-values	Marginal Effects	Coefficients	*z*-values	Marginal Effects
IQ stanine				0.047	11.82	0.013
Lowest	-0.363	-4.35	-0.095			
2	-0.388	-6.80	-0.100			
3	-0.323	-6.36	-0.086			
4	-0.198	-6.24	-0.056			
5	-0.187	-7.11	-0.053			
6	-0.110	-4.26	-0.032			
7	-0.081	-2.81	-0.024			
8	-0.051	-1.77	-0.015			
Education						
Basic	0.001	0.58	0.000	0.001	0.56	0.000
Vocational	-0.002	-1.60	-0.001	-0.002	-1.63	-0.001
Matricular	0.000	0.23	0.000	0.000	0.17	0.000
Ordinary income decile						
No Income	-0.229	-3.51	-0.064	-0.228	-3.50	-0.056
Lowest	-0.371	-9.04	-0.099	-0.371	-9.04	-0.087
2	-0.345	-8.09	-0.093	-0.345	-8.10	-0.082
3	-0.300	-7.09	-0.082	-0.300	-7.11	-0.073
4	-0.371	-8.82	-0.099	-0.373	-8.87	-0.087
5	-0.301	-7.95	-0.082	-0.302	-8.00	-0.073
6	-0.261	-7.58	-0.073	-0.263	-7.55	-0.065
7	-0.213	-6.33	-0.060	-0.214	-6.37	-0.054
8	-0.151	-4.95	-0.044	-0.151	-4.96	-0.039
9	-0.123	-4.69	-0.036	-0.122	-4.65	-0.032
Income Log-Growth Rate	0.016	0.98	0.005	0.016	1.00	0.004
Wealth dummies by wealth type						
Housing	-0.081	-4.13	-0.025	-0.081	-4.15	-0.022
Forest	-0.090	-1.05	-0.027	-0.091	-1.05	-0.024
Private equity	-0.020	-0.56	-0.006	-0.020	-0.57	-0.006
Foreign assets excluding equity	-0.062	-0.21	-0.018	-0.057	-0.19	-0.015
Net Worth decile						
No Net Worth	-0.970	-31.96	-0.285	-0.968	-31.93	-0.257
Lowest	-0.046	-1.01	-0.014	-0.046	-0.99	-0.012
2	-0.365	-9.03	-0.097	-0.364	-9.01	-0.085
3	-0.216	-5.53	-0.061	-0.215	-5.49	-0.054
4	-0.295	-6.94	-0.080	-0.294	-6.92	-0.071
5	-0.358	-8.35	-0.095	-0.357	-8.31	-0.084
6	-0.364	-8.69	-0.097	-0.364	-8.69	-0.085
7	-0.449	-11.30	-0.115	-0.448	-11.32	-0.101
8	-0.313	-7.49	-0.085	-0.313	-7.47	-0.075
9	-0.222	-6.29	-0.063	-0.221	-6.26	-0.055
Other demographics						
Swedish speaker	0.219	7.39	0.071	0.217	7.30	0.064
Married	0.020	0.75	0.006	0.020	0.74	0.005
Cohabitor	0.056	1.19	0.017	0.054	1.14	0.015
Kids	-0.189	-6.23	-0.056	-0.188	-6.20	-0.050
Occupation						
Entrepreneur	-1.513	-14.88	-0.231	-1.513	-14.89	-0.195
Farmer	-0.549	-5.12	-0.132	-0.550	-5.11	-0.115
Finance professional	0.330	6.53	0.111	0.330	6.51	0.102
Unemployed	-0.115	-2.22	-0.034	-0.116	-2.24	-0.030
Cohort Fixed Effects	Yes			Yes		
Baseline probability			0.230			0.192
Wald-χ^2 (IQ1 = … = IQ8 = 0)	144.4					
Pseudo R-squared	0.0926			0.0924		
N	37,901			37,901		

Panel B: Negative Binomial Regression of the Number of Stocks Held

	IQ Dummy Specification			Linear IQ Specification		
Independent variables	Coefficients	*z*-values	Marginal Effects	Coefficients	*z*-values	Marginal Effects
IQ stanine				0.038	13.47	0.094
Lowest	-0.274	-5.44	-0.657			
2	-0.284	-7.99	-0.678			
3	-0.280	-9.88	-0.669			
4	-0.159	-8.38	-0.403			
5	-0.118	-6.66	-0.306			
6	-0.052	-2.99	-0.138			
7	-0.059	-2.73	-0.155			
8	-0.016	-0.86	-0.042			
Education						
Basic	-0.003	-2.69	-0.011	-0.004	-3.30	-0.010
Vocational	-0.007	-6.54	-0.018	-0.007	-6.22	-0.017
Matricular	-0.002	-1.07	-0.005	-0.002	-1.14	-0.005
Ordinary income decile						
No Income	-0.022	-0.50	-0.057	-0.020	-0.46	-0.049
Lowest	-0.130	-5.60	-0.338	-0.130	-5.58	-0.308
2	-0.180	-8.14	-0.459	-0.181	-8.17	-0.420
3	-0.203	-8.86	-0.511	-0.204	-8.91	-0.470
4	-0.244	-11.75	-0.604	-0.248	-11.93	-0.559
5	-0.247	-10.67	-0.610	-0.250	-10.77	-0.565
6	-0.256	-11.06	-0.631	-0.259	-11.17	-0.584
7	-0.194	-8.61	-0.491	-0.195	-8.70	-0.452
8	-0.132	-6.95	-0.345	-0.132	-6.93	-0.316
9	-0.107	-6.62	-0.283	-0.106	-6.53	-0.257
Income Log-Growth Rate	0.013	1.18	0.035	0.014	1.26	0.034
Wealth dummies by wealth type						
Housing	-0.036	-2.94	-0.102	-0.038	-3.04	-0.095
Forest	-0.024	-0.51	-0.064	-0.024	-0.50	-0.059
Private equity	0.060	1.95	0.170	0.060	1.95	0.155
Foreign assets excluding equity	0.089	0.60	0.265	0.101	0.67	0.266
Net Worth decile						
No Net Worth	-1.025	-47.22	-2.861	-1.024	-46.78	-2.618
Lowest	-1.071	-32.77	-1.875	-1.070	-32.56	-1.717
2	-1.013	-36.57	-1.828	-1.012	-36.33	-1.674
3	-0.834	-34.30	-1.609	-0.833	-33.94	-1.473
4	-0.722	-24.28	-1.455	-0.722	-24.08	-1.333
5	-0.703	-25.04	-1.427	-0.702	-24.73	-1.307
6	-0.627	-24.97	-1.315	-0.628	-24.82	-1.205
7	-0.635	-21.92	-1.329	-0.634	-21.71	-1.217
8	-0.511	-18.78	-1.126	-0.510	-18.77	-1.032
9	-0.394	-15.63	-0.915	-0.394	-15.50	-0.838
Other demographics						
Swedish speaker	0.058	2.88	0.160	0.055	2.70	0.140
Married	-0.047	-2.56	-0.128	-0.047	-2.57	-0.117
Cohabitor	0.017	0.61	0.045	0.014	0.51	0.035
Kids	-0.083	-4.30	-0.228	-0.084	-4.36	-0.208
Occupation						
Entrepreneur	-0.045	-1.64	-0.120	-0.046	-1.70	-0.114
Farmer	-0.063	-0.96	-0.169	-0.065	-1.00	-0.159
Finance professional	0.213	6.55	0.650	0.216	6.63	0.602
Unemployed	0.020	0.65	0.057	0.019	0.62	0.049
Cohort Fixed Effects	Yes			Yes		
Baseline Number of Stocks			2.737			2.508
Wald-χ^2 (IQ1 = … = IQ8 = 0)	217.8					
N	37,901			37,901		