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Stock Market Is a Game of High-IQ Investors

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ABSTRACT
Stock market participation is monotonically related to 10 High-1Q investors are more likely to hold mutual funds and larger numbers of stocks, experience lower risk, and cam higher Sharpe ratios. We discuss implications for policy and finance research interpret that to mean, you need some intelligence to have the confidence to take some risk, but the smarter you are, the more you realize this game is played best at the standard CAPM level: low fees, high diversification. That is, I agree with the CAPM as a normative theory, just not a positive one, I'm just not so naive to extrapolate my very minority preferences and interpretations to 'all investors."

I think the IQ and stock market participation finding makes sense only in the context that the stock market exists in the context of many investments with similar 'risk'. Smarter people understand you can gain an equity premium... but only applying indices, or as an insider! Sure you can get big return otherwise especially as a middleman-but the basic risk return payoff here is decidedly contextual.
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Household ?nance, by analogy with corporate ?nance, asks how household's use ?nancialinstruments to attain their objectives. Household nancial problems have many special features that give the ?eld its character. Households must plan overlong but ?nit horizons, they have important no traded assets, notably their human Capital, they hold illiquid assets, notably housing, they face constraints on their ability to borrow, and they are subject to complex taxation Household asset demands are of Course important in asset pricing too, but wealthy and risk-tolerant households have disproportionate impact on equilibrium asset returns whereas household ?nance is more concerned with the behavior of typical households Research in ?nance, as in other parts of economics, can be positive or normative. Positive research describes what economic agents actually do, while nonnative research prescribes what they should do. Economists have often hoped that actual and ideal behavior coincides, or can be made tocoincide by the selection of inappropriately rich model of agents' beliefs and preferences. Revealed preference theory (Samuelson 1938), for example, shows how one can work backwards from household's choices over multiple consumption goods to the implied preferences of the household. The revealed preference agenda leaves no room for normative economics as distinct from positive economics Household ?nance poses a particular challenge to this agenda, because many households seek advice from ?nancial planners and other experts, and some households make decisions that are hard to reconcile with this advice or with any standard model. One response to this is to maintain the hope that actual and ideal behavior coincides, but to consider non-standard behavioral models of preferences incorporating phenomena such as loss aversion and mental accounting. An alternative response is to abandon the agenda of revealed preference, and to consider the possibility that households may not express their preferences optimally. On this view behavioral Nance theory describes the choices households currently make, but standard ?Nance theory describes the choices that maximize household welfare, and that households can be educated to make Lack of cognitive skill is so fundamental as a driver of nonparticipation that it deters large amounts of wealth from entering the stock market. As verification of the latter conclusion, we also study the influence of IQ on the participation decisions of affluent individuals. These individuals face direct costs of participation that are relatively small in comparison to its benefits. If these market-based frictions fully accounted for nonparticipation, we would not expect IQ to influence the participation of the affluent to any great extent. However, we find that IQ's role in the participation decisions of the affluent is about the same as it is for the less affluent. The definition of affluence-net worth or income-does not affect this finding. The quality of our data offers other unique benefits that prior empirical research has not been able to take advantage of. Analysis of sibling data facilitates the use of several powerful econometric techniques. From these techniques, 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. A proper instrumental variables analysis of brothers employing the control function method indicates that IQ measured from a brother's IQ exam plays a significant role in the subject's participation-decision. (The finding extends to sisters' participation.) Moreover, probity analysis of brothers using Chamberlain's (1980) random effects approach indicates that individual IQ differences, even within families, help to explain differences in participation IQ could influence participation if a subject's risk-return trade-off is positively related this IQ. Motivated by this conjecture, we document that IQ correlates with participants' Sharpe ratios, controlling for the usual suspects, and trace this correlation to IQ-related differences in diversification and systematic risk.7 High-IQ participants are more likely to hold mutual funds, larger numbers of stocks, and have lower-beta portfolios than lower-IQ participants. High-IQ investors also have greater exposure to the risks of small and value stocks. These results lend credence to the story that high-IQsubjects participate because they face a superior risk-return trade-off and that low-IQ subjects shun participation because they make investment mistakes

2. DATA

A. Data Sources

We merge five data sets for our analysis.

Finnish Central Securities Depository (FCSD) registry. The FCSD registry reports the daily portfolios and trades of all Finnish household investors from January 1, 1995 through November 29, 2002. The electronic records we use e exact duplicates of the official certificates of ownership and trades, and hence are very reliable. Details on this data set, which includes date stamped trades, holdings, and execution prices of registry-listed stocks on the Helsinki Exchanges, are reported in Grinblatt and Keloharju (2000). The data set excludes mutual funds and trades by Finnish investors in foreign stocks that are not listed on the Helsinki Exchanges, but would include trades on foreign exchanges of Finnish stocks, like Nokia, that are listed on the Helsinki Exchanges. For the Finnish investors in our sample, the latter trades are rare. The FCSD registry also contains investor birth years, which we use to control for age.

HEX stock data. The Helsinki Exchanges (HEX) provides daily closing transaction prices for all stocks traded on the HEX. The daily stock prices are combined with the FCSD data to measure Daily financial wealth and return regressors used to study behavior

Thomson Worldscope. The Thomson Worldscope files for Finnish securities provide Annually updated book equity values for all Finnish companies traded on the HEX. We employ these data together with the HEX stock data to compute book-to-market ratios for each day a HEX-listed stock trades from January 1, 1995 through November 29, 2002.

FAF intelligence score data. Around the time of induction into mandatory military duty in The Finnish Armed Forces (FAF), typically at age 19 or 20, and thus generally prior to significant Stock trading, males in Finland take a battery of psychological tests to assess which conscripts are Most suited for officer training. One portion consists of 120 questions that measure cognitive Functioning in three areas mathematical ability, verbal ability, and logical reasoning. We have test results for all exams scored between January 1, 1982 and December 31, 2001 the results from this test are aggregated into a composite ability score. The FAF composite intelligence score, which we refer to as "1Q," is standardized to follow the stanine distribution. The stanine distribution partitions the normal distribution into nine intervals. Thus, IQ is scored as integers 1 through 9 with stanine 9 containing the most intelligent subjects-those with test scores at least 1.75 standard deviations above the mean, or approximately 4% of the population. Grinblatt, Keloharju, and Linnainmaa (2010) note that a high composite score predicts successful life outcomes, more stock market participation, and better diversification.

All investors in the sample were born between 1953 and 1983. We lack older investors because the IQ data commence in 1982 with military entry required before turning 29 years old. We lack younger investors because the IQ data end in 2001 and one cannot enter the military before turning 17. The average age of our sample of investors at the middle of the sample period is about 29 years, corresponding to an IQ test taken about ten years earlier. This time lag between the military's test date and trading implies that any link between IQ test score and later equity trading arises from high IQ causing trading behavior, rather than the reverse.

B. Summary Statistic

Table 1 provides summary statistics on the data. We necessarily restrict the sample to those Trading at least once over the sample period. Panel A describes means, medians, standard deviations, and interquartile ranges for a number of investor characteristics. The sample contains both investors who enter the market for the first time and those who are wealthy and experienced at stock investing Thus, it is not surprising that trading activity varies considerably across investors, as indicated by Panel A's high standard deviation for the number of trades. The distribution of the number of trades is also positively skewed because a few investors execute a large number of trades. The turnover measure, calculated monthly as in Barber and Odean (2001), and then annualized, also reveals skewness and heterogeneity in turnover activity. Panel A also shows that the intelligence scores of the males in our sample exceed those from the overall male population. "5" is the expected stanine in a population. Our sample average of 5.75 and median of 6 is considerably higher, even more so in comparison to the unconditional sample average for all males of 4.8

Panel B, which provides further detail on the distribution of the FAF intelligence scores, Shows that the higher intelligence for our sample arises because stock market participation rates increase with IQ. The below-average IQ stanines, 1-4, which constitute 41% of the full sample but only 24% of our investor sample, are underrepresented. The IQ comparison between those who do and do not participate in the market is also important for practical purposes: because we have

Relatively few observations of investors with below-average intelligence, we group stanines I through 4 into one category in subsequent analyses. We later refer to these investors as the "below-average IQ" or "benchmark" group

Panel C describes means and medians for portfolio size and trading activity measures conditional on investors' intelligence scores. Here, the average and median portfolio value and number of trades show nearly monotonic patterns across the categories: high-IQ investors both have more financial wealth and trade more often. Despite a larger number of trades, high-IQ investors display, if anything, lower portfolio turnover. Panel D reports the average Scholes-Williams (1977) beta, book-to-market rank, and firm Size rank (on a rank scale measured as percentile/100) of the trades in our sample, sorted by IQ stanine. We compute a stock's beta, book-to-marketrank, and size rank for each trade. We estimate the Scholes-Williams betas using the same computation as the Center for Research in Securities Prices. The day t beta calculation uses one year of daily data from trading day t-291 to t-41. The beta estimate is replaced with a missing value code if there are fewer than 50 days of return data in the estimation window. Book value of equity is obtained from the end of the prior calendar year and the market value of equity is obtained as of the close of the prior trading day.

3. IQ AND TRADING BEHAVIOR

This section studies the relationship between IQ and trading behavior. We first extend Grinblatt and Keloharju's (2001) (henceforth GK) study of the factors motivating individuals' buys, holds, and sales. The analysis here differs from GK in that it adds interaction variables to capture IQ's marginal effect on potential trade-influencing regression coefficients. We also supplement GK's analysis with additional years of data and a family of new regressors that measure herding among IQ-partitioned Investors.

A. Participation Decisions of Affluent Individuals

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

B. Secondary Channels for IQ

IQ could drive many of these variables. Hence, there are secondary channels through which IQ may influence participation. For example, our data indicate that a high-IQ individual is more likely to be married, have a high income, be wealthy, and have children. He also is more likely to be in certain professions, like financial services. These secondary channels may lead to stock market investment. High-income subjects tend to save more; for them, a comfortable risk-free nest egg can coexist with stockholdings. Parent may hold risky assets to provide for a child's future. To assess IQ's influence on participation via secondary channels, Table 4 presents results from a decomposition developed in Blinder (1973), Oaxaca (1973), and Fairlie (1999, 2005).

4. IQ-RELATED PERFORMANCE

A. Intelligence and the Performance of Portfolio Holding

We restrict the sample to those who participate in the market for at least 252 trading days (about 1 year) during the nearly eight-year sample period. Thisrestriction, which does not materially change our results on IQ and performance, prevents the distribution from being unduly influenced by investors whose returns are driven by only a few days of realizations. For the period they are in the market, we first compute the average daily return of each investor's portfolio, and then annualize the daily return. The stanine 9-distribution function (except for the endpoints) is almost always below that of the stanine 1-4 investors. Hence, except for the returns in the extreme tails, which few investors of any 1Q carn, high-IQ investors have a larger probability of carning at least the same return realization or more than low-IQ investor

B. Intelligence and the Performance of Portfolio Holding

Green color indicates the IQ stanine with the highest entry rate across all stanines and red color is associated with the IQ stanine with the lowest entry rate. We focus on the technology sector because the rise and fall of this sector around year 2000 constituted such a significant shock to asset values. The solid line in the figure is the (log) of the 12-week average of the price index for HEX's technology sector

5. CONCLUSION

One's IQ stanine, measured early in adult life, is monotonically related to participation and diversification later in life. The high correlation between IQ and participation, which exists even among the 10% most affluent individuals, controls for wealth, income, age, and other demographic and occupational information. The economic size of the IQ effect is remarkably large: Controlling for each subject's observable characteristics, the participation rate for individuals in the lowest-IQ stanine is 20.5% lower than what it is for individuals at the other end of the IQ spectrum. IQ's effect on participation is monotonic, far larger than the effect of income on participation, and it generalizes to females. The importance of 120 questions from an IQ test taken years before one decides whether to participate is remarkable, indeed. Control function instrumentation of IQ with brothers' scores does not alter our conclusions about IQ and participation, suggesting that omitted variables bias does not account for the IQ-participation relationship at least for any omitted variable that is caused by own IQ Chamberlain (1980) random effects regressions for brother pairs also suggest that there is anown-IQ effect on participation that is separate from a family effect. Moreover, if the 1Qparticipationrelationship arises from an omitted variables bias (or related specification errors)

Our results on 1Q and trading behavior complement findings about diversification. For example, Grinblatt et al. (2010) observe that low-IQ individuals' portfolios often have fewer stocks, are less likely to include a mutual fund, and generate more diversifiable risk than higher-IQ investors' portfolios. Goetz Mann and Kumar (2008) find that under-diversification is more prevalent among "less-sophisticated" investors. Thus, in a number of dimensions, low-IQ investors engage in behaviors that appear to be "investment mistakes." Expanding the list of such mistakes would also be a worthy research pursuit

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